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# From Framework to Diagnostic Composite Indicator: The OECO_Sy Model for SME Innovation Propensity in University-Led Open Innovation Ecosystems

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**Abstract**

This paper extends a previous conceptual proposal on the role of the Grant Office Service of the University of Foggia in open innovation ecosystems by introducing a determinant-level composite indicator for Small and Medium-sized Enterprises. The proposed OECO_Sy model transforms three diagnostic questionnaires into twenty normalized determinants and three coefficients: the Preliminary Innovation Propensity Coefficient (PIPC), the Management Innovation Propensity Coefficient (MIPC), and the Composite Coefficient of SME Innovation Propensity (CCSIP). The methodological contribution is twofold. First, the university role of Expert is formalized as a measurable, replicable and non-discretionary diagnostic function. Secondly, the transition from the Preparation State to the Formation State is operationalized through a six-category analysis of project briefs, so that quantitative diagnosis is translated into tailored open-innovation actions. The framework is applied to a pilot sample of ten SMEs in the TCOREC case study in the Province of Foggia. The CCSIP ranges from 0.503 to 0.763; in eight firms out of ten MIPC exceeds PIPC, indicating solid organizational conditions but weaker formalization of innovation and intellectual property. A Monte Carlo sensitivity analysis on Q.2 weights supports the robustness of the equal-weight baseline. The results are exploratory, but they show that OECO_Sy can operate as a mathematically transparent decision-support model for university-led innovation ecosystems.

**Mathematics Subject Classification:** 90B50, 91B82, 62H20, 62P20, 68T37

**Keywords:** Open innovation ecosystem, Composite indicator, SMEs, University Grant Office, Innovation propensity, Intellectual property, Artificial intelligence

# 1 Introduction

The capacity of firms to innovate is no longer a purely internal managerial attribute. It depends increasingly on the ability to enter, navigate and exploit heterogeneous systems of knowledge, finance, technological expertise and institutional support. This is especially evident for Small and Medium-sized Enterprises (SMEs), whose flexibility is often counterbalanced by weak absorptive capacity, limited access to specialized intellectual property (IP) competences, and a shortage of dedicated resources for technological transformation. The policy relevance of this problem is consistent with the United Nations 2030 Agenda, which places innovation and sustainable industrialization at the centre of SDG 9 [24]. It is also consistent with the Oslo Manual, where business innovation capabilities are treated as a combination of managerial, human-resource and technological capabilities rather than as a single output variable [17].

Open innovation [5] and the innovation ecosystem perspective [6], [10] provide the theoretical foundation for addressing this problem. They shift the analytical focus from the isolated firm to the co-evolution of actors, roles and resources. Universities are among the actors that can reduce knowledge and coordination failures in such ecosystems, not only through technology transfer but also through entrepreneurial education, mentoring, networking and access to research infrastructures [2], [3]. However, the literature on SME-university collaboration still reports a gap between general claims about the benefits of collaboration and operational methods for measuring the readiness of firms to enter an innovation ecosystem [4].

The starting point of this paper is the OECO_Sy framework proposed by Di Letizia, Grilli and Di Noia [7]. That earlier work defined an organizational architecture through which the Grant Office Service of the University of Foggia

(GOS-Unifg) could support SMEs in the Preparation State of an open innovation ecosystem. Its contribution was primarily conceptual: it identified three questionnaires, the role of GOS-Unifg as an Expert, and the idea of a composite coefficient of innovation propensity. The present paper extends that work in a more rigorous mathematical and empirical direction. It introduces a determinant-level scoring system, formalizes the composite indicators, tests them on a pilot sample of firms, evaluates the robustness of the weighting assumptions, and connects the quantitative diagnosis with project briefs and open-innovation agreements.

The aim is not to claim that innovation can be reduced to a single number. Rather, the aim is to show how a bounded, transparent and reproducible composite indicator can support institutional decision-making when several qualitative and quantitative dimensions must be combined. In this sense, OECO_Sy is closer to a decision-support model than to a ranking exercise. Its value lies in making the diagnostic logic explicit, contestable and replicable.

The paper makes four contributions. First, it reinterprets the university function of Expert as a quantitative diagnostic function within the genesis phase of an innovation ecosystem. Secondly, it defines PIPC, MIPC and CCSIP as normalized composite indicators built from twenty determinants. Thirdly, it reports pilot evidence from ten anonymized SMEs participating in the TCOREC case study, thereby moving beyond the purely prospective framework of [7]. Fourthly, it introduces an operational bridge between the coefficients and the Formation State of the ecosystem by means of a six-category brief-analysis grid.

The remainder of the paper is organized as follows. Section 2 presents the theoretical background and the research gap. Section 3 formalizes the OECO_Sy diagnostic model. Section 4 reports the pilot application to the TCOREC SMEs. Section 5 discusses the implications for university-led innovation ecosystems. Section 6 concludes with limitations and future research directions.

# 2 Theoretical background

Innovation ecosystems are usually described as communities of heterogeneous actors that co-create value through complementary roles and resources [6], [10]. Recent extensions toward sustainability, resilience and human-centred digital transformation reinforce this ecosystem interpretation [1]. The lifecycle metaphor introduced by Moore [14], [15] and later applied to innovation ecosystems is particularly useful because it distinguishes the genesis of an ecosystem from later stages of expansion, operation and renewal. During ecosystem genesis, roles are not yet stabilized; firms must identify needs, universities and other knowledge actors must articulate their possible contributions, and trust must be generated before formal collaboration becomes possible.

Dedehayir, Makinen and Ortt [6] classify roles during innovation ecosystem genesis into leadership roles, direct value-creation roles, value-creation support roles and entrepreneurial ecosystem roles. In this taxonomy, the university can be interpreted as an Expert: it does not replace the entrepreneur, and it does not directly create the commercial value of the innovation; rather, it supports the actors that do so by generating, organizing and transferring knowledge. This interpretation is important for SMEs. It is also consistent with recent Italian open-innovation evidence that stresses the operational need to strengthen university-enterprise interfaces [25]. An Expert service should not impose a project on the firm; it should diagnose the firm, decode the demand for innovation and then activate the appropriate set of academic, technological, financial and market resources.

The specific role of universities in innovation ecosystems is broader than classical technology transfer. Universities provide skills, research infrastructures, access to finance, entrepreneurial education, long-term networks and system integration [3]. At the same time, SME-university collaboration is not automatic. A recent systematic literature review identifies fragmentation in the evidence on how SMEs and universities collaborate and how such collaboration can be structured [4]. In parallel, research on open innovation in micro-enterprises shows that ecosystem participation can help firms overcome internal-resource limitations and absorb external knowledge [18]. These findings justify the need for an operational framework that is both ecosystem-oriented and SME-specific.

The measurement issue is central. Because technological innovation lacks a single universally accepted operational method [23], the Oslo Manual recommends observing innovation capabilities through managerial, human-resource and technological dimensions [17]. Yet these dimensions are rarely available as standardized firm-level indicators in the early stages of collaboration. The Grant Office is therefore confronted with incomplete, heterogeneous and partly qualitative information. This is precisely the type of problem for which composite indicators can be useful, provided that the assumptions about normalization, weighting, aggregation and interpretation are made explicit [17]. A composite indicator is not an objective truth; it is a transparent aggregation rule used to represent a multidimensional construct.

OECO_Sy is situated in this methodological space. It combines the ecosystem role theory of [6], the open-innovation perspective of [5], the SME capability view of [17], the university integration perspective of [3], and the composite-indicator methodology of [16]. Its originality is not the claim that universities support innovation; this is well established. The originality lies in transforming this support function into a measurable diagnostic workflow that can be used by a university Grant Office before the firm enters a formal open-innovation agreement.

# 3 The OECO_Sy diagnostic model

## 3.1 Architecture and system boundary

The OECO_Sy framework, whose name derives from the Latin root oecosystema, is designed around the genesis phase of an innovation ecosystem. It distinguishes three states: Preparation, Formation and Operation. The Preparation State includes preliminary investigation, innovation-process evaluation and measurement of innovation propensity. The Formation State includes consultation, expertise, matching between demand and available university or ecosystem services, and the negotiation of open-innovation agreements. The Operation State includes technology transfer, commercialization and support networking.

In the earlier framework [7], the analytical boundary was concentrated on the Preparation State. The present extension keeps that boundary for the construction of the coefficients but explicitly adds the initial part of the Formation State through the analysis of project briefs. This extension is methodologically relevant: a coefficient can estimate how ready a firm is, but it cannot identify what the firm wants to build, which competences are required, or which agreement form is appropriate. Consequently, OECO_Sy uses a sequential rule. The quantitative diagnosis comes first; the brief analysis comes second. The order is not interchangeable because the sixth category of the brief grid measures coherence between the brief and the already computed diagnostic profile.

The model is administered by GOS-Unifg to SME representatives as an innovation-nudging device [22], typically the legal representative or the person responsible for innovation projects. The three questionnaires are Q.1 on funding, innovation and artificial intelligence (AI); Q.2 on industrial property diagnosis; and Q.3 on organizational innovation capability. Q.1 and Q.2 are original instruments developed from field experience and from the interaction between GOS-Unifg and knowledge-transfer activities. Q.3 operationalizes the innovation capability determinants identified by Saunila [20], [21] through a structured Likert-based questionnaire.

Table 1. Diagnostic determinants of OECO_Sy and their role in the coefficients.

| Block | Determinants | Coefficient role |
|---|---|---|
| Q.1 Funding, innovation and AI | I.a opportunities and calls; I.b needs and priorities; I.c role of GOS-Unifg; I.d innovation; I.e other innovation information; I.f AI projects; I.g benefits of AI; I.h obstacles to AI | PIPC and CCSIP |
| Q.2 Industrial property | II.a innovation and R&D; II.b IP awareness; II.c IP protection; II.d IP management; II.e IP valorization | PIPC and CCSIP |
| Q.3 Innovation capability | III.a participatory leadership; III.b structures; III.c working climate; III.d know-how development; III.e regeneration; III.f external knowledge; III.g individual activity | MIPC and CCSIP |

## 3.2 Normalization and determinant-level aggregation

Let $E = \{1, \ldots, n\}$ be the set of firms. For each firm i, let $x_{ij}$ be the normalized value of determinant j, with 0 <= x_ij <= 1. The determinant set is partitioned into D1, D2 and D3, corresponding respectively to Q.1, Q.2 and Q.3. D1 contains eight determinants, D2 contains five determinants and D3 contains seven determinants, for a total of twenty determinants. Some determinants can be structurally missing because of questionnaire branching. Let $A_{k,i}$ be the set of available determinants in block k for firm i.

The block scores are computed as simple means over the available determinants:

$$Q_{k,i} = \frac{1}{|A_{k,i}|} \sum_{j \in A_{k,i}} x_{ij}, \qquad k = 1, 2, 3. \tag{1}$$

The use of a simple mean is not an implicit claim that all determinants have the same empirical importance in every context. It is a conservative baseline. At the pilot stage, differential weights would introduce a second layer of expert judgment without sufficient data to validate it. This is consistent with the literature on composite indicators, where equal weighting is acceptable when the conceptual model treats dimensions as jointly necessary and when no external criterion is available [16].

Three details deserve emphasis. First, Q.1 includes both objective-like items, such as participation in calls, and coded open responses, such as the description of innovation activities. The latter are scored through an explicit content-analysis rubric based on ordered evidence levels, following general principles of reproducible qualitative coding [11], [13]. Secondly, Q.2 measures the maturity of industrial-property management along the cycle from innovation to awareness, protection, management and valorization. This is justified by empirical evidence that firms owning IP rights tend to show higher revenue per employee, with the effect particularly relevant for SMEs [8]. Thirdly, Q.3 captures latent organizational conditions rather than observed innovation outputs; this is why its interpretation must be combined with Q.1 and Q.2.

## 3.3 PIPC, MIPC and CCSIP

The previous conceptual proposal [7] defined the preliminary and composite coefficients at a more aggregate level. The present paper refines the aggregation by working at determinant level. The Preliminary Innovation Propensity Coefficient (PIPC) is the mean of all available Q.1 and Q.2 determinants for firm i:

$$PIPC_i = \frac{1}{|A_{1,i} \cup A_{2,i}|} \sum_{j \in A_{1,i} \cup A_{2,i}} x_{ij}. \tag{2}$$

This choice avoids mechanically assigning one half of the preliminary score to Q.1 and one half to Q.2 when the two blocks have different numbers of determinants. PIPC therefore measures the visible and formalized side of innovation: access to funding and support, innovation history, AI adoption, and IP maturity.

$$MIPC_i = \frac{1}{|A_{3,i}|} \sum_{j \in A_{3,i}} x_{ij}. \tag{3}$$

The Management Innovation Propensity Coefficient (MIPC) is the Q.3 aggregate. It measures the organizational and managerial conditions enabling future innovation. Finally, the Composite Coefficient of SME Innovation Propensity (CCSIP) is defined as:

$$CCSIP_i = \frac{PIPC_i + MIPC_i}{2}. \tag{4}$$

The equal aggregation of PIPC and MIPC reflects the theoretical assumption that formalized innovation propensity and internal organizational capability are both necessary. A firm with high PIPC and low MIPC may possess external innovation assets but lack the internal conditions for implementation. A firm with high MIPC and low PIPC may have a good organizational substrate but weak IP, AI or funding readiness. The sign and magnitude of the gap $G_i = MIPC_i - PIPC_i$ are therefore read together with CCSIP. In the pilot study, $|G_i| \leq 0.073$ is treated as balanced, $0.073 < |G_i| \leq 0.146$ as a mild predominance of one component, and $|G_i| > 0.146$ as a structural gap. These thresholds are descriptive and sample-specific, not normative.

## 3.4 Robustness of Q.2 weights

The Q.2 block is the most innovative from the measurement perspective because IP maturity is multidimensional and the relative importance of awareness, protection, management and valorization may vary across sectors. In the baseline model all five Q.2 determinants are weighted equally. To verify whether this baseline is excessively fragile, a Monte Carlo sensitivity analysis is performed on the TCOREC data.

For each simulation b, a random vector of weights w^(b) is generated from a Dirichlet distribution on the five Q.2 determinants. Three concentration levels are considered: alpha = 2, alpha = 1 and alpha = 0.5. Lower alpha values generate more extreme weights. For a firm with a missing determinant due to branching, the simulated weights are renormalized over the available determinants. The simulated Q.2 score is then:

Q2_i^(b) = sum_{j in A2i} w_tilde_j^(b) x_ij. (5)

For each b the ranking of firms is compared with the equal-weight ranking by Kendall's tau. The stability of the top-three firms is also recorded. This procedure follows the logic of global sensitivity analysis [19] and provides a proportional robustness check for a pilot sample. It does not replace a full external validation or a Delphi calibration with IP experts [12].

## 3.5 From diagnosis to brief-based intervention

A composite coefficient alone is insufficient for the Formation State. OECO_Sy therefore adds a structured brief-analysis grid with six categories: object of the project, required competence, project maturity, external relations already active, urgency signal, and coherence with the quantitative diagnosis. The grid deliberately does not produce an additional score. Its purpose is to extract operational information that can guide GOS-Unifg in matching the firm's demand with the University DataBase and the Innovation Service Map. In methodological terms, the grid links the numerical answer to the question how ready is the firm? with the operational answer to the question what should be built, with whom and under which agreement form?

# 4 Pilot application to the TCOREC SMEs

## 4.1 Case study and data

The pilot application concerns the TCOREC case study, developed within the OPEN APULIA project and the training laboratory Technological Core Competencies and Digital Transformation. The sample comprises ten anonymized SMEs located in the Province of Foggia and more broadly in the Apulian innovation context. The firms are coded by macro-area: tourism and hospitality, retail and distribution, agri-food, industrial automation or manufacturing, energy, and health or biotechnology. The anonymization rule is essential because the diagnostic process collects sensitive information on innovation needs, IP management and possible open-innovation agreements.

Data were collected through the three OECO_Sy questionnaires. Project briefs were then produced in the first operational stream of the laboratory. The empirical objective is exploratory. The sample size is too small for inferential claims, but it is sufficient to test whether the coefficients differentiate firms, whether determinant-level reading produces useful information, and whether the brief grid can translate diagnosis into action.

Table 2. PIPC, MIPC and CCSIP in the TCOREC pilot sample (N = 10).

| **Code** | **Sector** | **PIPC** | **MIPC** | **CCSIP** | **Diagnostic pattern** |
|---|---|---|---|---|---|
| IND-01 | Industrial automation | 0.799 | 0.726 | 0.763 | Above sample mean; nearly balanced |
| AGR-03 | Agri-food transformation | 0.660 | 0.664 | 0.662 | Moderately above mean; balanced |
| TUR-01 | Tourism and hospitality | 0.517 | 0.773 | 0.645 | MIPC » PIPC |
| AGR-02 | Agri-food nursery | 0.672 | 0.607 | 0.640 | PIPC ≈ MIPC |

| Code | Sector | PIPC | MIPC | CCSIP | Diagnostic pattern |
|---|---|---|---|---|---|
| HEA-01 | Health / food laboratory | 0.494 | 0.702 | 0.598 | MIPC » PIPC |
| IND-02 | Industry / aerospace | 0.519 | 0.660 | 0.590 | Mild MIPC predominance |
| RET-01 | Retail / distribution | 0.478 | 0.695 | 0.587 | MIPC » PIPC |
| ENE-01 | Renewable energy | 0.481 | 0.681 | 0.581 | MIPC » PIPC |
| HEA-02 | Health / diagnostics | 0.405 | 0.683 | 0.544 | MIPC » PIPC |
| AGR-01 | Agri-food | 0.334 | 0.672 | 0.503 | MIPC » PIPC |
| Mean | | 0.536 | 0.686 | 0.611 | |

## 4.2 Main empirical evidence

The CCSIP values range from 0.503 to 0.763, with mean 0.611 and standard deviation 0.071. The range of 0.260 confirms that the coefficient differentiates the firms in a non-trivial way, even though the dispersion is modest relative to the theoretical interval [0,1]. This justifies a relative interpretation based on the sample mean and standard deviation rather than absolute categories. IND-01 is the only firm clearly above the mean by more than one standard deviation, while AGR-01 is the lowest case. Most firms are concentrated around the mean, as expected in a small pilot sample selected through an innovation-oriented programme.

The most important result is the asymmetry between PIPC and MIPC. In eight firms out of ten, MIPC is higher than PIPC. The average gap MIPC - PIPC is +0.150. This pattern is not a computational artefact; it is diagnostic evidence. It suggests that the sampled SMEs have relatively solid organizational conditions for innovation, but weaker formalized innovation assets, especially in IP management and AI adoption. This is precisely the type of gap that a university Grant Office can address through mentoring, IP support, funding design and ecosystem matching.

The descriptive statistics also show that PIPC is the most discriminating component. Its range is 0.465 and its standard deviation is 0.137, compared with a MIPC range of 0.166 and standard deviation of 0.044. Therefore, the differences among firms are not primarily located in the internal organizational substrate, which is comparatively homogeneous. They are located in the formal, external and IP-related side of innovation. The determinant-level analysis confirms this interpretation.

Table 3. Systemic strengths and weaknesses detected at determinant level.

| **Evidence** | **Value or pattern** | **Diagnostic implication** |
|---|---|---|
| Lowest Q.2 determinant | II.d IP management mean = 0.175 | Weak monitoring of infringements, scarce dedicated resources and weak preventive procedures. |
| Lowest Q.1 determinant | I.f AI projects mean = 0.320 | Six firms report no active AI adoption; four firms show structured adoption. |
| Highest Q.3 determinant | III.f external knowledge mean = 0.775 | The sample is open to external knowledge and collaboration, a favourable condition for ecosystem genesis. |
| Highest Q.1 determinant | I.a knowledge of calls mean = 0.917 | The information burden on GOS-Unifg is reduced; support can focus on design and implementation. |
| Dominant coefficient gap | MIPC > PIPC in 8/10 firms | The intervention priority is formalization of innovation, IP and AI readiness rather than basic organizational change. |

## 4.3 Monte Carlo sensitivity analysis

The sensitivity analysis supports the equal-weight baseline for Q.2. With 5,000 simulations for each concentration level, the median Kendall tau remains high: 0.911 for alpha = 2, 0.867 for alpha = 1 and 0.822 for alpha = 0.5. The top-three ranking is unchanged in 75.2%, 62.0% and 49.9% of the simulations, respectively. The minimum observed Kendall tau never falls below 0.556, even in the most severe scenario. These results indicate that the Q.2 ranking is not dominated by an arbitrary weighting assumption. The more unbalanced profiles, especially HEA-01 and IND-02, are the most sensitive to weights; this is useful information for future Delphi validation rather than a reason to reject the baseline.

Table 4. Monte Carlo robustness of the Q.2 equal-weight baseline.

| **Indicator** | **Result** |
|---|---|
| Median Kendall tau (alpha = 2 / 1 / 0.5) | 0.911 / 0.867 / 0.822 |
| Unchanged top-three ranking | 75.2% / 62.0% / 49.9% |
| Minimum Kendall tau | Never below 0.556 |
| Most sensitive firms | HEA-01, IND-02 |
| Most stable firm | AGR-02 |

### 4.4 Brief analysis and expected open-innovation agreements

The brief analysis adds operational meaning to the coefficients. The ten firms show different levels of project maturity. AGR-03, IND-02 and HEA-02 have mature technical briefs centred on AI applications, such as adaptive training, quality co-piloting and automated public-call discovery. TUR-01, RET-01, AGR-01, AGR-02 and ENE-01 present a defined direction but require co-design to transform the need into an operational plan. HEA-01 has an articulated initial idea around the communication of food-safety culture. IND-01 is a special case: it presents a mature commercial plan for moving from subcontracting to direct B2B market access, rather than a strictly technical plan.

This reading shows why the quantitative and qualitative sources must be combined. A firm can have a moderate CCSIP but a mature brief in a specific technological area. Conversely, a good CCSIP does not automatically imply that the brief is ready for an agreement. The brief grid therefore prevents two errors: treating the coefficient as if it prescribed the intervention, and treating the brief as if it were comparable without a prior diagnostic profile.

Table 5. From brief maturity to GOS-Unifg action in the Formation State.

| Brief maturity | Firms | GOS-Unifg action | Expected output |
|---|---|---|---|
| Mature technical plan | AGR-03, IND-02, HEA-02 | Direct matching with AI or technical teams; feasibility check; IP protection review where required. | Letter of interest, feasibility sheet, NDA or software-development agreement. |
| Defined direction | TUR-01, RET-01, AGR-01, AGR-02, ENE-01 | Co-design sessions with a domain expert to define scope, phases and responsibilities. | Document of Understanding; for AGR-01, preliminary IP pathway. |
| Articulated initial idea | HEA-01 | Exploratory multi-stakeholder session to transform a broad cultural objective into project options. | Two or three concrete project options before matching. |
| Mature commercial plan | IND-01 | Qualified networking and B2B market-opening through industrial associations and university-industry liaison. | Prospect map and commercial partnership or co-marketing agreement. |

# 5 Discussion

The empirical results suggest that OECO_Sy is useful not because it produces a high or low score, but because it produces a structured diagnostic map. The composite coefficient identifies the relative position of each firm, while the determinant-level values identify the levers of intervention. In the TCOREC sample, the decisive levers are IP management and AI adoption. At the same time, the high value of external knowledge indicates that the firms are not closed to ecosystem interaction. This combination is strategically relevant: the bottleneck is not the absence of collaborative orientation, but the lack of formal tools for transforming collaboration into protected, financed and implementable innovation projects.

From the university perspective, the model clarifies the function of the Grant Office. GOS-Unifg is neither an incubator replacing the entrepreneur nor a technology-transfer office restricted to patent commercialization. It is an Expert that organizes the first diagnostic layer of the ecosystem. This interpretation advances the Third Mission because it connects research, project finance, IP awareness, AI adoption and entrepreneurial education in a single operational workflow.

From the methodological perspective, the paper contributes to the literature on composite indicators by applying transparent normalization and aggregation to an innovation-ecosystem problem. The model explicitly states what is measured, how it is measured, and where interpretation must be cautious. It also combines numerical and qualitative evidence without confusing the two. The brief grid is not a hidden score; it is a decision-support device for the Formation State. This separation is important for scientific rigor.

The framework also opens a path toward an innovation observatory. With a larger sample, the CCSIP distribution could be analysed by sector, firm size, technological area or territory. The model could then complement regional indicators such as the Regional Innovation Scoreboard [9] by providing firm-level granularity. This development would require a DataOps-oriented infrastructure capable of integrating questionnaires, briefs, administrative data, IP databases and external territorial sources [26]. The present paper provides the diagnostic layer on which such an infrastructure could be built.

Finally, the results invite a cautious interpretation of AI readiness. The pilot shows a bimodal pattern: several firms report no active AI project, while a smaller group reports structured adoption. The TCOREC laboratory, which is oriented toward generative AI, is therefore aligned with a real diagnostic need. Nevertheless, explicit AI in a brief should not be read as direct evidence of higher innovation propensity. It can reflect the way in which the firm translated a common laboratory mandate into project language. The coefficient and the brief must therefore be interpreted jointly.

# 6 Conclusions

This paper has extended the 2025 OECO_Sy framework from an organizational proposal into a mathematically explicit diagnostic model. The extension introduces twenty normalized determinants, three coefficients and a sequential bridge from quantitative diagnosis to qualitative brief analysis. The pilot evidence from ten SMEs shows that the CCSIP differentiates firms, that MIPC exceeds PIPC in most cases, and that the main support priorities are IP management, AI adoption and the transformation of project briefs into formal open-innovation agreements.

The scientific value of the contribution lies in the formalization of an institutional support function. The university Expert role becomes a measurable process: data are collected through structured questionnaires; determinants are normalized; coefficients are calculated by transparent rules; robustness is checked by sensitivity analysis; and the resulting diagnosis is used to design the Formation State intervention. This makes the model replicable by other university Grant Offices, provided that they preserve the scoring rules and confidentiality safeguards.

The limitations are clear. The sample is small, territorially specific and not statistically representative. The Q.1 coding rubric has not yet been tested through inter-rater reliability. The coefficients have not yet been validated against external outcomes such as successful grant applications, new IP titles, revenue from innovative products or employment growth. The brief analysis observes the initial Formation State but not the subsequent implementation of agreements. These limits do not invalidate the pilot; they define the next research agenda.

Future research should proceed in four directions. First, the sample should be expanded to at least 50-100 firms to enable stable thresholds, cluster analysis and predictive validation. Secondly, Q.2 weights should be calibrated through a Delphi panel of IP experts, KTM professionals and university Grant Office managers, using the Monte Carlo results as prior evidence. Thirdly, a contextual coefficient could be developed by combining CCSIP with a normalized measure of brief maturity, so that a firm with a moderate general score but a mature technical project is not underestimated. Fourthly, the framework should be extended to academic spin-offs and entrepreneurial PhD projects through a dedicated Q.4 for pre-firm actors. In this perspective, the CCSIP is not the end point of OECO_Sy. It is the first layer of a scalable observatory of SME innovation propensity.

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# References

[1] B. Afzal, X. Li and A.B. Hernandez-Lara, The innovation journey and crossroads of sustainability, resilience and human-centeredness: a systematic literature review, *Transforming Government: People, Process and Policy*, **18** (2024), no. 3, 368 - 383. https://doi.org/10.1108/tg-10-2023-0151

[2] A. Alam, A. Ghatak, B. Bhowmick and S. Chatterjee, Developing a reflective-formative-formative scale for measuring university entrepreneurial ecosystem from students' viewpoints, *IEEE Transactions on Engineering Management*, **72** (2025), 240 - 251. https://doi.org/10.1109/tem.2024.3508613

[3] T. Bedford, Y. Kinnaird, R. Migueis, E. Paolucci, B. Wijlands and A. Vos, Role of Universities of Science and Technology in Innovation Ecosystems: Towards Mission 3.1 - White Report, CESAER, Leuven, 2021.

[4] Z. Cao, M.-L. Verreynne and R.T. de Oliveira, Reflecting back and looking forward: a systematic literature review of SME-university collaborations, *International Journal of Management Reviews*, (2024), 1 - 47. https://doi.org/10.2139/ssrn.4783386

[5] H.W. Chesbrough, *Open Innovation: The New Imperative for Creating and Profiting from Technology*, Harvard Business School Press, Boston, 2003. https://doi.org/10.5465/amp.2006.20591014

[6] O. Dedehayir, S.J. Makinen and R. Ortt, Roles during innovation ecosystem genesis: a literature review, *Technological Forecasting and Social Change*, **136** (2018), 18 - 29. https://doi.org/10.1016/j.techfore.2016.11.028

[7] C. Di Letizia, L. Grilli and A.E. Di Noia, Innovation ecosystem and university system: the framework proposal for SMEs by the Grant Office Service of the University of Foggia, in Quality Innovation and Sustainability, Editors: Federica Murmura, Laura Bravi, Giada Pierli, Fabio Musso, João Carlos Gonçalves dos Reis, Gilberto Santos, Springer Cham, ISBN: 978-3-032-19627-9, Series ISSN 2198-7246, 2026.

[8] EPO and EUIPO, Intellectual property rights and firm performance in the European Union: firm-level analysis report, European Patent Office and European Union Intellectual Property Office, January 2025.

[9] European Commission, Regional Innovation Scoreboard 2023, Publications Office of the European Union, Luxembourg, 2023.

[10] M.G. Jacobides, C. Cennamo and A. Gawer, Towards a theory of ecosystems, *Strategic Management Journal*, **39** (2018), no. 8, 2255 - 2276. https://doi.org/10.1002/smj.2904

[11] K. Krippendorff, *Content Analysis: An Introduction to Its Methodology*, 2nd ed., Sage Publications, Thousand Oaks, 2004. https://doi.org/10.4135/9781071878781

[12] H.A. Linstone and M. Turoff (eds.), *The Delphi Method: Techniques and Applications*, Addison-Wesley, Reading, 1975. https://doi.org/10.1016/0160-9327(76)90011-9

[13] P. Mayring, *Qualitative Content Analysis: Theoretical Foundation, Basic Procedure and Software Solution*, GESIS - Leibniz-Institut fur Sozialwissenschaften, Klagenfurt, 2014. https://doi.org/10.4135/9781036231798

[14] J.F. Moore, Predators and prey: a new ecology of competition, *Harvard Business Review*, **71** (1993), no. 3, 75 - 86.

[15] J.F. Moore, *The Death of Competition: Leadership and Strategy in the Age of Business Ecosystems*, Harper Paperbacks, New York, 1996.

[16] OECD/European Union/EC-JRC, Handbook on Constructing Composite Indicators: Methodology and User Guide, OECD Publishing, Paris, 2008. https://doi.org/10.1787/9789264043466-en

[17] OECD/Eurostat, Oslo Manual 2018: Guidelines for Collecting, Reporting and Using Data on Innovation, 4th ed., OECD Publishing, Paris/Eurostat, Luxembourg, 2018. https://doi.org/10.1787/9789264304604-en

[18] J. Oliveira and O. Lima Rua, Innovation ecosystems and open innovation on micro-enterprises, *Journal of Open Innovation: Technology, Market, and Complexity*, **11** (2025), no. 1. https://doi.org/10.1016/j.joitmc.2024.100443

[19] A. Saltelli, M. Ratto, T. Andres, F. Campolongo, J. Cariboni, D. Gatelli, M. Saisana and S. Tarantola, *Global Sensitivity Analysis: The Primer*, Wiley, Chichester, 2008. https://doi.org/10.1002/9780470725184

[20] M. Saunila, Performance measurement approach for innovation capability in SMEs, *International Journal of Productivity and Performance Management*, **65** (2016), no. 2, 162 - 176. https://doi.org/10.1108/IJPPM-08-2014-0123

[21] M. Saunila, Understanding innovation performance measurement in SMEs, *Measuring Business Excellence*, **21** (2017), no. 1, 1 - 16. https://doi.org/10.1108/MBE-01-2016-0005

[22] M. Stieler and T. Henike, Innovation nudging - a novel approach to foster innovation engagement in an incumbent company, *Creativity and Innovation Management*, **31** (2022), no. 1, 35 - 48. https://doi.org/10.1111/caim.12475

[23] F. Turetta and E. Costanzo, Introducing Progressia: a simple, field-validated method for technological innovation, *CERN IdeaSquare Journal of Experimental Innovation*, **8** (2024), no. 2, 11 - 22.

[24] United Nations, Transforming our world: the 2030 Agenda for Sustainable Development, Resolution adopted by the General Assembly on 25 September 2015, A/RES/70/1, United Nations, 2015.

[25] VV.AA., Open Innovation Lookout 2025: I player dell'ecosistema, lo stato del Venture Building in Italia e la misurazione dell'impatto dell'Open Innovation - Report 2025, Innovation and Strategy, 2025.

[26] J. Xu, H. Naseer, S. Maynard and J. Filippou, Using analytical information for digital business transformation through DataOps: a review and conceptual framework, *Australasian Journal of Information Systems*, **28** (2024). https://doi.org/10.3127/ajis.v28.4215

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