“Digital transformation and entrepreneurship: A comparative analysis of EU11 and selected EU15 economies”

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DIGITAL TRANSFORMATION AND ENTREPRENEURSHIP: A COMPARATIVE ANALYSIS OF EU11 AND SELECTED EU15 ECONOMIES

Abstract

This study examines the association between multidimensional digital transformation and national startup ecosystem performance across 23 European Union economies, comparing EU11 with 12 selected EU15 economies from 2017 to 2024. The balanced panel contains 184 country-year observations. Principal component analysis is used to construct three composite indicators: the Digital Services Index, Digital Connectivity Index, and Digital Human Capital Index. The indices demonstrate satisfactory factorial adequacy, internal consistency, and one-component structures supported by parallel analysis. Their associations with startup ecosystem performance are estimated using two-way fixed-effects models. Because the panel contains only 23 country clusters, the principal inference uses CR2 bias-reduced country-clustered standard errors with Satterthwaite-adjusted degrees of freedom. In the full-sample specification, DSI has a positive but only marginally significant association with startup ecosystem performance ($\beta = 0.0834$, $p = 0.082$), while DCI, DHCI, and e-government are statistically insignificant. R&D intensity has a negative contemporaneous coefficient that is also marginally significant ($\beta = -0.0145$, $p = 0.053$). Regional heterogeneity is jointly significant and is concentrated primarily in digital connectivity: DCI is negatively associated with startup ecosystem performance in the EU11 group, whereas its total slope is approximately zero in the selected EU15 group. DHCI has a positive total slope within the selected EU15 group, although the difference between the EU15 and EU11 slopes is not statistically significant. A one-year-lagged specification produces a positive but marginal DSI coefficient and does not identify statistically significant associations for the remaining predictors. These estimates should be interpreted as conditional associations rather than causal effects.

Keywords digital transformation, digital entrepreneurship, EU11, EU15, digital services, digital connectivity, digital human capital, startup ecosystems

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INTRODUCTION

Digital transformation has become a major driver of structural change in modern economies, influencing production processes, labor markets, public administration, and entrepreneurial ecosystems. Digital technologies reduce information and transaction costs, facilitate market access, support new business models, and improve interactions among firms, consumers, financial institutions, and public authorities. Within the European Union, these developments are closely linked to the Digital Decade 2030 agenda, which prioritizes digital skills, infrastructure, business digitalization, and digital public services (EC, 2023, 2024a, 2024b; UNCTAD, 2024). However, the entrepreneurial benefits of digitalization depend on complementary factors such as human capital, institutional quality, innovation systems, and broader economic conditions. Despite substantial progress, digital transformation remains uneven across Europe. Differences persist in digital skills, broadband infrastructure, e-government services, innovation capacity, and the adoption of advanced technologies. These disparities are particularly evident between post-socialist countries that joined the European Union after 2004 and member states that joined before 2004. In this study, these groups are defined as the EU11 economies and 12 selected EU15 economies, reflecting differences in economic transition, institutional development, and entrepreneurial and innovation systems.

Previous studies show that digitalization contributes to economic growth, productivity, innovation, and entrepreneurship in European economies (Borowiecki et al., 2021; Dabbous et al., 2023; Mura & Donath, 2023). Research on digital entrepreneurship demonstrates that digital technologies lower market-entry barriers, expand access to information and customers, and facilitate the creation of new firms and business models (Nambisan, 2017; Autio et al., 2018; Fossen & Sorgner, 2021). Other studies emphasize the importance of digital skills, infrastructure, human capital, and institutional quality in enabling firms and economies to benefit from digital transformation (Bruno et al., 2023; Duarte & de Oliveira Carvalho, 2024). However, several gaps remain. Many studies rely on aggregate digitalization indicators, making it difficult to distinguish the effects of digital services, connectivity, and digital human capital. In addition, entrepreneurship outcomes are often overlooked in favor of broader measures such as digital readiness, productivity, or economic growth. Comparative evidence on the EU11 and established EU economies also remains limited.

This study addresses these gaps by examining the relationship between digital transformation and entrepreneurial activity in 23 European Union economies during 2017–2024. Using principal component analysis, three composite indicators are constructed: the Digital Services Index, the Digital Connectivity Index, and the Digital Human Capital Index. The aggregate DESI measure is used only as a contextual benchmark and is not treated as an outcome variable because several of its components overlap with the indicators used to construct DSI, DCI, and DHCI. The study evaluates which dimensions of digital transformation are associated with national startup ecosystem performance, whether these associations differ between the EU11 and selected EU15 groups, and how institutional digitalization and research intensity relate to startup ecosystem performance. The study contributes to the literature by disaggregating digital transformation into its key dimensions, linking them to national startup ecosystem performance, and providing a comparative panel-data analysis of EU11 and selected EU15 economies while accounting for country heterogeneity and common cross-country dynamics. The findings offer evidence relevant to policies strengthening digital capabilities, institutional efficiency, and startup ecosystems.

1. LITERATURE REVIEW

Digital transformation refers not only to the adoption of individual technologies but also to broader changes in the organization of economic activity, firm interaction, market access, and institutional coordination. Within entrepreneurship research, digital technologies are viewed as mechanisms that alter how opportunities are identified, resources are mobilized, and new ventures are created and scaled. The issues of digitalization, human capital, and innovation activity are the subject of active debate in contemporary scholarship. Recent studies underscore that digital transformation constitutes a key driver of economic growth, innovation, and diversification, particularly in European contexts (European Investment Bank, 2023; EC, 2023; OECD, 2021). The development of the digital economy in Europe rests on EU strategic frameworks, including the "Digital Decade 2030" agenda and the methodology of the Digital Economy and Society Index (DESI). The latter is employed for cross-country benchmarking of digital progress and encompasses such dimensions as infrastructure, skills, and the integration of digital technologies (EC, 2023; Borowiecki et al., 2021). Empirical evidence suggests that DESI captures not only technological maturity but also countries' institutional capacity to adapt to digital challenges (Bruno et al., 2023).

Within the concept of digital entrepreneurship, digitalization is viewed as a process that transforms the entrepreneurial ecosystem (Kraus et al., 2023; Zhanbozova et al., 2024; Huseynov et

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al., 2025). Such a digital entrepreneurial ecosystem emerges through the diffusion of digital technologies (Startup Genome, 2025; Elia et al., 2020). Digital technologies lower market entry barriers and enable new forms of networked interaction (Autio et al., 2018; Nambisan, 2017), thereby strengthening the link between digitalization and the market entry of new firms (Fossen & Sorgner, 2021). The availability of digital skills and a well-developed stock of human capital enhances firms' innovative capacity, whereas skills deficits constrain the effective use of digital tools (Liu et al., 2025; Vasilescu et al., 2020). In EU member states, higher levels of digital transformation are associated with employment growth predominantly in knowledge-intensive sectors (Sobczak, 2025; Tiutiunyk et al., 2021). Digital transformation also catalyzes the emergence of new business models and the refinement of existing ones.

The association between digital skills and innovation outcomes has been corroborated by numerous empirical studies. Aleca and Mihai (2025) and Dabbous et al. (2023) show that investment in digital skills and STEM education exerts a positive effect on productivity and entrepreneurial activity. Zhang and Li (2023) document a robust relationship between infrastructure (e.g., broadband penetration and cloud adoption) and overall digital readiness. In the economics of innovation literature (Aghion & Howitt, 2009; Hall et al., 2010), the impact of R&D investment on innovative activity is found to materialize with a temporal lag. Short-run effects may be negative due to process inertia and the concentration of resources in large organizations, consistent with the "innovation lag" hypothesis (Romer, 1990). In shaping innovative business models, salient digitalization factors include e-commerce, CRM integration, and R&D investment (Silva et al., 2025). Digital transformation, in turn, facilitates the efficient allocation of innovation resources (Duarte & de Oliveira Carvalho, 2024). Empirical studies indicate that the development of e-government fosters entrepreneurship by reducing transaction costs and increasing transparency (Liu & Guo, 2025; L. Zhang & X. Zhang, 2025). In countries with less mature institutions, digital governance functions as a compensatory mechanism that accelerates firms' adaptation to digital practices (Gkika et al., 2025).

Research by the European Commission and the World Bank confirms a persistent digital divide between Western and Central-Eastern European countries (EC, 2022; World Bank, n.d.). Northern and Western Europe are characterized by higher levels of digital maturity and stronger R&D integration, while Eastern and Southern EU member states remain on a catch-up trajectory (Herman & Georgescu, 2025). These differences are predominantly structural – rooted in the quality of human capital and digital infrastructure rather than geography or income (Szerb et al., 2024; EC, 2025b). Taken together, the contemporary literature affirms that human capital, digital skills, and infrastructure are the principal drivers of digital transformation, while institutional and regional heterogeneity shapes its trajectories. Nonetheless, the relationships between component digitalization indices (DCI, DSI, and DHCI) and entrepreneurial activity (GStartup) in a panel setting – and the role of regional factors in conditioning these relationships – remain insufficiently explored. The present study addresses this gap by combining panel-data econometrics with a component-wise decomposition of digital indicators.

The reviewed literature establishes that digitalization is relevant to entrepreneurship, innovation, and economic performance. However, three limitations remain. First, many studies rely on an aggregate digitalization measure, making it difficult to distinguish the roles of business digital services, connectivity infrastructure, and digital human capital. Second, existing European research frequently focuses on economic growth, productivity, digital readiness, or sustainable competitiveness rather than directly examining national startup ecosystem performance. Third, comparative studies of EU11 and established EU economies often pay limited attention to the combined effects of digital capabilities, institutional digitalization, country heterogeneity, and common European dynamics. The present study addresses these limitations by constructing separate Digital Services, Digital Connectivity, and Digital Human Capital indices and examining their associations with startup ecosystem performance. The analysis also incorporates e-government development, R&D intensity, economic development, and an EU-group indicator.

The objective of this study is to examine the relationship between digital transformation and national startup ecosystem performance in 23 European Union economies during 2017–2024. The analysis focuses on digital services, connectivity, digital human capital, and e-government, while also comparing the EU11 and selected EU15 economies. Drawing on theoretical and empirical literature regarding the influence of digitalization, human capital, and institutional conditions on entrepreneurship and innovation, the study advances the following hypotheses:

H1: *A higher level of digital service adoption is positively associated with national startup ecosystem performance.*

H2: *A higher level of digital connectivity is positively associated with national startup ecosystem performance.*

H3: *A higher level of digital human capital is positively associated with national startup ecosystem performance.*

H4: *A higher level of e-government development is positively associated with national startup ecosystem performance.*

H5: *The strength of the associations between digital transformation and startup ecosystem performance differs between the EU11 and selected EU15 economies.*

2. METHOD

2.1. Country classification, data sources, and variable definitions

This study employs a quantitative comparative panel-data design to examine the association between digital transformation and national startup ecosystem performance. The unit of analysis is the country-year observation. The dataset covers 23 European Union economies over the period 2017–2024 and contains 184 observations, forming a balanced panel. The countries are classified into two institutionally and historically defined groups. The EU11 group includes Bulgaria, Croatia, Czechia, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, and Slovenia. The comparison group consists of 12 selected EU15 economies: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, the Netherlands, Portugal, Spain, and Sweden. This classification reflects differences in the timing of EU accession, post-socialist transition, and institutional development rather than a strictly geographical division. The EU11 economies constitute the reference group. The United Kingdom was excluded because the analysis is limited to EU member states operating within the common European digital-policy framework. Cyprus and Malta do not belong to either the EU11 or EU15 institutional groups, while Greece and Luxembourg were excluded because complete and comparable observations were unavailable for the full study period.

The empirical dataset was assembled by merging annual observations by country and calendar year. Before estimation, country identifiers were harmonized, duplicate country-year records were checked, and the measurement direction of each indicator was verified. Unless otherwise indicated, higher values represent stronger entrepreneurial, digital, institutional, or economic development. National startup ecosystem performance is the dependent variable. National startup ecosystem performance is measured using the composite country scores published in the annual StartupBlink Global Startup Ecosystem Index Reports for 2017–2024. The score captures the overall strength of a country's startup ecosystem, including the quantity and quality of startups and the broader business environment. The original score is used instead of the ordinal rank because differences between adjacent rank positions are not necessarily equal. In contrast, the score preserves information about the magnitude of cross-country differences. Because the startup ecosystem scores are positive and right-skewed, the variable is transformed using the natural logarithm:

$$Y_{it} = \ln\left(S_{it}\right), \quad (1)$$

where S_{it} is the original startup ecosystem score for country i in year t, and Y_{it} is its logarithmic transformation.

The indicators (Table 1) used to construct the Digital Services Index, Digital Connectivity Index, and Digital Human Capital Index were obtained

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from the European Commission's DESI and Digital Decade databases (European Commission, 2025a). The Digital Services Index represents firm-level adoption of digital technologies. The Digital Connectivity Index represents broadband and 5G development. The Digital Human Capital Index represents ICT-specialist capacity and population-level digital skills. E-government development is measured using the European Commission indicator of digital public services for businesses. Higher values indicate more advanced availability and delivery of digital public services. R&D intensity controls for national innovation capacity, while GDP per capita controls for economic development. GDP per capita is measured in purchasing-power-parity international dollars and transformed using the natural logarithm. The aggregate DESI measure is retained only as contextual descriptive information and is not used as an outcome variable. Several of its components overlap with the indicators used to construct DSI, DCI, and DHCI; using aggregate DESI as a dependent variable would therefore create a mechanical part-whole relationship. The European Commission revised the structure and presentation of DESI indicators during the study period, particularly following the integration of DESI reporting into the Digital Decade monitoring framework. Annual observations were collected from the relevant yearly editions, aligned by country and year, and combined into a harmonized panel. Although the substantive direction of the retained indicators remained consistent, changes in coverage, definitions, or reporting procedures may limit strict year-to-year comparability. Year fixed effects are included to absorb common temporal and methodological changes affecting all countries in a given year. Country fixed effects additionally control for persistent national differences. These procedures reduce, but do not eliminate, the influence of measurement discontinuities. No missing observations were interpolated or imputed.

2.2. Construction and validation of the digital indices

The three composite digital-transformation indices were constructed using principal component analysis. Before component extraction, all underlying indicators were standardized over the pooled country-year sample:

$$z_{kit} = \frac{x_{kit} - \overline{x}_k}{s_k}, \tag{2}$$

Table 1. Definitions, measurement, transformations, and sources of the analytical variables

Variable	Role	Definition	Unit or scale	Transformation	Source
GStartup	Dependent variable	Composite measure of a country's startup ecosystem performance	Original score	Natural logarithm	StartupBlink. Global Startup Ecosystem Index Report (annual editions 2017–2024)
DSI	Principal predictor	PCA-based index of enterprise adoption of digital technologies	PC1 score	Component indicators pooled-z-standardized	European Commission, DESI/ Digital Decade
DCI	Principal predictor	PCA-based index of broadband and 5G connectivity	PC1 score	Component indicators pooled-z-standardized	European Commission, DESI/ Digital Decade
DHCI	Principal predictor	PCA-based index of digital human capital and skills	PC1 score	Component indicators pooled-z-standardized	European Commission, DESI/ Digital Decade
EGOV*	Principal predictor	Digital public services for businesses	Index (0–100)	None	European Commission, DESI/ Digital Decade
R&D	Control	Exact national R&D expenditure indicator	Current international dollars	None	World Bank, World Development Indicators
GDPpc	Control	GDP per capita at purchasing power parity	Current international dollars	Natural logarithm	World Bank, World Development Indicators
EU15	Group indicator	1 for selected EU15 economies and 0 for EU11 economies	Binary	None	Authors' classification

Note: * The EGOV series was available for all 23 countries and all eight years, and no missing values were replaced or carried forward.

where x_{kit} is the value of indicator k for country i in year t, $\bar{x}_k$ is the pooled sample mean, and s_k is the pooled standard deviation.

PCA was conducted using the correlation matrix of the standardized indicators. The suitability and dimensional structure of each indicator set were evaluated through a comprehensive diagnostic procedure.

Overall sampling adequacy was assessed using the Kaiser–Meyer–Olkin statistic. Individual measures of sampling adequacy were also examined for each indicator. Bartlett's test of sphericity was used to test whether each correlation matrix differed significantly from an identity matrix. The number of components was determined primarily through parallel analysis, supplemented by the Kaiser eigenvalue criterion, the proportion of explained variance, theoretical coherence, and the interpretability of component loadings. Parallel analysis was conducted using 1,000 simulated and resampled datasets. We prioritized cases where a second empirical eigenvalue was close to the conventional threshold of one. For all three final indicator sets, only the first observed eigenvalue exceeded the corresponding simulated and resampled eigenvalues, supporting a one-component solution. PC1 component loadings were used to interpret the contribution of each indicator. Communality was calculated as the squared PC1 loading and represents the proportion of an indicator's variance explained by the retained component:

$$h_k^2 = \lambda_k^2, \tag{3}$$

where λ_k is the PC1 loading of indicator k. Uniqueness was calculated as:

$$u_k^2 = 1 - h_k^2. \tag{4}$$

PCA score coefficients (Table 2) were used to calculate the composite index scores, whereas component loadings were used for substantive interpretation. Internal consistency was assessed using standardized Cronbach's alpha and McDonald's omega. Standardized alpha-if-item-deleted statistics were also examined to determine whether removing an indicator materially improved reliability. Indicators were not excluded solely to maximize reliability coefficients when their individual MSA, PC1 loading, and theoretical contribution remained acceptable.

The initial DSI specification included seven indicators. The ICT-sustainability indicator was excluded because the preliminary diagnostics indicated weak sampling adequacy, weak representation by the first component, and reduced internal consis-

Table 2. Composition of the PCA-based digital indices

Index	Database variable	Indicator definition	Original unit	Final status
DSI	idt_ai	Enterprises using artificial intelligence technologies	% of enterprises	Retained
DSI	idt_bigdat	Enterprises analyzing big data	% of enterprises	Retained
DSI	idt_cloud	Enterprises using cloud-computing services	% of enterprises	Retained
DSI	idt_einv	Enterprises using electronic invoicing	% of enterprises	Retained
DSI	idt_eis	Enterprises using electronic information-sharing systems	% of enterprises	Retained
DSI	idt_socmed	Enterprises using social-media tools	% of enterprises	Retained
DSI	idt_ictsust	ICT sustainability and digitalization efforts	Index (0–100)	Excluded
DCI	c_mbb	Mobile broadband penetration rate	Subscriptions per 100 inhabitants	Retained
DCI	c_fbbtc	Fixed-broadband take-up	% of households	Retained
DCI	c_fbbc	Fixed-broadband coverage	Connections per 100 inhabitants	Retained
DCI	desi_5g1	5G readiness – spectrum assigned for 5G	% of total harmonized spectrum	Retained
DCI	desi_5g2	5G coverage – population covered by 5G networks	% of population	Retained
DCI	desi_5g3	5G performance – speed and quality of 5G network deployment	Index (0–100)	Retained
DCI	c_bbpi	Broadband-price indicator	Index (0–100)	Excluded
DHCI	hc_ict	ICT specialists	% of employed persons	Retained
DHCI	hc_bsu	Individuals with at least basic digital skills	% of individuals	Retained
DHCI	hc_asd	Advanced-digital-skills indicator	% of population	Retained

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tency. The final DSI therefore contains six indicators. The initial DCI specification also included seven indicators. The broadband-price indicator was removed because it showed weak correlations with the remaining indicators and an almost negligible contribution to the first component. The final DCI contains six indicators. DHCI retained all three original indicators because their MSA values, component loadings, communalities, and theoretical contributions were acceptable.

The final indices were calculated as weighted sums of standardized indicators:

$$Index_{it} = \sum_{k=1}^{K} w_k z_{kit}, \tag{5}$$

where w_k is the PCA score coefficient associated with the retained first principal component.

The final DSI score is:

$$\begin{aligned} DSI_{it} &= 0.450z(idt\_ai)_{it} \\ &+0.434z(idt\_bigdat)_{it} \\ &+0.474z(idt\_cloud)_{it} \\ &+0.280z(idt\_einv)_{it} \\ &+0.333z(idt\_eis)_{it} \\ &+0.442z(idt\_socmed)_{it}. \end{aligned} \tag{6}$$

The final DCI score is:

$$\begin{aligned} DCI_{it} &= 0.490z(c\_mbb)_{it} \\ &+0.281z(c\_fbbtc)_{it} \\ &+0.312z(c\_fbbc)_{it} \\ &+0.484z(desi\_5g1)_{it} \\ &+0.367z(desi\_5g2)_{it} \\ &+0.464z(desi\_5g3)_{it}. \end{aligned} \tag{7}$$

The final DHCI score is:

$$\begin{aligned} DHCI_{it} &= 0.609z(hc\_ict)_{it} \\ &+0.543z(hc\_bsu)_{it} + 0.577z(hc\_asd)_{it}. \end{aligned} \tag{8}$$

The orientation of each component was checked to ensure that higher scores consistently represented stronger digital development. Overall PCA diagnostics are reported in the Results section. Complete item-level diagnostics, including individual MSA values, PC1 loadings, communalities, uniqueness statistics, score coefficients, and alpha-if-item-deleted values, are reported in Appendix A, Table A1. Panel-model specification and diagnostic tests are reported in Appendix A, Table A2.

2.3. Econometric specification and statistical inference

The principal model examines the associations between digital transformation and national startup ecosystem performance:

$$\begin{aligned} Y_{it} &= \alpha_i + \lambda_t + \beta_1 DSI_{it} + \beta_2 DCI_{it} \\ &+\beta_3 DHCI_{it} + \beta_4 EGOV_{it} + \beta_5 RD_{it} \\ &+\beta_6 \ln GDPpc_{it} + \varepsilon_{it}, \end{aligned} \tag{9}$$

where α_i denotes country fixed effects, λ_t denotes year fixed effects, and ε_{it} is the idiosyncratic error term.

Country fixed effects control for time-invariant national characteristics, including historical, institutional, cultural, and structural differences. Year fixed effects capture common European macroeconomic shocks, policy changes, technological developments, and common changes in indicator methodology. The coefficients of DSI, DCI, DHCI, and EGOV are used to evaluate *H1–H4*. A hypothesis is considered supported when the relevant coefficient has the predicted positive sign and is statistically significant at the 5% level in the preferred CR2 specification. Results with $0.05 \le p < 0.10$ are treated as marginal evidence and do not constitute full hypothesis support.

To test whether the digital-transformation associations differ between the EU11 and selected EU15 economies, the baseline model is extended with interaction terms:

$$\begin{aligned} Y_{it} &= \alpha_i + \lambda_t + \sum_{k=1}^{3} \beta_k D_{kit} \\ &+\sum_{k=1}^{3} \delta_k (D_{kit} \cdot EU15_i) + X_{it}^{'}\theta + \varepsilon_{it}, \end{aligned} \tag{10}$$

where D_{kit} denotes DSI, DCI, and DHCI, and X_{it} contains EGOV, R&D, and log GDP per capita.

The variable $EU15_i$ equals one for the selected EU15 economies and zero for the EU11 economies. Because EU11 is the reference group, β_k represents the slope for EU11. The total slope for the selected EU15 economies is:

$$\beta_k^{EU15} = \beta_k + \delta_k. \tag{11}$$

The time-invariant EU15 indicator is not entered separately because it is absorbed by the country fixed effects. The total *EU*15 slopes are estimated as formal linear combinations. Their CR2 standard errors, Satterthwaite-adjusted degrees of freedom, *p*-values, and 95% confidence intervals are calculated using the covariance matrix of the interaction model.

Regional heterogeneity is evaluated through the joint null hypothesis:

$$H_0 : \delta_1 = \delta_2 = \delta_3 = 0. \tag{12}$$

Rejection of this null indicates that at least one digital-transformation slope differs between the two country groups. A coefficient being statistically significant in one group but insignificant in another is not interpreted as evidence of a group difference unless the corresponding interaction or formal equality test is significant. No directional hypothesis is imposed on R&D or GDP per capita. In particular, a negative contemporaneous R&D coefficient is not interpreted as evidence of a negative causal effect, a positive long-run effect, or an innovation-lag mechanism.

The hypothesis-testing and empirical identification framework, including the corresponding coefficients, restrictions, expected directions, and decision criteria, is summarized in Table 3.

Pooled OLS, fixed-effects, and random-effects models were initially estimated for specification comparison. The joint *F*-test was used to assess whether country fixed effects were required. The Breusch–Pagan Lagrange Multiplier test evaluated whether a panel specification was preferable to pooled OLS. The Hausman test was used as supplementary evidence when comparing fixed and random effects. The Hausman test was not treated as the sole model-selection criterion because it does not assess serial correlation, heteroskedasticity, or cross-sectional dependence. The fixed-effects specification was retained as the principal model because the analysis focuses on within-country changes and because unobserved country characteristics may be correlated with both digital development and startup ecosystem performance. Cross-sectional dependence was assessed using the Pesaran CD test. Serial correlation was evaluated using the Wooldridge and Breusch–Godfrey/Wooldridge procedures. Heteroskedasticity was examined using the Breusch–Pagan test. Pairwise correlations and variance inflation factors were used to assess multicollinearity. Because the panel contains only 23 country clusters, conventional cluster-robust standard errors may produce downward-biased standard errors, overly narrow confidence intervals, and over-rejection of null hypotheses. The preferred inference therefore uses CR2 bias-reduced country-clustered standard errors with Satterthwaite-adjusted degrees of freedom.

For the principal and interaction models, the following are reported:

Table 3. Hypothesis-testing and empirical identification framework

Hypothesis or analysis	Tested coefficient or restriction	Expected direction	Principal decision criterion
H1: Digital-service adoption	βDSI	Positive	(p < 0.05) under CR2 inference
H2: Digital connectivity	βDCI	Positive	(p < 0.05) under CR2 inference
H3: Digital human capital	βDHCI	Positive	(p < 0.05) under CR2 inference
H4: E-government	βEGOV	Positive	(p < 0.05) under CR2 inference
H5: Regional heterogeneity	δDSI = δDCI = δDHCI = 0	Not predetermined	CR2–HTZ joint test, (p < 0.05)
EU15 group-specific slopes	Bk +δk	Not predetermined	CR2 linear contrast and 95% CI
Temporal robustness	βk,t–1	Sign consistent with baseline	Comparison with one-year-lagged CR2 model
R&D and GDP per capita	βRD, βGDPpc	Not predetermined	Reported as controls; no causal interpretation

Note: Results with 0.05 ≤ p < 0.10 are classified as marginal evidence.

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1) coefficient estimates;
2) CR2 standard errors;
3) coefficient-specific Satterthwaite degrees of freedom;
4) two-sided p-values;
5) 95% confidence intervals.

The joint significance of the three regional interaction terms is assessed using a CR2-adjusted approximate Hotelling T_z^2 Wald test. Conventional country-clustered results are retained only for comparison and are not used for the final hypothesis decisions. Driscoll–Kraay standard errors are reported only as supplementary sensitivity evidence. They are not used as the main inference procedure because the time dimension contains only eight annual periods. An exploratory Common Correlated Effects model was considered but became excessively saturated because of the short time dimension and the number of regressors and cross-sectional averages. It is therefore not used in the final hypothesis assessment. All analyses were conducted in R. PCA and reliability diagnostics were implemented using the stats and psych packages. Fixed-effects models were estimated using fixest, while CR2 standard errors, Satterthwaite-adjusted tests, linear contrasts, and the Hotelling-type joint test were calculated using clubSandwich.

2.4. Endogeneity and robustness strategy

The observational panel design does not permit definitive causal identification. Country fixed effects reduce bias caused by time-invariant cross-country heterogeneity, while year fixed effects absorb common European shocks and common temporal changes. However, these controls do not eliminate reverse causality, simultaneity, or omitted time-varying factors.

To mitigate temporal-endogeneity concerns and establish temporal ordering, an additional specification replaces all contemporaneous explanatory variables with their one-year lags:

$$\begin{aligned}Y_{it} &= \alpha_i + \lambda_t + \beta_1 DSI_{i,t-1} + \beta_2 DCI_{i,t-1} \\ &+ \beta_3 DHCI_{i,t-1} + \beta_4 EGOV_{i,t-1} + \beta_5 RD_{i,t-1} \\ &+ \beta_6 \ln GDPpc_{i,t-1} + \varepsilon_{it}.\end{aligned} \tag{13}$$

The lagged model retains country and year fixed effects and uses CR2 country-clustered standard errors with Satterthwaite-adjusted degrees of freedom. Because one annual observation is lost for each country, the lagged specification is estimated using 161 country-year observations covering 23 countries and seven effective annual periods. The lagged specification relates explanatory variables measured at $(t-1)$ to startup ecosystem performance measured at t. This establishes temporal ordering and reduces immediate simultaneity concerns. It does not, however, constitute an instrumental-variable strategy and cannot eliminate reverse causality or omitted-variable bias.

Robustness is evaluated by comparing:

1) the restricted specification containing the three digital indices;
2) the fully controlled two-way fixed-effects specification;
3) the EU11–EU15 interaction model;
4) conventional country-clustered inference;
5) CR2 small-cluster-corrected inference;
6) formal EU15 linear combinations;
7) the joint CR2–HTZ interaction test;
8) the one-year-lagged specification;
9) supplementary Driscoll–Kraay estimates.

The final conclusions are based primarily on the fully controlled two-way fixed-effects model with CR2 inference, the group-specific linear combinations, the joint CR2 interaction test, and the one-year-lagged specification. All estimates are interpreted as conditional associations rather than causal effects.

3. RESULTS

3.1. Descriptive statistics and preliminary diagnostics

The final balanced panel contains 184 country-year observations for 23 European Union economies over the period 2017–2024. Of these observations, 88 belong to the EU11 group and 96 to the 12 selected EU15 economies.

The contextual descriptive evidence indicates a substantial difference in startup ecosystem de-

Table 4. Descriptive statistics of the analytical variables

Variable	N	Mean	SD	Median	Minimum	Maximum
Log startup ecosystem score (**GStartup_log**)	184	2.04	0.61	1.88	0.59	3.56
Digital Services Index (DSI)	184	0.00	1.81	−0.18	−3.05	6.39
Digital Connectivity Index (DCI)	184	0.00	1.93	−0.71	−2.37	5.45
Digital Human Capital Index (DHCI)	184	0.00	1.55	−0.21	−2.67	4.38
E-government (**egov_le**)	184	82.82	11.71	82.86	42.27	100.00
R&D intensity (**RD**)	184	37.61	6.25	37.89	18.00	51.96
Log GDP per capita (**ln_GDPpc**)	184	10.79	0.32	10.77	10.01	11.82

Note: DSI, DCI, and DHCI are first-principal-component scores constructed from pooled standardized indicators. Their means are approximately zero by construction. GStartup_log and ln_GDPpc are natural-logarithmic transformations.

velopment between the two groups. The selected EU15 economies had an average startup ecosystem score of 12.40, compared with 6.17 in the EU11 group. Their mean startup-ranking position was also stronger, at 16.23 compared with 37.72 for EU11, where a lower rank represents a better position. The corresponding aggregate DESI means were 52.34 and 39.68. These differences provide descriptive evidence of intergroup heterogeneity but do not establish the independent contribution of particular digital dimensions.

Table 4 reports the descriptive statistics for the variables used in the econometric analysis. Because the three PCA indices were constructed from pooled standardized indicators, their sample means are approximately zero.

3.2. Validation of the PCA-based digital indices

The suitability of the final indicator sets for PCA was evaluated using the Kaiser–Meyer–Olkin measure and Bartlett's test of sphericity. The overall KMO statistics were 0.768 for DSI, 0.802 for DCI, and 0.667 for DHCI. All individual measures of sampling adequacy exceeded 0.60, with item-level MSA values ranging from 0.659 to 0.856 for DSI, from 0.699 to 0.854 for DCI, and from 0.610 to 0.770 for DHCI. Bartlett's tests rejected the null hypothesis that the respective correlation matrices were identity matrices. The results were statistically significant for DSI, $\chi^2(15) = 456.970$, $p < 0.001$; DCI, $\chi^2(15) = 856.901$, $p < 0.001$; and DHCI, $\chi^2(3) = 317.714$, $p < 0.001$. Thus, the retained indicators contained sufficient shared correlation for component extraction. Parallel analysis based on 1,000 iterations recommended one component for each final indicator set. For DSI and DCI, the second empirical eigenvalues were close to the Kaiser threshold of one, at 1.052 and 1.001, respectively. However, both remained below the corresponding simulated and resampled eigenvalues. Only the first empirical component was retained for each index. The same one-component pattern was obtained for DHCI.

The first component explained 54.65% of the total variance in DSI, 62.17% in DCI, and 79.84% in DHCI. All retained indicators had positive PC1 loadings exceeding 0.50. DSI loadings ranged from 0.508 for electronic invoicing to 0.858 for cloud-technology adoption. DCI loadings ranged from 0.543 for fixed-broadband take-up to 0.946 for mobile broadband. DHCI loadings were uniformly strong, ranging from 0.841 to 0.943.

Internal-consistency estimates were also satisfactory. Standardized Cronbach's alpha equaled 0.825 for DSI, 0.867 for DCI, and 0.873 for DHCI. McDonald's omega values were 0.834, 0.882, and 0.882, respectively. The overall PCA and reliability diagnostics are summarized in Table 5.

Table 5. Overall PCA and reliability diagnostics

Index	Items	Overall KMO	Bartlett (\chi²)	Df	p-value	PC1 eigenvalue	PC1 variance	Standardized (\alpha)	McDonald's (\omega)
DSI	6	0.768	456.970	15	< 0.001	3.279	54.65%	0.825	0.834
DCI	6	0.802	856.901	15	< 0.001	3.730	62.17%	0.867	0.882
DHCI	3	0.667	317.714	3	< 0.001	2.395	79.84%	0.873	0.882

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The complete item-level results, including individual MSA values, loadings, communalities, uniqueness values, score coefficients, and alpha-if-item-deleted diagnostics, are reported in Appendix A, Table A1. These results show that some indicators, particularly electronic invoicing and fixed-broadband take-up, had lower communalities than the other retained variables. Nevertheless, their loadings and MSA values remained acceptable, and their retention preserved the conceptual breadth of the indices.

3.3. Baseline two-way fixed-effects results

The preferred baseline specification includes country and year fixed effects and controls for e-government, R&D intensity, and log GDP per capita (Table 6). Because the analysis contains only 23 country clusters, the principal statistical inference is based on CR2 bias-reduced country-clustered standard errors and Satterthwaite-adjusted degrees of freedom. The DSI coefficient was positive, with an estimate of 0.0834. Under conventional country-clustered inference, this coefficient was significant at the 5% level. However, after applying the CR2 small-cluster correction, its standard error increased to 0.0414 and the p-value increased to 0.082. The 95% confidence interval, from −0.0136 to 0.1804, included zero. The DSI result therefore represents marginal positive evidence at the 10% level but does not satisfy the study's prespecified 5% criterion for supporting H1. DCI and DHCI also had positive coefficients, but neither was statistically significant. The DCI estimate was 0.0285 ($p = 0.440$), while the DHCI estimate was 0.1049 ($p = 0.194$). The corresponding confidence intervals included zero. E-government had a small positive coefficient of 0.0035 but was statistically insignificant ($p = 0.645$). Accordingly, the preferred baseline model does not provide evidence of an independent association between e-government development and startup ecosystem performance. R&D intensity had a negative coefficient of −0.0145. The CR2-adjusted p-value was 0.053, and the 95% confidence interval was [−0.0295, 0.0004]. This result is marginal at the 10% level but is not statistically significant at 5%. Log GDP per capita was also statistically insignificant.

Standard errors are clustered by country using the CR2 bias-reduced correction. P-values and confidence intervals use coefficient-specific Satterthwaite-adjusted degrees of freedom. The change from conventional clustered inference to CR2 inference materially affected the interpretation of the results. In particular, DSI changed from significant at 5% to marginal at 10%, while the strong conventional significance of R&D was reduced to a marginal result. This confirms the importance of correcting for the limited number of country clusters.

3.4. Regional heterogeneity between EU11 and selected EU15 economies

The interaction model examines whether the DSI, DCI, and DHCI slopes differ between the EU11 and selected EU15 groups (Table 7). EU11 is the reference category. Therefore, the main digital-index coefficients represent the EU11 slopes, while the interaction coefficients represent differences between the selected EU15 and EU11 slopes. For EU11, DSI had a positive but statistically insignificant slope of 0.0656 ($p = 0.422$). DCI had a nega-

Table 6. Baseline two-way fixed-effects model with CR2 inference

Variable	Estimate	CR2 SE	Satterthwaite df	p-value	Lower 95% CI	Upper 95% CI
DSI	0.0834	0.0414	7.35	0.082	−0.0136	0.1804
DCI	0.0285	0.0354	10.69	0.440	−0.0498	0.1067
DHCI	0.1049	0.0772	15.07	0.194	−0.0595	0.2693
E-government	0.0035	0.0072	5.03	0.645	−0.0149	0.0219
R&D intensity	−0.0145	0.0037	2.17	0.053	−0.0295	0.0004
Log GDP per capita	−0.7337	0.6170	10.65	0.260	−2.0971	0.6298
Country fixed effects	Yes	Within (R^2)	0.314	Adjusted (R^2)	0.923	–
Year fixed effects	Yes	RMSE	0.153	–	–	–
Observations	184	Countries	23	–	–	–

Note: The dependent variable is the natural logarithm of the national startup ecosystem score.

tive and statistically significant slope of −0.1509 (p = 0.0145), with a 95% confidence interval of [−0.2652, −0.0366]. DHCI had a positive but insignificant EU11 slope of 0.0586 (p = 0.523).

The DCI × EU15 interaction was positive and statistically significant. Its estimate was 0.1600, with a CR2 standard error of 0.0451 and p = 0.0038. This indicates that the DCI slope was significantly higher in the selected EU15 economies than in EU11. In contrast, the DSI × EU15 and DHCI × EU15 interactions were statistically insignificant. The total slopes for selected EU15 were calculated as formal linear combinations of the EU11 coefficient and the relevant interaction. The selected EU15 DSI slope was 0.0307 and was not statistically significant (p = 0.272). The total DCI slope was 0.0092 and was also insignificant (p = 0.690). Thus, while DCI was negatively associated with startup ecosystem performance in EU11, its estimated slope was approximately zero in selected EU15. The selected EU15 DHCI slope was positive and statistically significant, at 0.1069 (p = 0.0368, 95% CI [0.0080, 0.2059]). However, the DHCI × EU15 interaction itself was insignificant. Consequently, DHCI showed a significant positive within-group slope in selected EU15, but the difference between the EU15 and EU11 DHCI slopes was not statistically established.

The three interaction terms were also tested jointly (Table 8). The CR2-adjusted approximate Hotelling T_z^2 test rejected the joint null hypothesis that all three interaction coefficients were equal to zero: $F_{HTZ}(3, 8.41) = 5.01$, $p = 0.0285$.

The joint test provides evidence that the set of digital slopes differs between the two groups. Nevertheless, the coefficient-specific results show that this heterogeneity is concentrated primarily in DCI. The differences in the DSI and DHCI slopes were not statistically significant.

The interaction model also had stronger within-sample fit than the baseline specification. Its within R^2 increased from 0.314 to 0.535, while RMSE declined from 0.153 to 0.126. This indicates that allowing the digital slopes to differ between the two groups captures additional within-country variation. It does not, however, establish that the interaction model has superior causal validity.

3.5. One-year-lagged specification

A one-year-lagged model was estimated to strengthen temporal ordering and reduce immediate simultaneity concerns (Table 9). Because the first observation for each country was lost after lagging, this specification contains 161 observations for 23 countries over seven effective annual periods. Lagged DSI retained a positive coefficient of 0.1171. Under CR2 inference, its p-value was 0.0817 and its confidence interval included zero. The result is therefore marginal at the 10% level, closely matching the conclusion from the contemporaneous baseline

Table 7. Group-specific digital slopes and EU11–EU15 differences

Index	DSI	DCI	DHCI
EU11 slope	0.0656	−0.1509	0.0586
CR2 SE	0.0755	0.0517	0.0880
EU11 p-value	0.422	0.0145	0.523
EU11 95% CI	[−0.1246, 0.2558]	[−0.2652, −0.0366]	[−0.1426, 0.2598]
Selected EU15 slope	0.0307	0.0092	0.1069
CR2 SE	0.0248	0.0222	0.0442
EU15 p-value	0.272	0.690	0.0368
EU15 95% CI	[−0.0338, 0.0952]	[−0.0407, 0.0590]	[0.0080, 0.2059]
EU15–EU11 difference	−0.0349	0.1600	0.0483
Difference p-value	0.674	0.0038	0.626

Note: EU11 is the reference group. Selected EU15 slopes are calculated as (βk + δk). All tests and confidence intervals use CR2 country-clustered inference with Satterthwaite-adjusted degrees of freedom.

Table 8. Joint CR2 test of the regional interaction terms

Joint null hypothesis	Test	F-statistic	Numerator df	Denominator df	p-value
DSI × EU15 = DCI × EU15 = DHCI × EU15 = 0	CR2–HTZ	5.01	3	8.41	0.0285

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Table 9. Contemporaneous and one-year-lagged estimates with CR2 inference

Variable	Contemporaneous estimate	Contemporaneous p-value	Lagged estimate	Lagged CR2 SE	Lagged df	Lagged p-value	Lagged 95% CI
DSI	0.0834	0.082	0.1171	0.0593	8.47	0.0817	[−0.0183, 0.2526]
DCI	0.0285	0.440	0.0266	0.0374	10.97	0.492	[−0.0557, 0.1088]
DHCI	0.1049	0.194	0.0486	0.1070	15.99	0.656	[−0.1782, 0.2754]
E-government	0.0035	0.645	0.0042	0.0066	4.89	0.554	[−0.0129, 0.0213]
R&D intensity	−0.0145	0.053	−0.0230	0.0145	12.72	0.138	[−0.0544, 0.0085]
Log GDP per capita	−0.7337	0.260	−0.8714	0.8868	12.73	0.344	[−2.7913, 1.0485]
Observations	184	–	161	–	–	–	–
Countries	23	–	23	–	–	–	–
Effective periods	8	–	7	–	–	–	–
Country fixed effects	Yes	–	Yes	–	–	–	–
Year fixed effects	Yes	–	Yes	–	–	–	–
Within (R^2)	0.314	–	0.324	–	–	–	–
Adjusted (R^2)	0.923	–	0.922	–	–	–	–
RMSE	0.153	–	0.156	–	–	–	–

Note: The lagged model relates explanatory variables measured at (t – 1) to startup ecosystem performance measured at t. Both specifications use CR2 standard errors and Satterthwaite-adjusted inference.

model. Lagged DCI and DHCI were positive but statistically insignificant. Lagged e-government was also insignificant. Lagged R&D retained a negative coefficient, but its *p*-value increased to 0.138. Consequently, the negative contemporaneous R&D result was not robust to temporal lagging. Lagged GDP per capita was also statistically insignificant.

The consistency of the positive DSI sign across the contemporaneous and lagged models provides limited evidence of temporal robustness. However, neither estimate reaches statistical significance at the 5% level. The lagged specification improves temporal ordering but does not eliminate reverse causality or omitted time-varying factors.

3.6. Summary of hypothesis testing

Hypothesis decisions (Table 10) were based on the preferred two-way fixed-effects models with CR2 inference and a 5% significance threshold. Results significant only at 10% were classified as marginal evidence rather than full hypothesis support.

Taken together, the preferred results do not identify a digital predictor that is statistically significant

Table 10. Summary of hypothesis testing

Hypothesis	Main empirical evidence	Decision
H1. DSI is positively associated with startup ecosystem performance	Baseline β = 0.0834, (p = 0.082); lagged β = 0.1171, (p = 0.0817)	Not supported at 5%; marginal positive evidence
H2. DCI is positively associated with startup ecosystem performance	Baseline (p = 0.440); negative EU11 slope and approximately zero EU15 slope	Not supported
H3. DHCI is positively associated with startup ecosystem performance	Baseline (p = 0.194); positive significant slope within EU15, but insignificant DHCI interaction	Not supported in the full sample; group-specific evidence for selected EU15
H4. E-government is positively associated with startup ecosystem performance	Baseline (p = 0.645); lagged (p = 0.554)	Not supported
H5. Digital-transformation relationships differ between EU11 and selected EU15	Joint CR2–HTZ (p = 0.0285); significant DCI interaction; insignificant DSI and DHCI interactions	Partially supported
R&D control result	Baseline (p = 0.053); lagged (p = 0.138)	Marginal contemporaneous evidence; not temporally robust

at the 5% level in the full-sample baseline model. DSI provides consistent but only marginal positive evidence in the contemporaneous and one-year-lagged specifications. The strongest comparative finding concerns DCI, whose estimated slope differs significantly between EU11 and selected EU15. DHCI has a positive significant slope within selected EU15, but the formal difference between the two regional slopes is not significant. E-government does not show an independent association, while the negative contemporaneous R&D estimate is not robust to lagging.

The findings therefore support an interpretation of heterogeneous conditional associations rather than uniform or causal effects of digital transformation on startup ecosystem performance.

4. DISCUSSION

This study examined how different dimensions of digital transformation relate to national startup ecosystem performance and whether these relationships differ between the EU11 and selected EU15 economies. The findings indicate that digital transformation is not a uniform construct. Business adoption of digital technologies shows the most stable positive association with startup ecosystem performance, whereas digital connectivity, digital human capital, and e-government are statistically insignificant in the full-sample baseline model. Regional heterogeneity is concentrated primarily in digital connectivity.

The DSI coefficient was positive in both the contemporaneous and one-year-lagged specifications. However, under the preferred CR2 small-cluster-corrected inference, both results were only marginally significant: the baseline estimate was 0.0834 ($p = 0.082$), and the lagged estimate was 0.1171 ($p = 0.0817$). H1 was therefore not supported at the prespecified 5% level, although the stable positive sign provides limited evidence that the practical use of digital technologies may be associated with stronger startup ecosystem performance. DSI includes artificial intelligence, big data analytics, cloud computing, electronic invoicing, electronic information-sharing systems, and social media tools. These technologies may reduce coordination and transaction costs, improve access to information and markets, and support scalable business models (Nambisan, 2017; Autio et al., 2018; Dabbous et al., 2023). Nevertheless, the confidence intervals include zero, and the estimates do not establish a causal effect.

No statistically significant difference was found between the EU11 and selected EU15 DSI slopes. Digital connectivity was also insignificant in the full-sample model, and H2 was not supported. However, DCI had a significantly negative slope in EU11 and an approximately zero slope in selected EU15, while the difference between the groups was statistically significant. The joint CR2–HTZ test also confirmed regional heterogeneity across the interaction terms. This finding should not be interpreted as evidence that connectivity harms entrepreneurship. It may instead indicate that infrastructure does not automatically generate entrepreneurial outcomes without complementary firm adoption, financing, managerial capacity, digital skills, and institutional support. This interpretation is consistent with evidence that Central and Eastern European digital entrepreneurial ecosystems differ in their capacity to convert digital resources into entrepreneurial performance (Szerb et al., 2024).

DHCI was positive but statistically insignificant in the full-sample model, and *H3* was rejected. Its total slope was nevertheless positive and significant within the selected EU15 group. This may suggest that digital skills and ICT-specialist capacity are more readily connected to entrepreneurship where mature innovation, financing, and business-support institutions are present. However, the DHCI × EU15 interaction was insignificant. The study therefore identifies a positive association within selected EU15 but does not establish that the DHCI relationship differs statistically between the two country groups. The relatively strong correlation between DSI and DHCI may also indicate complementarity between digital skills and firms' practical adoption of technologies, although no mediation or complementarity mechanism was formally tested.

E-government did not show a statistically significant independent association with startup ecosystem performance in the baseline model of 184 observations. *H4* was therefore not supported. This

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result does not imply that digital public services are irrelevant to entrepreneurship. Their potential contribution may occur through reduced administrative burdens, greater transparency, service interoperability, and actual business use, which may not be fully captured by an aggregate national indicator (Ha, 2024).

R&D intensity had a negative contemporaneous coefficient, but the result was only marginally significant under CR2 inference ($p = 0.053$). Moreover, the one-year-lagged R&D coefficient was statistically insignificant. The relationship was therefore not temporally robust and should not be interpreted as evidence that R&D expenditure reduces entrepreneurship. Endogenous growth theory associates research investment with technological change and long-term innovation, but these effects may require time and effective commercialization institutions (Romer, 1990; Aghion & Howitt, 2009; Hall et al., 2010). The present analysis does not directly measure technology transfer, patents, university spin-offs, venture financing, or commercialization and therefore cannot confirm an innovation-lag or commercialization-gap mechanism.

The comparison between conventional country-clustered and CR2 inference is methodologically important. Conventional clustered standard errors suggested stronger significance for DSI and R&D, whereas the CR2 correction with Satterthwaite-adjusted degrees of freedom produced more conservative conclusions. With only 23 country clusters, the CR2 results provide a more appropriate basis for hypothesis assessment. The one-year-lagged model strengthens temporal ordering but does not eliminate reverse causality or omitted time-varying factors.

Overall, the findings show that digital transformation dimensions are not interchangeable. Business digital adoption provides limited positive evidence, connectivity displays substantial regional heterogeneity, and digital human capital is positively associated with startup ecosystem performance only within the selected EU15 group. Policy strategies may therefore consider combining infrastructure investment with support for firm-level technology adoption, digital skills, startup finance, managerial capabilities, and technology-transfer mechanisms. However, because the analysis is observational, these implications should be understood as areas for policy evaluation rather than evidence of the causal effectiveness of particular interventions. Future research should employ longer panels, more granular firm- or regional-level data, and stronger identification strategies.

CONCLUSION

This study examined the associations between multidimensional digital transformation and national startup ecosystem performance in 23 European Union economies over the period 2017–2024.

The results do not support the conclusion that all dimensions of digital transformation are uniformly associated with stronger startup ecosystems. DSI produced the most consistent positive pattern, but its contemporaneous and lagged coefficients were only marginally significant under CR2 inference. H1 was therefore not supported at the prespecified 5% level, although the results provide limited evidence that firms' practical adoption of artificial intelligence, cloud services, data analytics, electronic business systems, and related technologies may be associated with startup ecosystem performance.

DCI, DHCI, and e-government were statistically insignificant in the full-sample baseline model. Accordingly, *H2–H4* were not supported. Nevertheless, the regional analysis revealed important heterogeneity. DCI had a negative conditional association in the EU11 group and an approximately zero total slope in the selected EU15 economies. The difference between these slopes was statistically significant, and the three interaction terms were jointly significant under the CR2-adjusted HTZ test. *H5* was therefore partially supported, with regional heterogeneity concentrated primarily in connectivity. DHCI had a positive and statistically significant total slope within the selected EU15 group. However, the DHCI interaction was insignificant, meaning that the analysis did not establish a statistically significant difference between the selected EU15 and EU11 slopes. This distinction demonstrates the importance of reporting complete group-specific linear combinations rather than inferring regional differences from significance within only one group. R&D intensity showed a negative contemporaneous coefficient that was marginally significant under CR2 inference, but the corresponding lagged coefficient was insignificant. The result is therefore not temporally robust and should not be interpreted as evidence that R&D expenditure reduces entrepreneurial performance or as confirmation of an innovation-lag mechanism. Similarly, the absence of a significant e-government coefficient does not demonstrate that digital public services are irrelevant, because their contribution may depend on service quality, business use, institutional conditions, and indirect transmission mechanisms not captured by the model.

The findings have two broader implications. First, business adoption, digital infrastructure, and human capital should not be treated as interchangeable dimensions of digital transformation. Second, connectivity alone may be insufficient to generate entrepreneurial outcomes without complementary firm capabilities, skilled labor, financing, managerial capacity, and commercialization institutions. Policymakers may therefore consider evaluating integrated digital strategies that connect infrastructure development with business adoption, digital skills, startup finance, and technology-transfer support. These implications identify areas for further policy evaluation rather than demonstrating the causal effectiveness of particular interventions.

The study is limited by its short time dimension, small number of country clusters, reliance on national aggregate indicators, possible changes in digital-indicator definitions over time, and the persistence of reverse causality and omitted time-varying factors. Although fixed effects, CR2 inference, and lagged predictors reduce selected methodological concerns, the estimates remain conditional associations. Future research should use longer panels, firm- or regional-level observations, direct measures of commercialization and technology transfer, and stronger causal identification strategies. Overall, the evidence indicates that the relationship between digital transformation and entrepreneurship is multidimensional and context-dependent rather than uniform across European economies.

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DECLARATION OF GENERATIVE AI IN THE WRITING PROCESS

During the preparation of this work, the authors used Generative AI and AI-assisted technologies to improve the readability and language of the manuscript. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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APPENDIX A

Table A1. Indicator-level PCA diagnostics

Index	Indicator	Individual MSA	PC1 loading	Communality	Uniqueness	Score coefficient	Alpha if deleted
DSI	idt_ai	0.856	0.815	0.664	0.336	0.450	0.773
DSI	idt_bigdat	0.775	0.786	0.617	0.383	0.434	0.786
DSI	idt_cloud	0.716	0.858	0.736	0.264	0.474	0.761
DSI	idt_einv	0.659	0.508	0.258	0.742	0.280	0.843
DSI	idt_eis	0.782	0.602	0.363	0.637	0.333	0.826
DSI	idt_socmed	0.796	0.800	0.640	0.360	0.442	0.780
DCI	c_mbb	0.800	0.946	0.895	0.105	0.490	0.806
DCI	c_fbbtc	0.699	0.543	0.294	0.706	0.281	0.882
DCI	c_fbbc	0.854	0.602	0.362	0.638	0.312	0.873
DCI	desi_5g1	0.842	0.935	0.873	0.127	0.484	0.810
DCI	desi_5g2	0.849	0.708	0.501	0.499	0.367	0.861
DCI	desi_5g3	0.760	0.897	0.804	0.196	0.464	0.824
DHCI	hc_ict	0.610	0.943	0.889	0.111	0.609	0.728
DHCI	hc_bsu	0.770	0.841	0.707	0.293	0.543	0.896
DHCI	hc_asd	0.667	0.894	0.799	0.201	0.577	0.825

Table A2. Panel-model specification and diagnostic tests

Diagnostic test	Null hypothesis	Test statistic	df	p-value	Interpretation
Joint F-test for country fixed effects	All country fixed effects are jointly equal to zero	F = 41.325	22.148	< 0.001	The null is rejected. Country fixed effects are jointly significant, and pooled OLS is inadequate
Breusch-Pagan LM test	There is no country-level panel effect	χ^2 = 431.78	1	< 0.001	The null is rejected. A panel-data specification is preferred to pooled OLS
Hausman test	The random-effects estimator is consistent	χ^2 = 4.042	13	0.991	The null is not rejected. The test does not identify a systematic difference between FE and RE estimates. FE is retained on theoretical and design grounds
Pesaran CD test	The regression residuals are cross-sectionally independent	(z = –1.705)	–	0.088	Cross-sectional dependence is not detected at the 5% level, although weak evidence is present at the 10% level
Wooldridge test for serial correlation	There is no first-order serial correlation	(F = 47.538)	1. 22	0.001	The null is rejected; Strong first-order within-country serial correlation is detected
Studentized Breusch-Pagan test	The regression errors are homoskedastic	BP = 22.30	13	0.051	Homoskedasticity is not rejected at the 5% level, but the result provides marginal evidence of heteroskedasticity at the 10% level
Breusch–Godfrey/ Wooldridge test	There is no serial correlation in the idiosyncratic errors	χ^2 = 32.30	8	< 0.001	The null is rejected, confirming substantial within-country serial correlation
Maximum variance inflation factor	No severe multicollinearity among the explanatory variables	3.98	–	–	All VIF values are below 5; severe multicollinearity is not indicated

Note: The joint F-test and Breusch-Pagan LM test reject pooled OLS and confirm the relevance of country-level panel effects. Although the Hausman test does not reject the consistency of the random-effects estimator, the two-way fixed-effects model is retained because the analysis focuses on within-country variation and unobserved national characteristics may be correlated with the explanatory variables. The strong evidence of serial correlation, together with marginal evidence of heteroskedasticity and the limited number of country clusters, motivates the use of CR2 bias-reduced country-clustered standard errors with Satterthwaite-adjusted degrees of freedom.