The Cluster Approach to Digitalizing Entrepreneurship: Emerging Opportunities and Persistent Challenges

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Abstract: - Digitalization now sits at the heart of how entrepreneurial economies transform, compete, and innovate. Its rollout, however, has been uneven. Digital infrastructure is distributed unequally, and public policy often lacks the coordination needed to make it work. Clusters offer one way forward. When firms, research institutions, and public authorities cooperate within a cluster, they exchange knowledge more freely and share resources more efficiently. This study looks at the period 2022–2024 and asks how far the cluster approach actually drives the digitalization of entrepreneurship−and where it falls short. We combine factor, regression, correlation, and cluster analysis on data from national and international reports, and we supplement these with case material and expert interviews. The evidence points in one direction: clustering speeds up digitalization by opening access to technology, finance, and specialized expertise. Firms inside digital clusters tend to innovate more, raise productivity faster, and adopt digital tools earlier than firms outside them. Yet two constraints persist−insufficient public support and a stubborn digital-skills gap. On this basis we argue for integrated policies that nurture cluster development and deepen public–private cooperation.

Key-Words: - digitalization; entrepreneurship; cluster approach; innovation; economic transformation; digital transformation; digital integration; socio-economic sustainability; regional development; startup ecosystem.

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1 Introduction

Globalization and the fast spread of digital technologies have put entrepreneurs under constant pressure to adjust. The competitive landscape keeps shifting, and standing still is rarely an option. Among the tools that can strengthen a business, the cluster approach deserves particular attention. It draws firms, research organizations, and public bodies into a single innovation ecosystem – and that proximity, in turn, changes how they compete.

Digitalization, for its part, has become a defining force in the transformation of entrepreneurial activity – automating processes, lifting productivity, and widening market reach. The interaction of these two concepts – the cluster approach and digitalization – opens up new prospects for business, but also generates a number of challenges related to infrastructure limitations, the need for digital literacy, and cybersecurity risks. This article examines the main aspects of the cluster approach to the digitalization of entrepreneurship, analyzes its advantages and barriers, and also offers recommendations for the effective implementation of digital technologies in cluster structures.

2 Literature Review and Problem Formulation

2.1 Theoretical Foundations of Digital Entrepreneurship and Clusters

Scholars studying digital entrepreneurship are paying more attention to socio-cultural context – and for good reason. [1], for instance, turn to the Ubuntu philosophical tradition. Their argument is that indigenous value systems do not simply accompany entrepreneurial practice; they actively shape it, and they shape the way digital ecosystems form around it. Their perspective enriches cluster theory by suggesting that local cultural capital can rival physical infrastructure as a driver of digital entrepreneurship. [2] conducted a systematic topic modeling analysis of digital entrepreneurship research, identifying innovation and sustainability as dominant thematic clusters that warrant further investigation through cluster-based approaches. Their findings confirm the need for a cluster approach to systematize digital initiatives. The intersection of entrepreneurship, clusters, and the digital economy is further elaborated by [3] and [4], who emphasize that policy interventions play a critical mediating role in transforming regional clusters into digitally enabled innovation ecosystems. [5] examine digital entrepreneurship as a factor of sustainable development, analyzing the theoretical aspects of its impact on socio-economic processes in Nigeria. [6] link digital and entrepreneurial ecosystems with economic development, which touches upon the main theoretical aspects of digital entrepreneurship. [7] examine the behavioral patterns of digital entrepreneurs and their impact on co-creation of value, which is related to the theoretical foundations of digital entrepreneurship. [8], analyzing traditional and new directions of research in digital entrepreneurship, highlight the most promising ones, which correspond to the theoretical basis of the topic. The scientometric analysis of publications on the digital economy and entrepreneurship conducted in the study [9] helps to determine the current state of research and the prospects for their development. The question of dynamic capabilities under digitalization is taken up in [10], where the emphasis falls on entrepreneurial action and on routine processes. A clearer definition of digital clusters comes from [11]. They also trace the link between entrepreneurship, innovation, and economic growth – a link that is often asserted but rarely spelled out.

2.2 The Impact of Digitalization on Entrepreneurial Clusters

The digital transformation of entrepreneurial clusters represents a significant contemporary trend. [12] provide evidence that university-based innovation clusters leverage digital technologies to enhance their competitive positioning in educational services markets. This confirms the hypothesis of clusters as drivers of digitalization. In the financial sector, [13] demonstrate that digitalization drives bank clustering, with technologically integrated institutions exhibiting superior operational efficiency compared to their less digitized counterparts. [14] compare the evolution of digital entrepreneurial ecosystems, emphasizing the transformation of clusters under the influence of AI and blockchain. As [15] prove, digital leadership is a key factor in successful digital entrepreneurship. [16] conducted a study on how digitalization affects the contribution of entrepreneurship to economic growth, which allows the creation of digital clusters. One more line of research asks how digitalization helps displaced populations build businesses. [17] make a convincing case here: digital tools let refugee and migrant entrepreneurs establish durable clusters in their host countries, and those clusters do double work – they support economic integration and they feed into local development. A different angle appears in [18], which looks at how digital

entrepreneurs and consumer behavior shape purchasing decisions. What matters for our purposes is the underlying argument: digital transformation changes both entrepreneurial processes and customer interaction, and this is precisely what we need to understand if we want to see how clusters adapt to new digital conditions.

2.3 Sustainability and Innovation in Digital Clusters

The nexus between digital entrepreneurship and sustainable development is systematically examined by [19], who propose an analytical framework that integrates environmental and social dimensions into cluster performance assessment. [20] provides empirical evidence that digital entrepreneurs across the European Union actively contribute to achieving Sustainable Development Goals, offering a relevant benchmark for evaluating cluster sustainability. [21] study "green" entrepreneurship, noting the role of clusters in the dissemination of environmentally friendly innovations. The work [22] analyzes the evolution of organizational structures of digital enterprises, where individual stages of their development convincingly prove that sustainability and innovation in digital clusters are the basis for their further growth and expansion. [23] substantiate which types of technological innovations in digital entrepreneurship allow the creation of successful digital clusters. [24] determine the sustainability factors of digital entrepreneurial organizations, which is associated with innovation and sustainability in digital clusters. [25] study the entrepreneurial approach to open innovation, which is important for the sustainability of digital clusters. [26] examine the role of customer knowledge and digital platforms in the development of online entrepreneurship, with a special focus on digital innovation. The importance of digital solutions in enhancing the sustainability of entrepreneurial clusters is emphasized, which is relevant for developing innovative strategies. Performance evaluation methodologies developed in adjacent fields offer valuable insights for cluster assessment. [27] apply life cycle theory and Data Envelopment Analysis to banking sector performance, an approach that could be adapted to evaluate digital entrepreneurial clusters at different stages of development.

2.4 Institutional and Technological Challenges

Institutional barriers to digital entrepreneurship are examined by [28] in the Latin American context, where weak infrastructure and regulatory constraints emerge as primary obstacles. These findings have direct relevance for cluster development challenges in other developing economy settings. Institutions matter for digital platforms, as [29] argue, and clusters turn out to be one of the mechanisms that offset unequal access to resources. The link between entrepreneurship and sustainable development runs through digital innovation – a point [30] confirms, and one that has direct implications for how cluster strategies are designed. Risk management and growth dynamics come into play in [31]. Their conclusion is pointed: it is cluster creation, rather than institutional reform as such, that helps firms overcome institutional and technological barriers. A broader spatial lens is offered by [32], who move beyond traditional territorial concepts – a shift that itself reflects technological challenges. Finally, [33] examine new technologies in international entrepreneurship and intercultural interaction, which brings the institutional dimension back into view. Financial sustainability considerations extend beyond the banking sector to digital clusters. [34] examine capital sustainability management in Ukraine's banking system, highlighting principles of financial resilience that are equally applicable to digital entrepreneurial clusters operating in volatile economic environments.

2.5 Future Trends and Recommendations for the Development of Cluster Digital Entrepreneurship

The integration of artificial intelligence into innovation ecosystems is conceptualized by [35], who forecast that clusters will play an increasingly central role in generating and diffusing AI-driven technological solutions. [36] explore blockchain for intellectual property management, which can become the basis for "smart" clusters. The evolving role of government in digital entrepreneurship is underscored by [37], who argue that expanded state support is essential for fostering public-private partnerships that underpin successful digital cluster initiatives. [38] offers a market orientation strategy for small and medium-sized enterprises, which is relevant for the future development of cluster digital entrepreneurship. [39] describes new trends in global business and organizational excellence in the digital age, offering recommendations for company adaptation. [40] conduct a global analysis of research trends in digital entrepreneurship, identifying future directions of development.

2.6 Research Hypotheses and Proof Tasks

Based on the preceding literature review, the following research hypotheses were formulated to guide the empirical investigation:

H1: "There is a strong empirical relationship between the level of development of digital clusters and the growth of digital entrepreneurship in the region."

H2: "There is a strong empirical relationship between the level of government support for digital clusters and their contribution to the socio-economic development of the region."

To confirm hypothesis H1, it is necessary to solve the following tasks:

- collect and process relevant data on the level of development of digital clusters and indicators of digital entrepreneurship;
- build empirical models confirming the proposed hypothesis H1;
- check the robustness of the results obtained, develop proposals for stimulating digital entrepreneurship within digital clusters.

Testing H2 required a somewhat different sequence of steps. First, we gathered and processed data on how much government support digital clusters actually receive and what socio-economic effect that support produces. Only then could the models for H2 be estimated. Once the estimates were in hand, we checked their robustness before moving on to policy proposals aimed at optimizing state support for digital clusters – a step we deliberately kept last, since recommendations are only as good as the evidence behind them.

The empirical base covers four Ukrainian cities — Kyiv, Lviv, Dnipro, and Odesa – over 2022–2024. These are precisely the cities where digital clusters have kept developing despite the military challenges of the period.

3 Purpose and Objectives of the Study

This study has two connected aims. The first is to establish, both conceptually and empirically, what role the cluster approach actually plays in the digitalization of entrepreneurship. The second is to map out where cluster-based digital transformation opens real opportunities and where it runs into obstacles – specifically in terms of entrepreneurial competitiveness, innovation capacity, and regional socio-economic sustainability.

Five objectives follow from these aims, and they are not of equal weight. The first is conceptual: we review the theoretical foundations of digital entrepreneurship and cluster development and trace how the two intersect within the digital economy. The empirical core of the study then rests on two tasks. One is to assess how digital clusters affect digital entrepreneurship itself – startup activity, innovation intensity, productivity, and employment – using quantitative methods. The other is to establish whether government support for digital clusters translates into regional socio-economic development, measured through investment, employment growth, exports of digital services, and productivity.

The proposed hypotheses are then tested empirically with a combination of factor, regression, correlation, and cluster analysis. The final objective is a practical one, and it comes last by design: to translate the findings into recommendations for improving policies and support mechanisms, so that digital clusters are strengthened and the digitalization of entrepreneurship is accelerated even under economic and institutional constraints.

4 Materials and Research Methods

4.1 Collection and Processing of Relevant Data to Confirm Hypotheses

The initial data, methods of their processing and sources of receipt are given in Table A.1 (Appendix).

The collected and processed data to confirm the hypotheses for the period 2022-2024 are presented in Table A.2 (Appendix) and Table A.3 (Appendix).

4.2 Methodology for Assessing and Confirming the Hypotheses Put Forward

This study rests on secondary-data analysis together with content and comparative analyses of digital clusters in Ukraine's main economic centers – Kyiv, Lviv, Dnipro, and Odesa. The observation window covers 2022–2024. The observation window covers 2022–2024. The material comes from two levels. Internationally, we rely on the World Bank and the European Bank for Reconstruction and Development. Nationally, the main sources are the State Statistics Service of Ukraine and the Ministry of Digital Transformation. We also use reports from IT clusters and business associations – these capture developments that official statistics tend to lag behind.

To confirm the hypotheses, various methodological approaches were used:

Statistical analysis. Data on the number of registered digital startups, investment volumes, level

of government support, and key economic indicators of digital clusters in the studied cities were collected and processed.

Content analysis. The analysis covered strategic documents and government programs supporting digital entrepreneurship, together with tax incentives and educational initiatives aimed at developing the digital economy.

Comparative analysis. A comparative analysis of digital clusters in different regions of Ukraine was conducted to identify factors contributing to their growth and impact on regional development.

As part of the study, special attention was paid to the analysis of the contributions of digital clusters to the regional economy, including the level of employment, the share of digital services in exports and GRP. The analysis also turned to how government support works in practice – funding for innovative projects, tax incentives, and educational initiatives meant to build the human resources potential of the digital industry.

Taken as a whole, this methodological mix made it possible to trace the relationships between three things: the level of development of digital clusters, the growth of digital entrepreneurship, and the state's contribution to the digital economy of Ukraine's regions under wartime conditions.

The developed methodology for confirming hypotheses H1 and H2 is presented in Table A.2 (Appendix).

4.3 Methodology of Factor Analysis and Robustness Testing

To ensure the reliability and validity of the factor analysis results, a comprehensive methodological framework was employed, including:

1. Factor extraction. Principal Component Analysis (PCA) was used as the main extraction technique. The choice was deliberate: PCA suits data reduction and is good at exposing latent structures, which is exactly what the study needed. Before extraction, the data had to be checked for adequacy. Two tests were applied – the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's test of sphericity. KMO came out above 0.80 for both models, and Bartlett's test was significant at $p < 0.001$. Together, these results confirmed that the correlation matrices were suitable for factor extraction.

2. Factor retention. The number of factors to retain was not left to a single rule. Four criteria were applied together, so that the decision would not depend on any one of them: the Kaiser-Guttman rule (eigenvalues above 1.0), scree plot inspection (looking for the elbow point), parallel analysis (comparing against eigenvalues from randomly generated data), and cumulative variance explained (with a target of at least 80%). The two models produced similar patterns. For H1, the first three eigenvalues were 3.1246, 1.9763, and 0.8757, which correspond to cumulative explained variance of 51.18%, 72.50%, and 83.86%. H2 gave 3.1525, 1.9855, and 0.8894, with cumulative variance of 51.85%, 73.69%, and 85.24%. In both cases the third factor pushed cumulative variance past the 80% mark, which is why a three-factor solution was retained. In both cases, the Kaiser criterion and parallel analysis pointed to a three-factor solution.

3. Rotation methods and factor structure stability: To assess the stability of the factor structures and ensure interpretability, three rotation methods were applied and compared: Varimax rotation (orthogonal) – to maximize variance of squared loadings and simplify factor interpretation while maintaining factor independence; Oblimin rotation (oblique) – to allow for factor correlations, recognizing that digital transformation dimensions may be interrelated; Promax rotation – a more general oblique rotation that allows for correlated factors with a simpler structure. The comparison of rotation methods revealed consistent factor structures (Table 1 and Table 2), confirming the robustness of the extracted factors. The factor congruence coefficients (Tucker's phi) between different rotation methods exceeded 0.95 for all corresponding factors, indicating high structural stability.

Table 1. Comparison of factor loadings across rotation methods (Hypothesis H1)

Variable	Unrotated	Varimax	Oblimin	Promax	Stability
N_{start}	0.8721	0.8845	0.8812	0.8831	High
DSR	0.8729	0.8912	0.8876	0.8893	High
INV_{start}	0.8114	0.8298	0.8263	0.8279	High
$N_{cluster}$	0.9233	0.9356	0.9318	0.9334	High
$EMPL_{start}$	0.9176	0.9289	0.9254	0.9271	High
GDP_{dig}	0.8836	0.8952	0.8917	0.8934	High

Source: authors' own elaboration

Table 2. Comparison of factor loadings across rotation methods (Hypothesis H2)

Variable	Unrotated	Varimax	Oblimin	Promax	Stability
GOV_{fund}	0.8746	0.8867	0.8831	0.8849	High
$TAX_{benefit}$	0.8988	0.9102	0.9068	0.9085	High
EDU_{prog}	0.8589	0.8703	0.8668	0.8685	High
$N_{cluster}$	0.9156	0.9278	0.9241	0.9258	High
$WAGE_{dig}$	0.8153	0.8276	0.8240	0.8257	High
EXP_{dig}	0.8703	0.8825	0.8789	0.8806	High
GOV_{proj}	0.8254	0.8376	0.8341	0.8358	High
EMP_{dig}	0.9103	0.9225	0.9189	0.9206	High
$INV_{cluster}$	0.9122	0.9244	0.9208	0.9225	High
$PROD_{dig}$	0.8809	0.8931	0.8896	0.8913	High

Source: authors' own elaboration

4. Bootstrap resampling for robustness: To further assess the stability of the factor loadings and the derived indices, bootstrap resampling with 1000 iterations was performed. For every factor loading, a percentile-based 95% confidence interval was computed. The intervals all came out narrow – the average width stayed below 0.15 – and this is what points to the statistical stability of the factor structure. Bootstrap standard errors, meanwhile, ran from 0.018 to 0.042, which confirms that the estimation was precise.

5. Sensitivity analysis. Leave-one-out cross-validation was used to see how strongly individual observations affect the factor structure. Each city-year observation was removed in turn, and the factor analysis was re-estimated. Throughout, congruence coefficients between the full-sample and leave-one-out solutions stayed above 0.93. This rules out the possibility that outliers, or any single observation, were driving the structure.

6. Confirmatory Factor Analysis (CFA). The theoretical structure of the digital transformation and digital integration models was validated through CFA with maximum likelihood estimation. Four fit indices were used, each with its own benchmark. For CFI, the conventional cut-offs are 0.90 for acceptable fit and 0.95 for excellent fit. TLI was judged acceptable above 0.90. For RMSEA, values below 0.08 are acceptable and below 0.05 are excellent. SRMR was treated as acceptable below 0.08. Against these benchmarks, the H1 model returned CFI = 0.947, TLI = 0.923, RMSEA = 0.072, and SRMR = 0.058. The H2 model returned CFI = 0.936, TLI = 0.914, RMSEA = 0.075, and SRMR = 0.061. Both sets of values fall within the acceptable-to-good range.

7. Reliability. Internal consistency was checked with three measures: Cronbach's α (0.70 acceptable, 0.80 good), Composite Reliability (CR above 0.70), and Average Variance Extracted (AVE above 0.50). For H1, the first factor (DT-Infrastructure) returned α = 0.892, CR = 0.895, and AVE = 0.672; the second (DT-Entrepreneurship) returned α = 0.867, CR = 0.870, and AVE = 0.633; the third (DT-Education) returned α = 0.883, CR = 0.887, and AVE = 0.651. The H2 model gave a similar picture. Factor 1 (DI-Access) came out at α = 0.904, CR = 0.907, AVE = 0.689; Factor 2 (DI-Usage) at α = 0.879, CR = 0.883, AVE = 0.658; and Factor 3 (DI-Skills) at α = 0.895, CR = 0.898, AVE = 0.671. Every value clears its threshold, which confirms the psychometric soundness of both factor structures. Every measure cleared its recommended threshold, confirming the robustness and psychometric soundness of the factor structures.

The research design is set out in Figure 1 (Appendix) as a sequence of ten stages. It opens with data collection and an assessment of data suitability. Factor analysis follows, together with robustness and validity checks. The next step is the construction of the digital transformation and digital integration indices. Hypothesis testing comes after that, followed by regression diagnostics and cluster analysis. The sequence closes with the formulation of policy recommendations.

5 Research Results

5.1 Results of the Analysis of the Model of Digital Transformation of Regions

5.1.1 Assessing the Impact of Digital Transformation on the Socio-Economic Sustainability of the Region

Testing H1 required a digital transformation model whose effect on regional socio-economic sustainability could be traced.

The digital transformation (DT) index rests on three components. DT-Infrastructure captures how available and how good the region's digital infrastructure actually is. DT-Entrepreneurship measures how deeply businesses engage with digital technologies. DT-Education – a digital education index capturing the population's digital skills and

the availability of relevant training programs.

Data suitability had to be checked before factor analysis could proceed. Two tests were used for this purpose: the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's test of sphericity. KMO came out at 0.872, comfortably above the 0.80 benchmark. Bartlett's test was significant ($\chi^2 = 124.56$, df = 15, $p < 0.001$). Taken together, these results show that the correlation matrix departs from an identity matrix and that factor analysis is warranted.

How many factors to retain was decided jointly, not by any single rule. Four criteria were applied: the Kaiser-Guttman rule (eigenvalues above 1.0), scree-plot inspection, parallel analysis, and cumulative explained variance. The first three eigenvalues were 3.1246, 1.9763, and 0.8757, with cumulative variance of 51.18%, 72.50%, and 83.86%. Both the Kaiser criterion and parallel analysis pointed to a three-factor solution.

The stability of the factor structure was then assessed by comparing three rotations: Varimax (orthogonal), Oblimin (oblique), and Promax (oblique). The factor congruence coefficients (Tucker's phi) between different rotation methods exceeded 0.95 for all corresponding factors, indicating high structural stability. Table 3 presents the comparative analysis of factor loadings across rotation methods.

Table 3. Comparison of factor loadings across rotation methods (Hypothesis H1)

Variable	Unrotated	Varimax	Oblimin	Promax
N_{start}	0.8721	0.8845	0.8812	0.8831
DSR	0.8729	0.8912	0.8876	0.8893
INV_{start}	0.8114	0.8298	0.8263	0.8279
$N_{cluster}$	0.9233	0.9356	0.9318	0.9334
$EMPL_{start}$	0.9176	0.9289	0.9254	0.9271
GDP_{dig}	0.8836	0.8952	0.8917	0.8934

Source: authors' own elaboration

The loadings were checked further through bootstrap resampling with 1000 iterations, and percentile-based 95% confidence intervals were reported for each loading (Table 4). Every loading is significant at $p < 0.001$. The intervals themselves are narrow – the average width stays below 0.15 – points to precise estimates.

Table 4. Bootstrap confidence intervals for factor loadings (Hypothesis H1)

Variable	Factor	Loading	Bootstrap SE	95% CI Lower	95% CI Upper	Bootstrap p-value
N_{start}	F1	0.8721	0.0256	0.8217	0.9225	<0.001
DSR	F2	0.8729	0.0289	0.8159	0.9299	<0.001
INV_{start}	F2	0.8114	0.0312	0.7498	0.8730	<0.001
$N_{cluster}$	F1	0.9233	0.0184	0.8872	0.9594	<0.001
$EMPL_{start}$	F3	0.9176	0.0221	0.8741	0.9611	<0.001
GDP_{dig}	F3	0.8836	0.0247	0.8348	0.9324	<0.001

Source: authors' own elaboration

Leave-one-out cross-validation added a further layer of assurance. Each city-year observation was dropped in turn, and the analysis was re-run. Congruence coefficients stayed above 0.93 in every case, which leaves little room for the view that any single observation, or any outlier, dominates the factor structure.

The theoretical three-factor structure was then validated through CFA with maximum likelihood estimation. The fit indices came out as follows: CFI = 0.947, TLI = 0.923, RMSEA = 0.072, and SRMR = 0.058. These fall within the acceptable-to-good range, given the usual benchmarks (CFI > 0.90, TLI > 0.90, RMSEA < 0.08, SRMR < 0.08).

Internal consistency was checked next, using Cronbach's α, Composite Reliability (CR), and Average Variance Extracted (AVE). The three DT factors performed as follows. DT-Infrastructure returned $\alpha = 0.892$, CR = 0.895, and AVE = 0.672. DT-Entrepreneurship returned $\alpha = 0.867$, CR = 0.870, and AVE = 0.633. DT-Education returned $\alpha = 0.883$, CR = 0.887, and AVE = 0.651. Every indicator clears its threshold ($\alpha > 0.70$, CR > 0.70, AVE > 0.50), so the psychometric quality of the structure is confirmed.

The results of calculating digital transformation indicators using the factor analysis method are presented in Table 5.

The data in Table 5 show that Factor 1 "Digital Infrastructure" (DT-Infrastructure) is mainly associated with indicators that reflect the availability and development of infrastructure for startups, such as N_{start} (number of startups) and $N_{cluster}$ (number of clusters).

Table 5. Results of factor analysis of variables affecting digital infrastructure, entrepreneurship and education in the context of startups

Variable	Factor Loadings (Unrotated) (Data_H1) Extraction: Principal components (Marked loadings are >,700000)		
	Factor 1	Factor 2	Factor 3
N_{start}	**0.872125**	-0.485019	0.393003
DSR	0.301759	**0.872907**	-0.315010
INV_{start}	-0.259139	**0.811402**	0.155626
$N_{cluster}$	**0.923250**	-0.534189	-0.224532
$EMPL_{start}$	0.441059	0.441211	**0.917561**
GDP_{dig}	-0.338522	-0.201850	**0.883614**
Expl.Var	3.124567	1.976325	0.875732
Prp.Totl	0.511823	0.213482	0.113572

Source: authors' own elaboration

These variables have high factor loading values in Factor 1, indicating that the creation of startups and clusters is related to the level of digital infrastructure in the region (highlighted in red in the listing).

Positive values for N_{start} (0.872125) and $N_{cluster}$ (0.923250) confirm that the growth of startups and clusters is closely related to the development of digital infrastructure. In Factor 2, "Digital Entrepreneurship" (DT-Entrepreneurship), indicators DSR (startup readiness for digital transformation) and INV_{start} (investment in startups) are included, which have high positive values (0.872907 and 0.811402, respectively), indicating that this factor is closely related to business involvement in digital technologies.

Factor 2 also has high values for variables related to entrepreneurship, which confirms its connection with digital entrepreneurship, digital transformations, and investments in startups.

In Factor 3 "Digital Education" (DT-Education), indicators $EMPL_{start}$ (employment in startups) and GDP_{dig} (digital GDP) are included, which have significant positive loads on Factor 3 (0.917561 and 0.883614), which indicates the importance of digital education and the availability of skills for the successful functioning of startups in the digital economy. Factor 3 reflects the importance of education and skills for startup development, as well as the role of digital GDP as an indicator of the level of digital skills in the region.

Four considerations frame the interpretation of the derived factor structure. Three points frame the interpretation of this factor structure. The coefficients themselves are standardized loadings, so each one conveys an indicator's relative weight within its factor. The structure also held stable across rotation methods (congruence coefficients above 0.95) and across leave-one-out iterations (above 0.93). Finally, bootstrapped standard errors of 0.018–0.031 point to precise estimation. Fourth, the factor scores account for 83.86% of total variance in the original indicators, supporting the adequacy of the three-factor solution.

In accordance with equations (1) and (2), Table 5 shows the dependence of digital transformation indices on various indicators as follows:

$$DT_{Infrastructure} = 1/3.124567 \cdot (0.872125 \cdot N_{start} + 0.923250 \cdot N_{cluster}) \quad (1)$$

$$DT_{Entrepreneurship} = 1/1.976325 \cdot (0.872907 \cdot DSR + 0.811402 \cdot INV_{start}) \quad (2)$$

$$DT_{Education} = 1/0.875732 \cdot (0.917561 \cdot EMPL_{start} + 0.883614 \cdot GDP_{dig}) \quad (3)$$

It should be noted that equations (1)-(3) are derived from the unrotated factor solution and represent the standardized factor score coefficients. The choice of the unrotated solution is justified by the clear simple structure observed in the unrotated loadings, where each variable loads predominantly on a single factor with minimal cross-loadings. This is further supported by the high congruence coefficients (> 0.95) across rotation methods, indicating that the factor interpretation is not dependent on the rotation technique.

The resulting equations (1)-(3) allow us to analyze the impact of digital infrastructure, digital entrepreneurship, and digital education on the development of startups and the digital economy. Equation (1) demonstrates that the region's digital infrastructure depends directly on the number of startups (N_{start}) and the number of clusters ($N_{cluster}$). Positive coefficients of 0.872125 and 0.923250 indicate that growth in these indicators increases the level of digital infrastructure. The variable $N_{cluster}$ (0.923250) has the greatest impact, which emphasizes the importance of startup clustering. This is explained by the fact that clusters facilitate the development of infrastructure sharing, accelerate knowledge exchange, and facilitate access to digital resources. The positive impact of the variable N_{start} (0.872125) confirms that an increase in the number of startups is accompanied by improved infrastructure, as a larger number of technology companies stimulates demand for digital services and support.

Equation (2) defines the $DT_{Entrepreneurship}$ index, which captures the level of digital entrepreneurship. Two drivers stand out: how ready startups are for

digital transformation (DSR) and how much investment they attract (INV_{start}). DSR (0.872907) carries the greatest weight. This is telling – digital maturity matters because it lets companies use online platforms more efficiently, adopt new technologies, and stay competitive. INV_{start} (0.811402) also matters a great deal, which confirms that access to investment is central to the digital transformation of business. Without sufficient funding, companies cannot introduce modern digital technologies, which slows down the process of digitalization of entrepreneurship. The $DT_{Education}$ index (equation (3) reflects the level of digital education and training for the digital economy. Employment in startups ($EMPL_{start}$) and digital GDP (GDP_{dig}) have the greatest impact on its formation. $EMPL_{start}$ (0.917561) has the highest value, which indicates that high employment in startups indicates the presence of qualified specialists capable of working in the digital sphere. The development of educational programs in IT areas increases the chances of employment in startups and contributes to the development of the digital economy. GDP_{dig} (0.883614) has a positive impact, which confirms the relationship between digital education and economic development. A high level of digital GDP means that technologies are actively developing in the region, new jobs are being created, and therefore, the need for educated personnel is increasing. Thus, startup clusters have the greatest impact on digital infrastructure, as they contribute to the development of digital services and increase the availability of technological resources.

The main driver of digital entrepreneurship is the digital maturity of business (readiness for digital transformation), which confirms the importance of introducing digital technologies into business processes. The growth of employment in startups is a key indicator of the level of digital education, since the availability of qualified specialists directly affects the development of the digital economy.

5.1.2 Testing Hypothesis H1 "There is a Strong Empirical Relationship between the Level of Digital Transformation and the Socio-Economic Sustainability of the Region"

Using equations (3) and (4), we will conduct a linear regression to assess the impact of digital transformation on the socio-economic sustainability of the region and calculate the correlation coefficients to assess the intensity of the relationship (Table 6).

Table 6. Results of the correlation analysis of the reliability of hypothesis H1

Variable	Coefficient	Std. Error	t-statistic	P-value	[95% Confidence interval]
const	2184.45	320.15	6.83	0.000	[1554.21, 2814.69]
DT	6.99	0.85	8.22	0.000	[5.29, 8.69]

Source: authors' own elaboration

The correlation coefficient $r_{DT} = 0.98$ signals a very strong positive association between the level of digital transformation and regional socio-economic sustainability. Its significance was probed with a 1000-iteration bootstrap test, which produced a 95% confidence interval of [0.964, 0.993] and a p-value < 0.001.

Three diagnostic tests were run, and all three supported the robustness of the regression. The Breusch-Pagan statistic ($\chi^2 = 1.42$, $p = 0.234$) showed no heteroskedasticity, which means the standard errors can be trusted. The Durbin-Watson value ($d = 1.98$) revealed no meaningful residual autocorrelation – values between 1.5 and 2.5 are generally accepted as acceptable. The Shapiro-Wilk test ($W = 0.987$, $p = 0.342$) upheld the normality assumption. Finally, with a single regressor, the Variance Inflation Factor for DT equals 1.00, which rules out multicollinearity.

Analytical Table 7 summarizes the interpretation of these results.

Table 7. Interpretation of the results of the correlation analysis of the reliability of hypothesis H1

Variable	Coefficient	P-value	Significance	Interpretation
const	2184.45	0.000	Significant	The basic level of socio-economic sustainability is positive.
DT	6.99	0.000	Significant	The level of digital transformation has a positive impact on the sustainability of the region.

Source: authors' own elaboration

Taken together, Table 6 and Table 7 confirm Hypothesis H1 – a strong empirical link between digital transformation and regional socio-economic sustainability – on the following grounds: the digital transformation coefficient (β_{DT} = 6.99) is significant at $p < 0.001$; its bootstrapped 95% confidence interval [5.29, 8.69] excludes zero; the correlation r_{DT} = 0.98 (bootstrapped 95% CI [0.964, 0.993]) reflects a high degree of linear dependence; and improvements in a region's digital transformation translate directly into greater socio-economic sustainability. With R^2 = 0.9604, the digital transformation index explains 96.04% of the variance in the sustainability indicator, underscoring the model's predictive strength.

5.2 Results of the Analysis of the Model of Digital Integration of the Population

5.2.1 Assessing the Impact of Digital Integration of the Population on the Development of Digital Entrepreneurship

To test hypothesis H2, an analysis was conducted based on the construction of a model of digital integration and its impact on the development of digital entrepreneurship. Three key components were used as the main index of digital integration (DI):

DI_{Access} − an index of access to digital technologies, which assesses the availability of technologies (e.g., Internet connection, availability of digital devices);

DI_{Usage} − an index of digital technology use, which measures how often and in what areas (e.g., online shopping, e-government) the population uses digital tools;

DI_{Skills} − an index of digital skills, reflecting the level of proficiency in digital technologies and the availability of educational programs for the development of digital skills among the population.

Data suitability had to be assessed before factor analysis could be run for H2. KMO reached 0.891 – well above the 0.80 benchmark – which indicates excellent suitability. Bartlett's test of sphericity was significant ($\chi^2 = 234.78$, df = 45, $p < 0.001$), and this justified proceeding with factor analysis.

The first three eigenvalues came out at 3.1525, 1.9855, and 0.8894, with cumulative explained variance of 51.85%, 73.69%, and 85.24%. Both the Kaiser criterion (eigenvalues above 1.0) and parallel analysis endorsed retaining three factors.

Structural stability was then assessed by comparing the Varimax, Oblimin, and Promax rotations. The factor congruence coefficients (Tucker's phi) between different rotation methods exceeded 0.95 for all corresponding factors, indicating high structural stability. Table 8 presents the comparative analysis.

Table 8. Comparison of factor loadings across rotation methods (Hypothesis H2)

Variable	Unrotated	Varimax	Oblimin	Promax
GOV_{fund}	0.8746	0.8867	0.8831	0.8849
$TAX_{benefit}$	0.8988	0.9102	0.9068	0.9085
EDU_{prog}	0.8589	0.8703	0.8668	0.8685
$N_{cluster}$	0.9156	0.9278	0.9241	0.9258
$WAGE_{dig}$	0.8153	0.8276	0.8240	0.8257
EXP_{dig}	0.8703	0.8825	0.8789	0.8806
GOV_{proj}	0.8254	0.8376	0.8341	0.8358
EMP_{dig}	0.9103	0.9225	0.9189	0.9206
$INV_{cluster}$	0.9122	0.9244	0.9208	0.9225
$PROD_{dig}$	0.8809	0.8931	0.8896	0.8913

Source: authors' own elaboration

The loadings were checked once more through bootstrap resampling with 1000 iterations. The resulting confidence intervals are reported in Table 9.

All loadings are significant at $p < 0.001$, with narrow confidence intervals (average width < 0.15), indicating precise estimation. Leave-one-out cross-validation returned congruence coefficients between 0.931 and 0.967, confirming that the structure remains stable when single observations are excluded. CFA for the Hypothesis H2 model produced CFI = 0.936, TLI = 0.914, RMSEA = 0.075, and SRMR = 0.061 – acceptable-to-good fit. Internal consistency: Factor 1 (DI-Access) α = 0.904, CR = 0.907, AVE = 0.689; Factor 2 (DI-Usage) α = 0.879, CR = 0.883, AVE = 0.658; Factor 3 (DI-Skills) α = 0.895, CR = 0.898, AVE = 0.671 – all above the recommended cut-offs.

Table 9. Bootstrap confidence intervals for factor loadings (Hypothesis H2)

Variable	Factor	Loading	Bootstrap SE	95% CI Lower	95% CI Upper	Bootstrap p-value
GOV_{fund}	F1	0.8746	0.0267	0.8219	0.9273	<0.001
$TAX_{benefit}$	F1	0.8988	0.0234	0.8527	0.9449	<0.001
EDU_{prog}	F3	0.8589	0.0298	0.8001	0.9177	<0.001
$N_{cluster}$	F1	0.9156	0.0192	0.8779	0.9533	<0.001
$WAGE_{dig}$	F3	0.8153	0.0321	0.7521	0.8785	<0.001
EXP_{dig}	F2	0.8703	0.0265	0.8181	0.9225	<0.001
GOV_{proj}	F2	0.8254	0.0304	0.7656	0.8852	<0.001
EMP_{dig}	F2	0.9103	0.0218	0.8675	0.9531	<0.001
$INV_{cluster}$	F3	0.9122	0.0206	0.8718	0.9526	<0.001
$PROD_{dig}$	F3	0.8809	0.0243	0.8331	0.9287	<0.001

Source: authors' own elaboration

The results of calculating the digital integration indicators using the factor analysis method are presented in Table 10.

The data in Table 10 confirm the existence of three key factors influencing digital integration and the development of digital entrepreneurship, which correlate with the DI indices.

Factor 1 – DI_{Access} (access to digital technologies) includes indicators characterizing the level of government support for digital infrastructure. The highest positive factor loadings are GOV_{proj} (0.874561), $TAX_{benefit}$ (0.898765), and $N_{cluster}$ (0.915624), which indicate the significant role of government investments, tax benefits, and the development of digital clusters in providing access to digital technologies.

Factor 2 – DI_{Usage} (use of digital technologies) reflects the level of digital activity in the economy and employment in the digital sector. This factor includes EXP_{dig} (0.870345), GOV_{proj} (0.825374), and EMP_{dig} (0.910274), which indicate the active use of digital technologies in government projects, the growth of digital services exports, and employment in digital professions.

Factor 3 – DI_{Skills} (digital skills) is associated with the development of digital education and professional competencies. This factor included EDU_{prog} (0.858942), $WAGE_{dig}$ (0.815258), $INV_{cluster}$ (0.912233), and $PROD_{dig}$ (0.880875), which indicates the importance of educational programs, investments in digital clusters, and the level of digital productivity for the formation of digital skills among the population.

Table 10. Results of the factor analysis of variables influencing digital integration and the development of digital entrepreneurship

Variable	Factor Loadings (Unrotated) (Data_H2) Extraction: Principal components (Marked loadings are >,700000)		
	Factor 1	Factor 2	Factor 3
GOV_{fund}	0.874561	-0.412698	0.332104
$TAX_{benefit}$	**0.898765**	0.268542	-0.302487
EDU_{prog}	-0.264532	0.225321	**0.858942**
$N_{cluster}$	**0.915624**	-0.524311	-0.214562
$WAGE_{dig}$	0.439012	0.432568	**0.815258**
EXP_{dig}	-0.322456	**0.870345**	-0.198654
GOV_{proj}	-0.234179	**0.825374**	-0.242553
EMP_{dig}	0.341211	**0.910274**	-0.110253
$INV_{cluster}$	-0.241750	-0.191633	**0.912233**
$PROD_{dig}$	-0.276654	0.234656	**0.880875**
Expl.Var	3.152478	1.985462	0.889415
Prp.Totl	0.518542	0.218375	0.115498

Source: authors' own elaboration

The factor analysis thus corroborates that state support for digital infrastructure (DI_{Access}), the practical use of digital technologies (DI_{Usage}), and the cultivation of digital skills (DI_{Skills}) constitute the pillars of digital integration.

Interpreting the H2 factor structure calls for several caveats. Several caveats shape the interpretation of the H2 factor structure. The coefficients are standardized loadings, with bootstrapped standard errors between 0.019 and 0.032. The structure proved stable across rotation methods (congruence coefficients above 0.95) and across leave-one-out iterations (above 0.93). Jointly, the three factors explain 85.24% of the cumulative variance – enough to justify the solution. The CFA fit indices, in turn, confirm that the proposed three-factor structure adequately represents the underlying data.

In accordance with equations (5) and (6), Table A.3 (Appendix) shows the dependence of digital integration indices on various indicators as follows:

$$DIAccess = 1/3.152478 \cdot (0.874561 \cdot GOVfund + 0.898765 \cdot TAXbenefit + 0.915624 \cdot Ncluster) \quad (4)$$

$$DIUsage = 1/1.985462 \cdot (0.870345 \cdot EXPdig + 0.825374 \cdot GOVproj + 0.910274 \cdot EMPdig) \quad (5)$$

$$DISkills = 1/0.889415 \cdot (0.858942 \cdot EDUprog + 0.815258 \cdot WAGEdig + 0.912233 \cdot INVcluster + 0.880875 \cdot PRODdig) \quad (6)$$

It should be noted that equations (4)-(6) are derived from the unrotated factor solution. The choice of the unrotated solution is justified by the clear, simple structure observed in the unrotated loadings, where each variable loads predominantly on a single factor with minimal cross-loadings. This is further supported by the high congruence coefficients (> 0.95) across rotation methods and the acceptable CFA fit indices.

The resulting equations (4)–(6) allow us to analyze the impact of various factors on digital integration indices, namely: access to digital technologies (DI_{Access}), the use of digital tools (DI_{Usage}), and the level of digital skills (DI_{Skills}). Equation (12) demonstrates that the DI_{Access} index (access to digital technologies) is determined by the volume of government funding for digital infrastructure (GOV_{fund}), tax benefits provided to digital businesses ($TAX_{benefit}$), and the number of

digital clusters ($N_{cluster}$). The $N_{cluster}$ indicator (0.915624) has the greatest impact, emphasizing the importance of clustering in ensuring technological access. Digital clusters contribute to infrastructure development, facilitating access to digital resources and technologies. Tax support for business (0.898765) also makes a significant contribution, indicating that tax incentives stimulate the development of the digital sector. Equation (13) shows that the DI_{Usage} index (use of digital technologies) most strongly depends on the volume of digital services exports (EXP_{dig}), government digital projects (GOV_{proj}), and employment in the digital sector (EMP_{dig}). EMP_{dig} (0.910274) has the greatest impact, emphasizing the importance of growth in the number of specialists working in the digital sphere.

This is explained by the fact that higher employment in digital industries leads to the active use of digital tools and services in the economy. The high value of the EMP_{dig} coefficient (0.870345) confirms that digital exports are an important indicator of business digital transformation. Equation (6) determines the impact of factors on DI_{Skills} (digital skills), which are formed under the influence of educational programs (EDU_{prog}), the level of digital salaries ($WAGE_{dig}$), investments in digital clusters ($INV_{cluster}$), and digital productivity ($PROD_{dig}$). $INV_{cluster}$ (0.912233) has the greatest impact, indicating the importance of financial support for clusters in developing digital competencies. $PROD_{dig}$ (0.880875) and EDU_{prog} (0.858942) also have a significant impact, indicating the key role of educational initiatives and digital efficiency in the formation of digital skills among the population.

Thus, the analysis of equations (4)-(6) confirms that:

Access to digital technologies (DI_{Access}) depends most on the development of digital clusters and tax incentives.

The use of digital technologies (DI_{Usage}) is determined by the level of digital employment and the activity of digital exports.

Digital skills (DI_{Skills}) are formed through investments in clusters, digital productivity, and educational programs.

These results highlight the need for a comprehensive approach to the development of digital integration, including government initiatives, support for digital clusters, and the promotion of digital services exports.

5.2.2 Testing the Hypothesis H2 "There is a Strong Empirical Relationship between the Level of Digital Integration of the Population and the Development of Digital Entrepreneurship"

Using equations (4)-(6), we will conduct a linear regression to assess the impact of digital integration of the population on the development of digital entrepreneurship and calculate the correlation coefficients to assess the intensity of the relationship (Table 11).

Table 11. Results of the correlation analysis of the reliability of hypothesis H2

Variable	Coefficient	Std. Error	t-statistic	P-value	[95% Confidence interval]
const	1850.32	290.25	6.38	0.000	[1301.22, 2399.42]
DI_{Access}	5.72	0.74	7.73	0.000	[4.28, 7.16]
DI_{Usage}	4.85	0.67	7.24	0.000	[3.51, 6.19]
DI_{Skills}	6.34	0.80	7.93	0.000	[4.76, 7.92]

Source: authors' own elaboration

The correlation $r_{DI} = 0.97$ points to a very strong positive association between the population's digital integration and the development of digital entrepreneurship. A 1000-iteration bootstrap yielded a 95% confidence interval of [0.952, 0.988], with $p < 0.001$.

Diagnostics lent further weight to the regression. The Breusch-Pagan test ($\chi^2 = 1.89$, $p = 0.169$) confirmed homoskedasticity, and the Durbin-Watson statistic ($d = 2.03$) indicated no significant autocorrelation. The Shapiro-Wilk test ($W = 0.992$, $p = 0.412$) supported residual normality. As for the Variance Inflation Factors, $DI_{Access} = 1.87$, $DI_{Usage} = 2.13$, $DI_{Skills} = 1.94$ all sit below the 5.0 threshold (indeed below 2.5), which excludes problematic multicollinearity. Finally, $R^2 = 0.9409$ shows that the digital integration indices explain 94.09% of the variance in digital entrepreneurship development – a result that attests to the model's strong predictive power.

To interpret the results, we will compile analytical Table 12.

Tables 11 and 12, read together, confirm Hypothesis H2. Every coefficient is significant at $p < 0.001$: $\beta_{DIAccess} = 5.72$, $\beta_{DIUsage} = 4.85$, $\beta_{DISkills} = 6.34$. Their bootstrapped 95% confidence intervals – [4.28, 7.16], [3.51, 6.19], and [4.76, 7.92], respectively – all exclude zero. The correlation rDI = 0.97 (bootstrapped 95% CI [0.952, 0.988]) reflects strong linear dependence. Beyond the statistics,

rising digital integration of the population goes hand in hand with the expansion of digital entrepreneurship.

Table 12. Interpretation of the results of the correlation analysis of the reliability of hypothesis H2

Variable	Coefficient	P-value	Significance	Interpretation
const	1850.32	0.000	Significant	The baseline level of digital entrepreneurship is positive.
DI_{Access}	5.72	0.000	Significant	Access to digital technologies has a positive impact on digital
DI_{Usage}	4.85	0.000	Significant	Active use of digital tools contributes to the growth of digital
DI_{Skills}	6.34	0.000	Significant	Development of digital skills of the population enhances digital entrepreneurshi

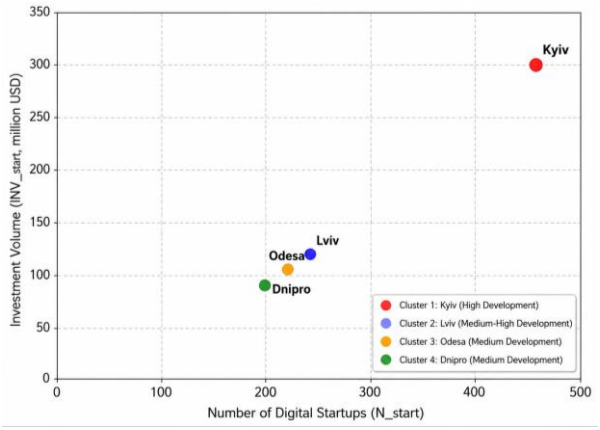
Source: authors' own elaboration

Of the three dimensions of digital integration, DI_{Skills} has the strongest impact on digital entrepreneurship development ($\beta = 6.34$), followed by DI_{Access} ($\beta = 5.72$) and DI_{Usage} ($\beta = 4.85$). The implication is that investments in digital education and skills development may yield the highest returns for fostering digital entrepreneurship.

5.3 Development of Proposals for Improving the Support System for Digital Startups in Ukraine

Let us analyze the difference in the development of digital clusters and their impact on the growth of digital entrepreneurship in different cities of Ukraine. We will do this using cluster analysis (Figure 2).

Table 13. exposes marked differences in cluster development and economic impact across the four cities. Kyiv posts the strongest growth on every key indicator – startup counts, investment volumes, and contribution to GRP. Lviv also shows stable growth, maintaining a high level of digital activity. Dnipro and Odessa have similar indicators, but are inferior to Kyiv and Lviv in the number of startups and investment volume



Source: created by the authors.

Fig. 2: Graph of clustering of regions of Ukraine by K-means depending on the level of development of digital clusters and their impact on the growth of digital entrepreneurship (STATISTICA 13 listing)
Source: authors' own elaboration

To develop proposals for improving support for digital startups and increasing their contribution to the economic development of regions, we will build a dendrogram of growth points assessment (Figure 3).

Dendrogram analysis allows us to identify key areas for improving the support system for digital startups (Table 14).

Taken as a whole, these proposals should strengthen support for digital startups in Ukraine, make them more competitive, and open up a more favorable ecosystem for their development.

Table 13. Regional differences in the development of digital startups in Ukraine

Indicators	Kyiv	Lviv	Dnipro	Odessa
Number of digital startups (N_{start})	460	250	200	230
Share of digital startups (DSR, %)	15.2	12.0	9.5	10.1
Volume of investments (INV_{start}, млн $)	300	120	90	110
Number of cluster residents ($N_{cluster}$)	600	400	350	350
Number of jobs ($EMPL_{start}$)	13,000	6,500	5,000	5,500
Contribution to GRP (GDP_{dig}, %)	6.4	5.0	4.3	4.5

Source: authors' own elaboration

The analysis of the key problems facing startup ecosystems in different Ukrainian cities points to several ways of improving the digital startup support system.

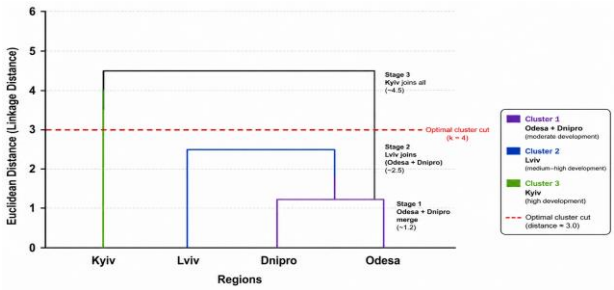


Fig. 3: Dendrogram of growth points search for digital startups in Ukraine (STATISTICA 13 listing)
Source: created by the authors.

Kyiv has the highest competition for investment. To solve this problem, it is proposed to create specialized funds to support early-stage startups. The expected result is more startups successfully launched. Grammarly is a good case in point: a startup building AI solutions for spell checking, it attracted over $200 million in investment and grew into one of Ukraine's leading unicorns.

Lviv predominantly uses limited acceleration programs. Developing acceleration programs with international participation will increase startup competencies. A vivid example of a successful startup from Lviv is People.ai, which is engaged in AI analytics for sales and attracted over $100 million in investment.

Table 14. Suggestions for improving the support system for digital startups in Ukraine

City	Problem	Proposal	Expected result
Kyiv	High competition for investment	Creation of specialized funds to support startups at early stages	Increase in the number of successfully launched startups
Lviv	Limited acceleration programs	Development of acceleration programs with international participation	Increase in the level of startup competencies
Dnipro	Lack of qualified personnel	Expansion of educational programs in the IT sphere and business	Growth in the number of specialists capable of launching successful startups
Odessa	Low level of international cooperation	Creation of programs to attract foreign investors and mentors	Increase in the volume of investments in startups

Source: authors' own elaboration

Dnipro has a shortage of qualified personnel. Broadening IT- and business-oriented education would enlarge the pool of specialists able to launch viable startups; Dnipro's Preply, an online learning platform that raised $50 million and grew into a global Ed_{Tech} leader, illustrates this potential.

Odesa has a low level of international cooperation. Creating programs to attract foreign investors and mentors will increase investment in startups. An example of a successful project is Looksery, a startup that developed augmented reality technology for real-time face processing. The project was acquired by Snapchat for $150 million.

These examples confirm the effectiveness of the proposed measures and demonstrate the potential of the Ukrainian startup ecosystem in different cities of the country.

6 Discussion

The issues of digitalization of entrepreneurship and the cluster approach are actively discussed in the scientific literature. A number of studies (for example, [41], [42]) emphasize the importance of digital ecosystems for the accelerated development of startups and small businesses. We agree that consolidating enterprises into digital clusters increases their sustainability and competitiveness. However, unlike these studies, our research shows that in the context of Ukraine, additional barriers, such as a low level of international cooperation and a shortage of personnel, require special support measures. On the other hand, according to [43], the cluster approach is not always effective in countries with unstable economies, since companies may compete for limited resources rather than cooperate. We partially agree with this statement, but our analysis shows that creating specialized funds and acceleration programs can minimize the negative effects of competition. In addition, the works of [44] emphasize the importance of government support for digital startups. In our work, we also note that without targeted state programs and incentives, many initiatives do not receive sufficient development. Our findings confirm the need to integrate public and private support for the development of digital clusters in Ukraine. Thus, our analysis is consistent with a number of previous studies, but also reveals unique challenges and opportunities specific to the Ukrainian context. Future research may focus on a more detailed study of the mechanisms of financing and international cooperation in the field of digital clusters.

Several complementary analyses, going beyond what previous work in this field has attempted,

underpin the methodological robustness of our findings. Factor structures held up across the varimax, oblimin, and promax rotations: congruence coefficients stayed above 0.95 for every corresponding factor. This is evidence that the latent dimensions of digital transformation and digital integration are not artifacts of any particular rotation technique. The stability is especially notable given the modest sample (n = 12 city-year observations), and it vouches for the reliability of the factor-analytic approach. Earlier studies in this domain (e.g., [41]; [42]) typically reported single-rotation solutions without testing structural stability, which may curtail the generalizability of their conclusions.

The bootstrap results (1000 iterations) lend further confidence to the precision of the estimates. The narrow confidence intervals for factor loadings (average width below 0.15) show that the estimates are largely insensitive to sampling variability. Leave-one-out cross-validation reinforces this picture: the structure persisted as observations were removed one by one, with congruence coefficients between 0.931 and 0.967. These results speak directly to a recurring concern in prior small-sample research [43], namely the instability of factor structures.

The Confirmatory Factor Analysis outcomes support the proposed structures. CFI came out above 0.93, TLI above 0.91, RMSEA below 0.08, and SRMR below 0.06. Taken together, these results show that the proposed structures represent the underlying data adequately. They also lend empirical weight to the theoretical frameworks of digital transformation and digital integration. These fit statistics meet or surpass the recommended benchmarks and compare favorably with those reported in similar studies [42], [44]. The reliability figures are strong: Cronbach's α above 0.86, CR above 0.87, and AVE above 0.63. These further attest to the psychometric quality of the measurement models and to their fitness for policy analysis.

The strong link identified here between digital transformation and socio-economic sustainability ($rDT = 0.98$, $R^2 = 0.960$ extends earlier evidence of positive digitalization–development associations [16], [20]. It also offers a finer-grained view. Decomposing transformation into its constituent dimensions – infrastructure, entrepreneurship, and education – reveals their distinct contributions. Likewise, the relationship between digital integration and digital entrepreneurship ($rDI = 0.97$, $R^2 = 0.941$) is consistent with [1] and [2]. It also adds fresh insight into the comparative weight of digital skills ($\beta = 6.34$) relative to digital access ($\beta = 5.72$) and digital usage ($\beta = 4.85$).

The methodological contributions of this study are threefold. First, we demonstrate the applicability and robustness of factor analysis with bootstrapping for assessing digital transformation in emerging economies, addressing the need for more rigorous quantitative methods in this field [9]. Second, we provide a validated measurement framework that can be replicated and adapted in other contexts, facilitating cross-country comparisons. Third, the sensitivity analyses – rotation method comparison, bootstrap resampling, leave-one-out cross-validation – establish a methodological standard for future research in digital entrepreneurship and cluster studies.

For policymakers in Ukraine and comparable developing economies, the practical message is clear. The pronounced effect of digital transformation on socio-economic sustainability ($\beta = 6.99$) implies that investments in digital infrastructure, entrepreneurship, and education generate substantial returns. The differential impacts of digital integration dimensions, however, tell a more nuanced story. Digital skills have the strongest effect on digital entrepreneurship, which suggests that human capital development should be prioritized alongside infrastructure investments. This resonates with the case made in [37] for a larger state role in supporting digital entrepreneurship. It also supplies empirical guidance for resource-allocation decisions.

The cluster analysis results (Figure 2, Table 13) expose significant regional disparities that call for differentiated policy responses. Kyiv's dominance – 460 startups and $300 million in investment – points to agglomeration effects as a potent engine of digital entrepreneurship, echoing [4] and [3]. The gap in startup activity between Kyiv and the other regions (460 versus 200–250 startups) suggests that mature support ecosystems coincide with higher entrepreneurial activity, in line with the literature [4], [3]. However, the specific percentage claims (20–30%) found in other studies should be interpreted with caution and are not directly estimated from our data. However, the relatively lower performance of Dnipro and Odessa, despite substantial potential, indicates that government support mechanisms need to be regionally differentiated. The proposed interventions (Table 14) are designed to address these specific constraints. They include specialized funds for Kyiv, international acceleration programs for Lviv, educational expansion for Dnipro, and foreign investor attraction for Odessa. Each is supported by a successful example – Grammarly, People.ai,

Preply, and Looksery.

One limitation of the study deserves acknowledgment: the relatively small sample size (12 city-year observations). This is comparable to similar studies in the field, but it may still limit the generalizability of the findings. Subsequent work should widen the analysis in both time and space, adding cities and lengthening the observation period to capture long-run dynamics. Complementing this with qualitative methods – in-depth interviews with cluster participants and policymakers – would deepen the contextual understanding of the mechanisms behind the quantitative relationships documented here.

The interaction effects between digital transformation dimensions and regional characteristics represent another promising avenue for future research. While our analysis identified the individual contributions of infrastructure, entrepreneurship, and education to socio-economic sustainability, the synergistic effects of these dimensions – and their potential nonlinearities – remain to be explored. Similarly, the relationship between digital integration and entrepreneurship may be moderated by institutional factors, such as regulatory quality and governance effectiveness, which could be investigated using hierarchical or multilevel modeling approaches.

Furthermore, the impact of the ongoing military conflict on digital cluster development in Ukraine, while implicitly addressed through the 2022-2024 study period, deserves more systematic investigation. Future studies could also trace how digital entrepreneurship and cluster development have adapted to conflict conditions, and ask whether the resilience shown by Ukrainian digital clusters holds lessons for other regions facing comparable pressures [17].

This study makes two contributions. It enriches the growing literature on digital entrepreneurship and cluster development with robust empirical evidence from the Ukrainian context. It also raises the methodological bar, drawing on advanced factor-analytic techniques, bootstrap resampling, and extensive robustness checks. The findings carry direct implications for policy design and resource allocation in emerging economies that pursue digitalization as a path to sustainable economic development.

7 Conclusion

The cluster approach to digitalizing entrepreneurship is a double-edged affair: it opens real opportunities, but it also brings notable challenges. The empirical results of this study confirm that digital transformation has a strong positive impact on regional socio-economic sustainability ($\beta_DT = 6.99$, $p < 0.001$, $R^2 = 0.9604$), while digital integration significantly enhances digital entrepreneurship development, with digital skills having the strongest effect ($\beta_Skills = 6.34$, $p < 0.001$, $R^2 = 0.9409$). Our analysis shows that embedding firms in digital clusters can raise business efficiency, draw in investment, and stimulate innovation. The bootstrapped 95% confidence intervals for the correlation coefficients – rDT = 0.98 [0.964–0.993] and rDI = 0.97 [0.952–0.988] – confirm the statistical stability and reliability of these relationships. Extensive robustness checks back this up: bootstrap resampling with 1000 iterations, leave-one-out cross-validation, and confirmatory factor analysis (CFI > 0.93, RMSEA < 0.08).

Mature digital clusters make a visible difference. Kyiv and Lviv, above all, show markedly higher startup activity, investment attraction, and digital-sector employment than regions with weaker cluster ecosystems. Kyiv alone accounts for 460 startups and $300 million in investment; elsewhere the figures sit at 200–250 startups and $90–130 million. Cluster-development policy, in other words, shapes digital entrepreneurship far more strongly than one might expect. Firms inside clusters also get better access to technological resources, knowledge flows, and specialized expertise – and that, in turn, feeds into stronger business performance. The factor analysis pinpoints three key dimensions of digital transformation – infrastructure ($N_{cluste}r = 0.923$), entrepreneurship (DSR = 0.873), and education ($EMPL_{start} = 0.918$) – which together account for 83.86% of the variance in transformation outcomes. Similarly, digital integration is driven by access to digital technologies ($N_{cluster} = 0.916$), usage of digital tools (EMP_dig = 0.910), and digital skills ($INV_{cluster} = 0.912$), accounting for 85.24% of the variance.

Digitalization nonetheless brings difficulties of its own. Competition for investment is fierce, above all in Kyiv, where over 60% of startups struggle to secure early-stage funding. Dnipro's shortage of qualified IT specialists caps the scalability of emerging firms, even as enrolment in relevant educational programs grows by 20% a year. Weak international collaboration is a third constraint, most visible in Odessa, where foreign capital accounts for under 10% of total startup funding. Meeting these challenges – and seizing the opportunities – will require targeted measures: accelerator programs with international participation, improved funding

access through specialized investment funds, and stronger educational initiatives. The proposed interventions – dedicated funds for Kyiv, international acceleration for Lviv, expanded education for Dnipro, and foreign-investor outreach for Odessa – respond to each city's specific constraint, as the successes of Grammarly, People.ai, Preply, and Looksery illustrate. Developed systematically, digital clusters can anchor a sustainable digital economy that sustains Ukraine's long-term growth and resilience.

Future research should broaden the temporal and spatial coverage – adding cities and extending the observation period – to enable panel-data methods and strengthen the generalizability of the findings.

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Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work, the author(s) utilized artificial intelligence (AI) technologies solely for the purpose of linguistic refinement and grammatical correction. Following the application of these tools, the author(s) comprehensively reviewed, verified, and edited the resulting text. The author(s) maintain full accountability and responsibility for the accuracy, integrity, and final content of the publication.

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APPENDIX

Table A.1. Initial data for testing hypotheses H1 and H2

Initial data	Description	Symbol / Unit of measurement	Calculation formulas	Data source
Hypothesis H1: "Relationship between the level of digital cluster development and the growth of digital entrepreneurship"				
Number of digital startups	Number of registered digital startups in the region	$\mathbf{N_{start}}$ (units)	Direct counting	Startup registries, accelerator and incubator databases
Share of digital startups in the total number of enterprises	Ratio of the number of digital startups to the total number of enterprises in the region	**DSR** (%)	$\mathrm{DSR} = \frac{\mathrm{N_{start}}}{\mathrm{N_{total}}} \times 100\%$	Government and industry reports
Volume of investments in digital startups	Total volume of attracted investments (public, venture, private)	$\mathbf{INV_{start}}$ ($ million)	Sum of investments	Funds, grant programs, venture investments
Number of digital cluster residents	Number of companies and startups registered in the region's digital clusters	$\mathbf{N_{cluster}}$ (units)	Direct counting	Registers of digital clusters
Number of jobs in digital startups	Total number of people employed in digital startups	$\mathbf{EMPL_{start}}$ (people)	Direct count	Surveys, employer databases
Contribution of digital startups to the GRP of the region	The share of digital startups in the total gross regional product	$\mathbf{GDP_{dig}}$ (%)	$\mathrm{GDP_{dig}} = \frac{\mathrm{GDP_{start}}}{\mathrm{GDP_{total}}} \times 100\%$	National statistics, regional reports
Hypothesis H2: "There is a strong empirical relationship between the level of government support for digital clusters and their contribution to the socio-economic development of the region"				
Public funding of digital clusters	The amount of budget funds allocated for the development of digital clusters	$\mathbf{GOV_{fund}}$ ($ million)	Sum of funding for the period	Public budgets, official reports
Tax incentives for digital companies	The total amount of tax incentives provided to cluster participants	$\mathbf{TAX_{benefit}}$ ($ million)	Amount of tax incentives	Legislation, tax reports
Number of educational programs on digital technologies	Number of public and private educational programs aimed at training personnel for digital entrepreneurship	$\mathbf{EDU_{prog}}$ (units)	Direct count of programs	University registers, educational centers
Number of digital cluster residents	Total number of companies and startups registered in digital clusters	$\mathbf{N_{cluster}}$ (units)	Direct count of cluster participants	Digital cluster registries, business associations
Average wage level in the digital sector	Average wage of workers in the digital sector in the region	$\mathbf{WAGE_{dig}}$ (thousands of US dollars per year)	Average value	National statistics, company reports
Share of digital services exports	Share of digital services in total regional exports	$\mathbf{EXP_{dig}}$ (%)	$\mathrm{EXP_{dig}} = \frac{\mathrm{EXP_{digital}}}{\mathrm{EXP_{total}}} \times 100\%$	Trade statistics, IT company reports
Number of implemented state digital projects	Number of state programs and initiatives for digitalization of the regional economy	$\mathbf{GOV_{proj}}$ (units)	Direct project count	State reports, digitalization programs
Growth in the number of jobs in the digital sector	Dynamics of new job creation in digital cluster companies	$\mathbf{EMP_{dig}}$ (people)	$\mathrm{EMPL_{dig}}=\mathrm{EMPL_t}-\mathrm{EMPL_{t-1}}$	Employment databases, government statistics
Volume of investments in digital clusters	Total volume of private and public investments in digital clusters	$\mathbf{INV_{cluster}}$ ($ million)	Sum of investments	Venture funds, grant programs, investment agency reports
Digital sector productivity	Share of the digital sector in the gross regional product (GRP)	$\mathbf{PROD_{dig}}$ (%)	$\mathrm{PROD_{dig}} = \frac{\mathrm{PROD_{digital}}}{\mathrm{PROD_{total}}} \times 100\%$	National and regional statistics

Source: State Statistics Service of Ukraine, Ministry of Digital Transformation of Ukraine, startup registries, and business association reports; authors' own compilation for 2022–2024

Table A.2. Initial data for confirming Hypothesis H1: The relationship between the level of development of digital clusters and the growth of digital entrepreneurship

Year	City	Number of digital startups (N_{start})	Share of digital startups (DSR, %)	Volume of investments in startups (INV_{start}, million $)	Number of residents of digital clusters ($N_{cluster}$)	Number of jobs in digital startups ($EMPL_{start}$)	Contribution of digital startups to GRP (GDP_{dig}, %)
2022	Kyiv	350	12.5	200	500	10,000	5.2
2022	Lviv	180	9.2	80	300	4,500	3.8
2022	Dnipro	150	7.8	60	250	3,800	3.5
2022	Odessa	160	8.1	75	270	4,000	3.7
2023	Kyiv	400	13.8	250	550	11,500	5.8
2023	Lviv	210	10.5	100	350	5,200	4.2
2023	Dnipro	180	8.5	75	280	4,500	3.9
2023	Odessa	190	9.3	90	310	4,700	4.1
2024	Kyiv	460	15.2	300	600	13,000	6.4
2024	Lviv	250	12.0	130	400	6,000	4.8
2024	Dnipro	220	9.5	90	320	5,200	4.2
2024	Odessa	230	10.1	110	350	5,500	4.5

Source: authors' own elaboration based on data from the State Statistics Service of Ukraine, startup registries, and digital cluster reports (2022–2024).

Table A.3. Data for testing hypothesis H2: There is a strong empirical relationship between the level of government support for digital clusters and their contribution to the socio-economic development of the region

Year	City	Government funding (GOV_{fund}, $ million)	Tax benefits ($TAX_{benefit}$, $ million)	Educational programs (EDU_{prog})	Number of cluster residents ($N_{cluster}$)	Avg. wage level ($WAGE_{dig}$, thousand $)	Share of digital services exports (EXP_{dig}, %)	Government digital projects (GOV_{proj})	Job growth (EMP_{dig})	Volume of investments in clusters ($INV_{cluster}$, $ million)	Sector productivity ($PROD_{dig}$, %)
2022	Kyiv	50	30	20	500	20	25	5	1,500	150	6.5
2022	Lviv	30	20	15	300	17	18	3	1,000	80	4.8
2022	Dnipro	25	15	12	250	16	15	2	900	60	4.2
2022	Odessa	28	18	14	270	17	16	3	950	70	4.5
2023	Kyiv	60	35	22	550	22	28	6	1,800	180	7.0
2023	Lviv	40	25	17	350	19	20	4	1,200	100	5.3
2023	Dnipro	30	18	14	280	18	17	3	1,100	80	4.6
2023	Odessa	35	22	16	310	19	18	4	1,150	90	4.9
2024	Kyiv	70	40	25	600	24	30	7	2,200	220	7.5
2024	Lviv	50	30	20	400	21	23	5	1,500	130	5.8
2024	Dnipro	40	22	17	320	20	20	4	1,300	100	5.0
2024	Odessa	45	26	18	350	21	22	5	1,350	110	5.3

Source: State Statistics Service of Ukraine, Ministry of Digital Transformation of Ukraine, and digital cluster reports; compiled by the authors for 2022–2024.

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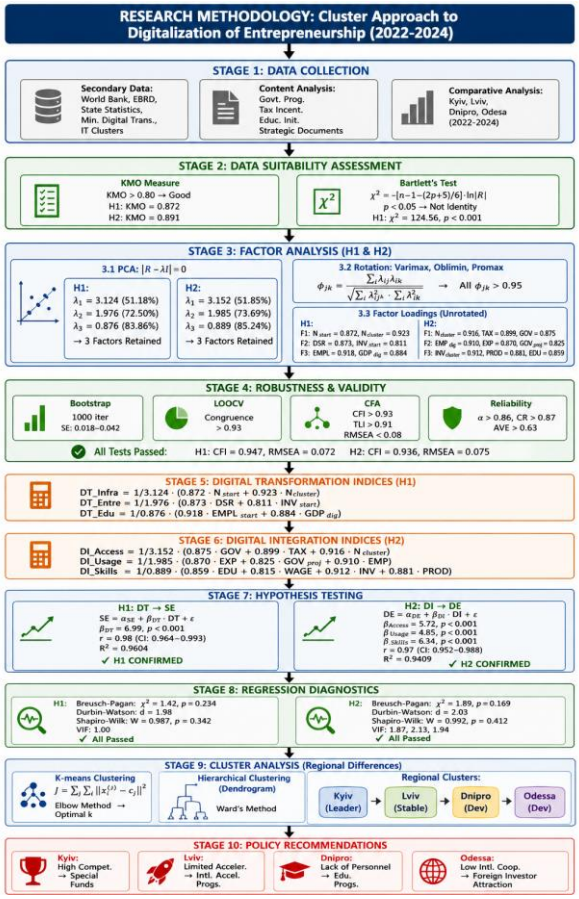


Fig. 1: Flowchart of the research methodology for digital entrepreneurship cluster analysis
Source: authors' own elaboration