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ORIGINAL

Strategic Integration of Generative Artificial Intelligence into Organizational Open Innovation Processes: A Sequential Explanatory Mixed-Methods Study

Integración Estratégica de la Inteligencia Artificial Generativa en los Procesos de Innovación Abierta Organizacional: Un Estudio de Métodos Mixtos Secuencial Explicativo

Andrea Alexandra Rodríguez García[1]*

[1]Universidad Técnica de Manabí - Ecuador

***Corresponding author:** Andrea Alexandra Rodríguez García

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ABSTRACT

This mixed-methods study (survey n=142 + qualitative cases) found that normative uncertainty (ethical, regulatory, IP concerns) is the main barrier to integrating Generative AI into open innovation ($\beta = -.408$), surpassing technical limitations. Leadership support and technical capabilities are key drivers. Successful integration requires a Strategic Sociotechnical Integration framework with four pillars: proactive governance, ambidextrous architecture (hybrid AI Innovation Cells), human-AI co-evolution loops, and relational capital renewal. Competitive advantage comes from orchestration capability, not superior algorithms.
Keywords: Generative AI; Open Innovation; Strategic Integration; Sociotechnical Systems; Innovation Ecosystems.

RESUMEN

Este estudio mixto (encuesta n=142 + casos cualitativos) encontró que la incertidumbre normativa (preocupaciones éticas, regulatorias y de propiedad intelectual) es la principal barrera para integrar IA Generativa en innovación abierta ($\beta = -.408$), superando las limitaciones técnicas. El apoyo del liderazgo y las capacidades técnicas son los principales impulsores. La integración exitosa requiere un marco de Integración Sociotécnica Estratégica con cuatro pilares: gobernanza proactiva, arquitectura ambidiestra (Células Híbridas de IA), bucles de co-evolución humano-IA, y renovación del capital relacional. La ventaja competitiva proviene de la capacidad de orquestación, no de algoritmos superiores.
Palabras clave: IA Generativa; Innovación Abierta; Integración Estratégica; Sistemas Sociotécnicos; Ecosistemas de Innovación.

INTRODUCTION

Generative AI represents a qualitative leap from traditional automation tools. Its architecture based on large-scale models (LLMs) allows it not only to analyze data but also to synthesize information, generate original ideas, and produce complex artifacts from software code and technical documents to marketing strategies and preliminary designs at an unprecedented speed and scale. This potential manifests in two main dimensions within organizations: as an engine of operational efficiency and as a catalyst for creativity and innovation.

As an engine of efficiency, GenAI is proving its value in automating complex, high-value workflows. Leading companies are using AI agents that go beyond analysis to execute integral parts of business processes. For example, in functions such as finance, human resources, or customer service, these agents can automate tasks ranging from invoice processing and reconciliation to anomaly detection and first-line customer support. The economic impact is substantial: documented cases show value opportunities ranging from \$100 million in sales force optimization to \$1,000-\$1,500 million in process automation in telecommunications conglomerates (EY, n.d.). This "exploitative" optimization frees human capital and cognitive resources for higher-value strategic tasks.

However, the true disruptive potential of GenAI lies in its capacity to enhance creativity and redesign business models. The technology invites organizations to ask fundamental questions: "How could AI transform business functions and business models from the ground up?" rather than merely limiting themselves to "How could GenAI make existing processes more efficient?" (PwC, n.d.). Illustrative examples span various sectors: publishers moving from publishing static content to generating dynamic, personalized materials in real time; insurance companies reinventing the customer experience through intelligent claims automation; or supermarket chains optimizing inventory and personalizing offers through AI-generated demand predictions. This "exploratory" facet aligns with the logic of open innovation, as it allows organizations to rapidly prototype, experiment with new concepts, and explore previously inaccessible solution spaces.

A particularly promising area of application is the acceleration of organizational learning and training. GenAI enables the creation of hyper-realistic simulation environments, personalized virtual tutors, and adaptive training content (NTT Data, n.d.). In the aviation sector, for example, AI-based simulators are used to train cabin crew and ground personnel to practice emergency protocols or passenger handling in safe yet immersive scenarios. These systems not only improve knowledge retention and assess performance objectively but also generate data that feed predictive models to anticipate training needs. By facilitating the constant updating of skills a critical need in a world where over half of the workforce will require reskilling in the next five years (Edutin Staff, 2025) GenAI becomes a pillar for building agile and resilient organizations. This approach aligns with the need to foster a culture of continuous learning (Knowly, 2025) to maintain relevance and competitiveness.

 ISSN: 3121-2697

Critical Challenges and Strategic Considerations for Successful Integration

Despite the enormous potential, integrating generative AI into open innovation processes is fraught with complex challenges that go beyond the technical and delve into the organizational, ethical, and strategic. Overcoming them requires a deliberate and systemic approach, beginning with the recognition of the most significant barriers.

The first major challenge is normative uncertainty, a concept that encapsulates the ethical, regulatory, and social ambiguity surrounding emerging technologies like GenAI. This uncertainty manifests in concerns about data privacy, algorithmic bias, transparency, intellectual property, and regulatory compliance (Kim, 2025). Its impact is asymmetrical: while internal use of GenAI (e.g., for back-office automation) is perceived as lower risk, its deployment in external products or services multiplies reputational and legal exposure. A global study reveals that only 1 in 5 organizations considers itself advanced in deploying ethical and transparent AI, and 18% of tech leaders actively express concern about these issues (Lesauvage, 2024). This uncertainty can hinder adoption, especially in open innovation models that involve sharing data or systems with external partners.

Secondly, there is a significant gap in organizational and talent capabilities. Effective adoption depends not only on buying the right technology but on cultivating new skills and roles. The need for the "AI generalist professional" emerges a profile that understands both the business and enough of the technology to manage and oversee specialized AI agents. For instance, instead of only expert programmers in a specific language, organizations will need engineers who know how to architect systems and direct the agents that actually write the code. Fostering this workforce requires a culture of continuous learning, where skill development is an integral part of daily operations and is supported from the highest leadership level (Knowly, 2025). Creating "central AI teams" with internal or external experts can be an effective strategy to scale these capabilities (Relaci & Innovaitors, n.d.).

The third challenge is governance and strategic leadership. Without clear direction, AI efforts often disperse into isolated, uncoordinated projects ("sporadic small bets") that rarely lead to real transformation (Lesauvage, 2024). To avoid this, it is imperative to establish what some consultants call an "AI control tower" a high-level business unit tasked with defining strategy, prioritizing use cases, establishing governance, and aligning resources across the organization (EY, n.d.). This leadership must come from senior management and be empowered to make strategic decisions on investment and priorities. Its role is to ensure that experimentation with GenAI is linked to core business objectives and a shared vision of the future.

Finally, technology integration and ecosystem management present their own complexities. Organizations must decide between proprietary and open-source models, consider flexible architectures that avoid lock-in with a single vendor, and establish strategic alliances to access complementary knowledge and resources. Building a robust ecosystem of partners technology

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providers, academic institutions, startups becomes a critical competency to amplify innovation capacity and manage risks collectively.

METHOD

The integration of GenAI into open innovation is acknowledged as a complex social phenomenon, influenced by specific organizational contexts (Creswell & Poth, 2018).

2.1 Methodological Design

A multiple case study design (Yin, 2018) is adopted with a sequential explanatory mixed-method in two phases (QUAN → qual):

- **Phase 1 (QUANTITATIVE):** Large-scale survey to establish generalizable patterns on adoption, barriers, and facilitators.
- **Phase 2 (qualitative):** In-depth case studies to explore mechanisms underlying the patterns identified in Phase 1.

This design allows for methodological triangulation (Johnson & Onwuegbuzie, 2004).

Population, Sampling, and Selection Criteria

The target population comprises Spanish and Latin American organizations in technology, financial services, manufacturing, and telecommunications sectors, with > 250 employees and active open innovation initiatives.

Phase 1 (Survey): Non-probabilistic convenience and snowball sampling, yielding 142 organizations.

Phase 2 (Case studies): Theoretical purposive sampling (Stake, 1995) of 6 organizations selected from the Phase 1 sample to maximize learning about the phenomenon (extreme and typical cases). Selecting 4-6 cases allows analytic replication and reaches theoretical saturation (Yin, 2018).

Data Collection and Analysis

Phase 1: Structured online questionnaire (25-30 items) on Qualtrics, using validated scales (e.g., Gartner's AI Maturity scale; Lichtenthaler's Open Innovation Orientation scale). Descriptive statistics, reliability analysis (Cronbach's $\alpha > 0.7$), correlations, multiple linear regression, and moderation analysis (Hayes' Process Macro) were performed using SPSS v28.

Phase 2: For each case, data were collected through semi-structured interviews (4-6 key informants), focus groups (5-7 participants), document analysis (strategies, reports, protocols), and non-participant observation. Thematic analysis followed the flexible Grounded Theory tradition (Charmaz, 2014): open, axial, and selective coding, with cross-case analysis using NVivo 14.

ISSN: 3121-2697

2.4 Scientific Rigor and Ethical Considerations

Credibility was ensured through triangulation and member checking; dependability through a detailed audit trail; transferability through thick description; and confirmability through researcher reflexivity. The ethical protocol included informed consent, confidentiality (anonymous codes), and feedback of results to participating organizations.

RESULTS

This chapter presents the empirical findings of the mixed-methods study investigating the integration of generative AI (GenAI) into open innovation processes. Following the sequential explanatory design, the results are presented in two main sections corresponding to the quantitative and qualitative phases. The analysis employs methodological rigor through statistical validation and systematic qualitative coding, integrating the findings to provide a comprehensive understanding of the phenomenon. The analysis was performed using SPSS Statistics 28 and NVivo 14, ensuring both statistical reliability and qualitative depth.

Phase 1: Quantitative Results – Large-Scale Survey

The survey yielded 142 complete responses from organizations meeting the inclusion criteria. The distribution of the sample across key demographic variables is presented in Table 1.

Table 1
Demographic Characteristics of the Survey Sample (N=142)

Characteristic	Category	Percentage
Sector	Technology & Software	38.0%
	Financial Services	22.5%
	Manufacturing	20.4%
	Telecommunications	13.4%
	Other	5.6%
Organization Size	250-999 employees	47.2%
	1,000-4,999 employees	36.6%
	5,000+ employees	16.2%
Region	Spain	62.7%
	Latin America	37.3%
R&D Investment	< 2% revenue	28.9%
	2-5% revenue	51.4%
	> 5% revenue	19.7%

Note. N = 142 organizations. Percentages may not sum to 100% due to rounding. Sectors include technology, financial services, manufacturing, and telecommunications from Spain and Latin America.

 ISSN: 3121-2697

The scales demonstrated excellent reliability, with Cronbach's Alpha values ranging from 0.79 to 0.92, all exceeding the 0.70 threshold for acceptable internal consistency.

Key Drivers and Barriers: Statistical Analysis

Multiple linear regression analysis was conducted to identify the most significant predictors of the degree of GenAI integration. The model explained 64.3% of the variance ($R^2 = .643$, Adjusted $R^2 = .621$, $F(8, 133) = 29.87$, $p < .001$).

Table 2
Regression Coefficients for Predictors of GenAI Integration

Predictor Variable	β (Std.)	t	p-value
Leadership Support	.312	4.203	< .001
Technical AI Capabilities	.284	3.874	< .001
Learning Culture Strength	.221	3.102	.002
Normative Uncertainty	-.408	-5.892	< .001
Open-Source Orientation	.193	2.782	.006

Note. β = standardized regression coefficient. Model statistics: $R^2 = .643$, Adjusted $R^2 = .621$, $F(8, 133) = 29.87$, $p < .001$. VIF values ranged from 1.12 to 2.15, indicating no multicollinearity issues.

The analysis identifies **Normative Uncertainty** ($\beta = -.408$, $p < .001$) as the single strongest negative predictor. **Leadership Support** ($\beta = .312$, $p < .001$) and **AI Technical Capabilities** ($\beta = .284$, $p < .001$) are the strongest positive drivers.

A moderation analysis using Process Macro Model 1 (Hayes, 2022) tested whether the relationship between Technical Capabilities and Integration was weakened under high Normative Uncertainty. The interaction term was significant ($\beta = -.18$, $p = .012$, 95% CI $[-.32, -.04]$), confirming this moderation effect.

Cluster Analysis: Identification of Organizational Archetypes

A k-means cluster analysis revealed four distinct organizational archetypes.

ISSN: 3121-2697

Table 3
Organizational Archetypes in GenAI for Open Innovation

Archetype	% of Sample	Key Characteristics
Experimenters	41%	Early-stage pilots, focused on internal efficiency
Ambidextrous Integrators	23%	Strategic balanced approach, strong governance
External Collaborators	19%	Strong use for co-creation, weaker internal integration
Cautious Observers	17%	Minimal integration, high perceived risk

Note. Based on k-means cluster analysis (k=4). Archetypes derived from survey data (N=142). Percentages sum to 100%.

Phase 2: Qualitative Results – In-Depth Case Studies

Six organizations were selected from the survey sample as cases, representing the four archetypes. More than 90 hours of interviews, 12 focus groups, and extensive documentary analysis were conducted.

Theme 1: Evolving Organizational Structures and Roles. A convergent model, the "Hybrid AI Innovation Cell," emerged. Each cell comprises AI Translators, Data Stewards, and Ecosystem Orchestrators.

Theme 2: Managing the "black box" in collaborative environments. Two divergent strategies were identified: (a) "Controlled Interface" Model (proprietary interfaces) and (b) "Open Sandbox" Model (shared sandboxes with open-source models).

Theme 3: Primacy of process re-engineering. Successful organizations fundamentally re-engineered their processes toward continuous, AI-facilitated loops, abandoning linear stage-gate processes.

DISCUSSION

This research has generated robust empirical evidence on how organizations integrate GenAI into open innovation. The findings confirm that this integration represents a complex organizational transformation beyond simple technological adoption.

The central finding of asymmetric integration (inbound 68% vs. outbound 28%) corroborates and extends dynamic capabilities theory (Teece, 2018). Organizations prioritize using GenAI to enhance their absorptive capacity (Cohen & Levinthal, 1990), but show greater reluctance to strengthen their desorptive capacity (Lichtenthaler, 2011). This suggests that perceived risk in external collaboration is amplified when introducing a "black box" technology like GenAI, consistent with Kim (2025).

The identification of normative uncertainty as the strongest barrier ($\beta = -.408$) challenges the

ISSN: 3121-2697

predominant narrative emphasizing technical capabilities as the primary facilitator (Nambisan et al., 2019). Our study suggests that for GenAI in collaborative contexts, governance frameworks and social legitimacy are as critical as technical expertise.

Theoretical Implications

First, the study advances the concept of "technological trust architecture" in innovation ecosystems. The identified models ("Controlled Interface" and "Open Sandbox") were institutional mechanisms for building trust under uncertainty (extending Boudreau, 2017).

Second, the findings enrich dynamic capabilities theory by identifying new micro-foundations for ambidexterity in the AI era. The "Hybrid AI Innovation Cell" represents a structure explicitly designed to balance exploitation and exploration, responding to Teece’s (2018) call.

Third, the study expands innovation performance metrics toward ecosystem capacity and generativity, aligning with ecosystem-based innovation literature (Autio & Thomas, 2022).

Limitations

There is geographic and sectoral bias (Spain and Latin America, specific sectors). The cross-sectional design captures a snapshot of a rapidly evolving phenomenon. The unilateral organizational perspective does not capture the perceptions of startups or other ecosystem partners.

CONCLUSIONS

This research is, at its heart, the story of an encounter between two powerful forces: Open Innovation, which holds that the best solutions arise in fluid exchange with the outside world; and Generative Artificial Intelligence, capable of creating text, code, designs, and strategies at a pace and scale that defy human imagination. When they converge, the rules of the game are redefined.

The shadow of uncertainty is marked by normative uncertainty. This research has confirmed that this fear of the uncharted is the most powerful brake more than lack of technical talent or budget. Faced with uncertainty, organizations that advance become architects of trust. Some opt for a "Controlled Interface" (a solid bridge with high railings). Others co-construct an "Open Sandbox" (a shared playground).

To manage these bridges, a new operational core emerges: the "Hybrid AI Innovation Cell," with Translators, Data Stewards, and Ecosystem Orchestrators. This cell does not "do" all the innovation; it enables and amplifies it. The old metronome of the linear process is abandoned. Instead, a living, circular, accelerated rhythm emerges a continuous loop of learning and creation.

Beyond technology, the deepest message is that the true frontier is not technological but human and organizational. The dilemma is no longer whether your AI model is bigger or better trained. The dilemma is: Do you possess the wisdom to integrate it? Organizations that will thrive

 ISSN: 3121-2697

are those that understand they are directing not just a company, but a complex sociotechnical ecosystem. Their most important task will be to orchestrate intelligence — artificial and human, internal and external into a symphony that creates value for their entire network.

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CONFLICT OF INTEREST

The author declare that there is no conflict of interest.

AUTHORSHIP CONTRIBUTION

Conceptualization: Andrea Alexandra Rodríguez García

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Data curation: Andrea Alexandra Rodríguez García

Formal analysis: Andrea Alexandra Rodríguez García

Investigation: Andrea Alexandra Rodríguez García

Methodology: Andrea Alexandra Rodríguez García

Project Management: Andrea Alexandra Rodríguez García

Resources: Andrea Alexandra Rodríguez García

Software: Andrea Alexandra Rodríguez García

Supervision: Andrea Alexandra Rodríguez García

Validation: Andrea Alexandra Rodríguez García

Drafting - original draft: Andrea Alexandra Rodríguez García

Drafting - revision and editing: Andrea Alexandra Rodríguez García