Same Ecosystem, Different Diagnosis? Comparing Composite Indicator Methods for Digital Entrepreneurial Ecosystems

Extended Abstract

Objective and contribution

Entrepreneurship research has increasingly shifted from explanations based on isolated determinants toward systemic approaches in which entrepreneurial outcomes emerge from interactions among multiple actors, resources, institutions, and contextual conditions. Entrepreneurial ecosystem (EE) research embodies this shift by conceptualizing entrepreneurship as a product of interdependent and complementary elements rather than independently functioning factors (Acs et al., 2014; Stam, 2015; Spigel, 2017; Stam & van de Ven, 2021). Digitalization reinforces these interdependencies by transforming opportunity structures, organizational boundaries, interactions among actors, and the processes through which entrepreneurial ventures are created and scaled (Nambisan, 2017; Autio et al., 2018; Nambisan et al., 2019).

The Digital Entrepreneurship Ecosystem (DEE) framework integrates digital infrastructure, digitally enabled users, platform-based interactions, institutions, and entrepreneurial agency within a unified systemic perspective (Sussan & Acs, 2017; Szerb et al., 2026). This systemic conception creates an important measurement problem. Ecosystems are multidimensional constructs and consequently require composite indicators, but constructing such indicators involves choices concerning weighting, aggregation, and compensability. These choices are not merely technical: different methodologies embody different assumptions about how ecosystem components contribute to overall performance and may therefore influence both measured performance and the policy diagnosis derived from it (OECD & JRC, 2008).

This issue is particularly important for ecosystem policy. Conventional market-failure reasoning justifies intervention where markets fail to allocate resources efficiently (Bator, 1958). The ecosystem perspective extends this reasoning to system failure, in which weaknesses arise from the configuration and interaction of complementary system components. Under bottleneck reasoning, strong performance in some components cannot fully offset weaknesses elsewhere; improving an already strong component may therefore generate limited systemic benefits when another component constrains overall functioning (Acs et al., 2014). Furthermore, because ecosystems differ in their configurations, policy priorities should be ecosystem-specific rather than uniform (Lafuente et al., 2022). The paper consequently connects composite-indicator methodology directly to ecosystem policy.

We ask:

To what extent do alternative composite-indicator methodologies generate similar aggregate assessments of digital entrepreneurial agency while producing different internal configurations and policy diagnoses?

The paper makes three contributions. First, it examines the robustness of ecosystem measurement across methodologies embodying substantially different weighting and aggregation principles. Second, it distinguishes **aggregate robustness from diagnostic robustness**: similar composite scores need not imply identical assessments of internal ecosystem configuration. Third, it introduces **bottleneck separation**—the distance between the weakest and second-weakest components—as an indicator of the confidence with which a unique ecosystem constraint can be identified. This distinction is policy-relevant because methodological disagreement may indicate genuinely different diagnoses, but it may also result from minor ranking reversals between nearly equivalent weaknesses.

Conceptual and methodological framework

The analysis focuses on four components underlying the Digital Technology Entrepreneurship (DTE) sub-index of the DEE Index: **Finance, Key Employees, Support Organizations, and Digital Technology Infrastructure**. Entrepreneurial agency is understood here not in the classical principal–agent sense but as distributed agency: the capacity of interconnected actors to mobilize and recombine resources, exploit opportunities, and contribute to structural change. Digital entrepreneurship increasingly distributes such agency among financiers, employees, support actors, technology providers, platform participants, and other complementors (Nambisan, 2017; Autio et al., 2018).

The original DTE structure contains three pillars—Digital Absorption, Digital Startup Support, and Digital Scaleup Support—each combining digital-technology and entrepreneurial-agent variables. We reorganize these underlying normalized measures horizontally into four functionally distinct components. Finance is the arithmetic mean of access to early-stage and later-stage venture capital. Key Employees combines digital skills, research and engineering talent, and professional and managerial talent. Support Organizations combines industry activity, startup-support infrastructure, and scaleup-supporting services. Digital Technology Infrastructure averages digital-use, startup, and scaleup digital-infrastructure measures. Thus, each component captures a comparable function across the absorption, startup, and scaleup stages while preserving the underlying DEE measurement architecture. The detailed construction is reported in the full paper.

Four composite-indicator methodologies, represented by five specifications, are applied to these components.

Principal Component Analysis (PCA) derives common weights from the covariance structure of the underlying variables and represents their dominant common statistical dimension (Jolliffe & Cadima, 2016). It permits full compensation and applies the same weighting structure to all ecosystems.

CRITIC (Criteria Importance Through Intercriteria Correlation) assigns common objective weights according to each component's variation and non-redundant information. Components displaying greater contrast and contributing information not already contained in correlated components receive greater weights (Diakoulaki et al., 1995).

Benefit-of-the-Doubt (BOD) uses Data Envelopment Analysis principles to assign observation-specific endogenous weights that maximize each country's relative composite performance (Cherchye et al., 2007). This ecosystem-specific weighting is attractive for heterogeneous ecosystem configurations, although unrestricted BOD weights can become extreme. We therefore estimate two specifications: BOD1 restricts weights to 20–30%, while BOD2 permits a wider range of 15–35%.

Penalty for Bottleneck (PFB) is explicitly grounded in systemic bottleneck reasoning (Acs et al., 2014). Component contributions are adjusted according to their distance from the weakest element. PFB is partially compensatory: stronger components can compensate for weaknesses, but not fully. Like BOD, its effective weighting is ecosystem-specific, but whereas BOD emphasizes relative strengths, PFB explicitly emphasizes systemic constraints.

Thus, the methods differ in both **weight structure**—common versus ecosystem-specific—and **diagnostic logic**—latent structure, distinctive information, optimized relative strengths, or bottlenecks.

Data and empirical strategy

The empirical analysis uses a balanced panel of **86 countries observed annually from 2017 to 2022**, yielding **516 country-year observations**. Countries with missing values for any of the four components are excluded, ensuring that all five specifications are applied to identical observations.

The analysis addresses three questions:

RQ1 – Aggregate robustness: To what extent do alternative methodologies produce similar aggregate entrepreneurial-agency scores?

RQ2 – Configurational robustness: To what extent do alternative methodologies identify the same weakest agency component?

RQ3 – Diagnostic ambiguity: When methodologies disagree about the weakest component, is disagreement associated with smaller separation between the first- and second-order constraints?

The empirical analysis proceeds in three stages. First, pairwise correlations among the five composite scores establish aggregate methodological robustness. Second, we identify the weakest weighted component under each specification and calculate pairwise and overall agreement rates. Third, we test whether disagreement is related to bottleneck separation. For each method, the bottleneck gap is defined as the difference between the weighted contributions of the second-lowest and lowest components. For each PFB–alternative-method comparison, we use the average gap between the two methods and regress this measure on an indicator of whether they disagree on the identity of the weakest component. The regressions include year fixed effects and country-clustered standard errors. A negative coefficient indicates that methodological disagreement is concentrated where the two weakest constraints are more closely positioned.

Results

The first result is **exceptionally strong aggregate robustness**. Pairwise correlations among PFB, BOD1, BOD2, PCA, and CRITIC all exceed **0.99**, despite their substantially different weighting principles. An important explanation lies in the underlying data structure: correlations among the four unweighted agency components range from approximately 0.67 to 0.91. Thus, all methodologies operate on components sharing substantial common information, limiting the effect of alternative weighting schemes on aggregate scores.

Configurational robustness is lower but remains substantial. All five specifications identify the **same weakest component in 69.8%** of country-year observations. At least four of the five agree in another 14.5% of observations, meaning that four or more methods provide the same diagnosis in **84.3%** of observations. Pairwise agreement ranges from 76.4% to 98.3%. PFB agrees with BOD1 in 84.1%, BOD2 in 84.7%, PCA in 88.0%, and CRITIC in 78.1% of observations. The two BOD variants agree in 98.3% of cases.

The substantive diagnosis is also consistent. **Key Employees are the most frequently identified constraint across all specifications, accounting for approximately 60% of cases under PFB and BOD,** and 72–75% under PCA and CRITIC. Finance is generally the second most frequent constraint, while Support Organizations and Digital Technology Infrastructure are rarely the weakest. Some temporal divergence occurs, particularly in 2021, when Finance and Key Employees changed relative positions in many ecosystems. Because these components were already closely positioned, comparatively small movements could reverse their ordinal ranking.

The bottleneck-gap analysis provides the most important qualification. Across all four PFB comparisons, disagreement is associated with a **significantly smaller first–second bottleneck gap ($p < .001$)**. For PFB–BOD1, the average gap falls from 0.0139 when the methods agree to 0.0053 when they disagree; for PFB–BOD2, from 0.0131 to 0.0050. The corresponding figures are 0.0247 versus 0.0066 for PCA and 0.0282 versus 0.0114 for CRITIC. These relationships remain highly significant after controlling for year effects.

Consequently, the approximately 30% of observations without complete five-method agreement should not be interpreted automatically as substantively different ecosystem diagnoses. Much of the disagreement occurs where no clearly separated unique bottleneck exists. Country examples reinforce this interpretation: Canada (2021) represents clear cross-method agreement; Ecuador (2021) shows nominal disagreement associated with extremely small first–second gaps; Sweden (2021) illustrates more substantive methodological divergence, although the BOD specifications themselves place Finance and Key Employees very close together.

Conclusions and policy implications

The findings indicate neither complete methodological invariance nor pervasive methodological sensitivity. Instead, **methodological robustness depends on the clarity of the underlying ecosystem configuration**. Alternative methodologies yield almost identical aggregate assessments, while diagnostic differences become more visible at the component level and are particularly concentrated where competing constraints are closely ranked.

This leads to an important distinction between **bottleneck identity and bottleneck confidence**. Knowing which component ranks lowest is insufficient for policy diagnosis; it also matters how clearly it is separated from other constraints. Cross-method convergence combined with substantial bottleneck separation provides a stronger basis for identifying a dominant policy priority. Conversely, disagreement accompanied by small gaps suggests that identifying a unique target exaggerates the precision of the evidence.

The policy implication is therefore to move beyond both uniform ecosystem policies and the mechanical targeting of a single weakest component. Where several constraints are closely positioned, a **prioritized policy mix** is more appropriate: interdependent weaknesses should be addressed jointly, with their relative severity determining the order of intervention priorities. This is consistent with the ecosystem concept itself, according to which systemic performance emerges from complementarities and interactions among multiple components rather than from the isolated optimization of individual factors.

The study is limited by measurement and cross-country comparability constraints inherited from the DEE Index, and by the analytical simplification entailed in reorganizing interdependent DTE indicators into four comparable components. Moreover, methodological weights should not be interpreted as causal effects. Future research should therefore assess the external validity of alternative weighting schemes against entrepreneurial outcomes such as startup formation, scaling, exits, and productivity, and investigate whether appropriate weighting structures vary systematically with development level, institutional quality, or ecosystem evolution.

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