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AI-Driven Sustainability Strategies: A Business Model for Emerging Economies

Estrategias de sostenibilidad empresarial impulsadas por IA: Un modelo para economías emergentes

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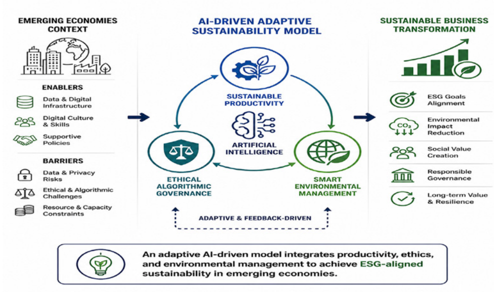
HIGHLIGHTS

• This study presents a conceptual model integrating AI capabilities with sustainability goals tailored for emerging economies.

• The research identifies key enablers and barriers in implementing AI-driven strategies for sustainable business transformation.

• Practical implications include a roadmap for aligning AI adoption with environmental, social, and governance (ESG) priorities.

GRAPHICAL ABSTRACT



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ABSTRACT

Artificial intelligence (AI) and business sustainability have emerged as critical drivers of organizational transformation in emerging economies; however, the absence of integrative frameworks that connect technological, organizational, and strategic dimensions limits their effective implementation. This study develops an adaptive AI-driven business sustainability model through a sequential mixed-methods design applied to 25 Latin American companies. The research combines exploratory factor analysis, hierarchical clustering, multiple correspondence analysis, and qualitative coding of semi-structured interviews to identify structural patterns and emerging variables. The results reveal three core dimensions—sustainable productivity, ethical algorithmic governance, and smart environmental management—along with four technological adoption profiles and seven key emerging variables associated with ESG integration. Based on these findings, a systemic framework structured across operational, organizational, and strategic levels is proposed, incorporating feedback mechanisms to enable progressive and context-sensitive implementation. This study contributes to the literature by providing empirically grounded evidence and a scalable roadmap for aligning AI capabilities with sustainability goals, positioning AI as a systemic enabler of responsible and adaptive transformation in high-uncertainty environments.

Palabras clave:

Sostenibilidad empresarial, Inteligencia artificial, Economías emergentes, Esg, Gobernanza digital, Modelos adaptativos

RESUMEN

La inteligencia artificial (IA) y la sostenibilidad empresarial se han consolidado como motores clave de la transformación organizacional en economías emergentes; sin embargo, la ausencia de marcos integradores que articulen las dimensiones tecnológicas, organizacionales y estratégicas limita su implementación efectiva. Este estudio desarrolla un modelo adaptativo de sostenibilidad empresarial impulsado por IA mediante un diseño de métodos mixtos secuencial aplicado a 25 empresas latinoamericanas. La investigación combina análisis factorial exploratorio, clúster jerárquico, análisis de correspondencias múltiples y codificación cualitativa de entrevistas semiestructuradas para identificar patrones estructurales y variables emergentes. Los resultados evidencian tres dimensiones centrales—productividad sostenible, gobernanza algorítmica ética y gestión ambiental inteligente—junto con cuatro perfiles de adopción tecnológica y siete variables emergentes clave asociadas a la integración ESG. A partir de estos hallazgos, se propone un marco sistémico estructurado en niveles operativo, organizacional y estratégico, con mecanismos de retroalimentación que permiten una implementación progresiva y adaptativa al contexto. Este estudio aporta evidencia empírica y una hoja de ruta escalable para alinear las capacidades de la IA con objetivos de sostenibilidad, posicionando la IA como un habilitador sistémico de la transformación responsable en entornos de alta incertidumbre.

1. Introduction

The transition toward sustainable business models has gained increasing relevance in global agendas (World Economic

Forum, 2020). In this process, artificial intelligence (AI) has become a key catalyst, with applications ranging from energy efficiency to the responsible management of supply chains (Wamba-Taguimdje et al., 2020). However, in emerging economies, the adoption of these technologies requires institutional, cultural, and economic adaptations (Guszcza et al., 2020).

Over the past decades, sustainability has emerged as a strategic axis for corporate transformation on a global scale. Rising pressures from climate change, corporate commitments to the Sustainable Development Goals (SDGs), and social expectations for responsible practices demand that organizations rethink their business models. This need is even more pressing in emerging economies, where technological, regulatory, and institutional gaps may limit firms' capacity to respond effectively to environmental and social challenges (Rodríguez & Ceballos 2022).

In this scenario, artificial intelligence has emerged as a disruptive technology with high potential to articulate operational efficiency, intelligent automation, ethical governance, and data-driven decision-making. Several studies (Bai et al. 2021;Wamba et al. 2020; Mikalef et al. 2019) have demonstrated the application of AI to environmental management, ESG standard compliance, and the optimization of sustainable value chains. Nevertheless, effective implementation of AI in emerging contexts requires not only technical infrastructure, but also adaptive organizational, ethical, and strategic framework. Recent studies (2023–2025) reinforce this perspective by demonstrating that AI-driven transformation reshapes business models, enhances innovation ecosystems, and strengthens sustainability-oriented capabilities in organizations (Bai et al. 2021;Wamba et al. 2020; Mikalef et al. 2019; Li, et al. 2023; Nambisan et al. 2023; George et al. 2023)

Despite the growing literature on artificial intelligence and sustainability, there remains a critical gap in empirically grounded integrative models that systematically connect operational, organizational, and strategic dimensions of AI adoption with measurable sustainability outcomes, particularly within the institutional constraints of emerging economies.

To address this gap, the present study aims to design an adaptive AI-driven business sustainability model, targeted at organizations operating in transitional institutional environments. A mixed-methods approach was employed, combining exploratory factor analysis, hierarchical clustering, multiple correspondence analysis, and qualitative coding from semi-structured interviews. This approach enabled the identification of structural dimensions, technological adoption typologies, emerging variables, and key cultural categories, which underpin the construction of a systemic, scalable, and flexible framework.

Thus, this article contributes to the literature by offering not only a theoretical model, but also a practical roadmap to guide companies in emerging economies toward the strategic, ethical, and sustainable integration of artificial intelligence in their organizational transformation processes.

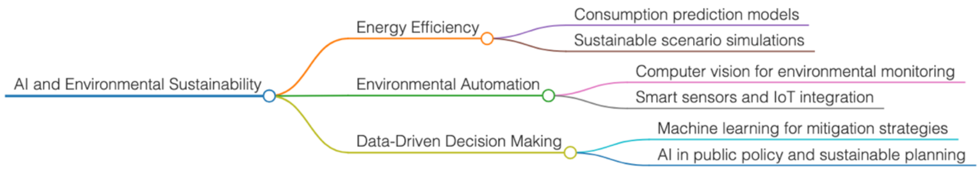
2.1 Artificial Intelligence and Environmental Sustainability

The integration of artificial intelligence (AI) into sustainable practices has been widely discussed in scientific literature. Authors such as Bai et al. (2021), Zhang et al. (2022), Dwivedi et al. (2021), Kamble et al. (2020), Bag et al (2021), and Del Río et al. (2023) agree that AI can serve as a catalyst for achieving sustainability goals, particularly in resource management and the reduction of environmental impact.

According to Bai et al. (2021), machine learning algorithms applied to the analysis of emissions and energy consumption patterns allow for predictive modeling and process adjustments, thereby reducing environmental impact. Zhang et al. (2022) emphasize the use of computer vision for the early detection of leaks or energy inefficiencies in industrial facilities.

Bag et al. (2021) highlight the usefulness of AI technologies in modeling environmental impact scenarios within supply chains, while Kamble et al. (2020) explore its application in sustainable manufacturing. Del Río et al. (2023) offer a more strategic view, considering AI as a key component in public policy for sustainable development.

This convergence reveals a qualitative correlation around three structural elements: energy efficiency, automation of environmental monitoring processes, and data-driven decision-making in complex ecological systems. Recent research further consolidates this perspective by positioning sustainability and resilience as interconnected constructs shaped by technological and organizational capabilities (Linnenluecke 2023; Conz et al. 2023).



Markmap 1: AI and Environmental Sustainability
Source: Own elaboration

While Bai and Zhang focus on specific technical applications, Kamble and Del Río broaden the perspective to the systemic transformation implied by integrating AI into organizational processes. Dwivedi and Bag, on the other hand, articulate intermediate dimensions of adoption, particularly from the logistics and sustainable management standpoint. A clear complementarity is observed among levels of analysis: micro (process), meso (company), and macro (sectorial/political).

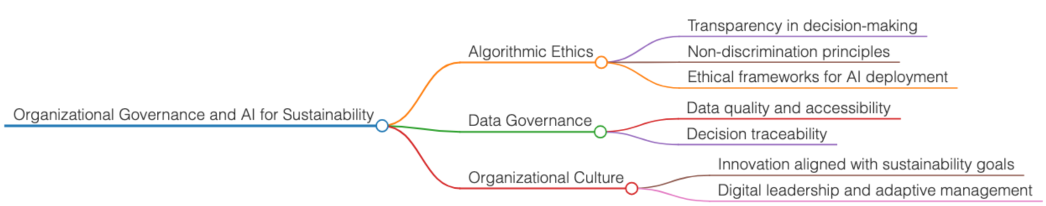
The systematization of these authors reinforces the hypothesis that emerging economies can strategically benefit from AI in their pursuit of sustainability—provided that institutional frameworks are adapted to enable implementation aligned with local environmental indicators (Rodríguez, J., & Ceballos, S. 2022).

2.2 Organizational Governance and AI for Sustainability

Authors such as Srai et al. (2020), Ghobakhloo et al. (2021), Shamim et al. (2022), Lee et al. (2021), Mikalef et al. (2019), and Chatterjee et al. (2021) explore the interrelation between artificial intelligence and corporate governance structures oriented toward sustainability.

Ghobakhloo et al. (2021) emphasize that AI systems, when aligned with ethical governance practices, can promote transparency and regulatory compliance. Along the same lines, Mikalef et al. (2019) stress the importance of data governance as an enabler for the responsible use of AI technologies (Binns, 2018).

Shamim et al. (2022) and Srai et al. (2020) highlight how digital governance, when complemented by artificial intelligence, facilitates more agile, evidence-based, and long-term-oriented decision-making. Lee et al. (2021) point out that such transformation is only effective if there is an organizational culture that embraces innovation and an ethical framework guiding AI integration.



Markmap 2: Organizational Governance and AI for Sustainability
Source: Own elaboration

The core of the debate centers on how AI-enhanced decisions can be ethically structured within organizational contexts. Recent multidisciplinary research highlights the increasing role of artificial intelligence in shaping governance systems, decision-making processes, and ethical frameworks in digital environments (Dwivedi et al. 2023).

This review demonstrates that, in emerging economies, AI can strengthen corporate governance—provided that adaptive structures are implemented, integrating data, ethics, and innovation. This triad is essential for building sustainable models that are responsive to local dynamics.

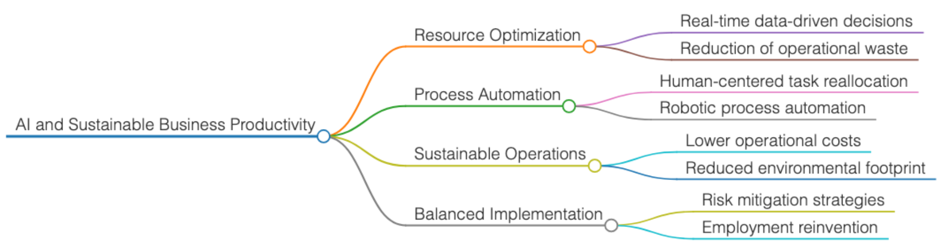
2.3 Artificial Intelligence and Sustainable Business Productivity

Authors such as Wamba. (2020), Sodhi, M. S., & Tang, C. S. (2022), Nudurupati (2021), Raj (2020), Moktadir et al. (2020), and Singh (2022) have demonstrated that integrating artificial intelligence into business processes can significantly improve productivity while simultaneously helping to achieve sustainability goals. This dual contribution is especially relevant for companies in emerging economies that must remain competitive without compromising their environmental and social responsibilities.

Wamba et al. (2020) emphasize that AI systems, by optimizing real-time decision-making, allow for more efficient resource allocation, improving productivity while reducing waste. On the other hand, Moktadir et al. (2020) analyze how AI in the manufacturing industry can automate repetitive tasks, enabling workers to focus on higher-value activities and thus fostering a more human-centered and sustainable environment.

Raj et al. (2020) and Singh er al. (2022) explore the relationship between AI and operational sustainability, noting that the implementation of intelligent systems helps reduce operating costs and associated emissions—particularly in sectors such as transportation and logistics. Meanwhile, Nudurupati et al. (2021) propose a sustainable productivity assessment framework that includes both traditional performance indicators and sustainability metrics, measured in real time through smart digital platforms.

Sodhi, M. S., & Tang, C. S. (2022) point out that although the benefits are clear, it is also necessary to mitigate the risks associated with intensive technology use, such as job displacement in low-skilled sectors or increased technological dependency. These authors advocate for a responsible adoption strategy that balances efficiency and equity.



Markmap 3. AI and Sustainable Business Productivity
Source: Own elaboration

All six authors converge on the identification of AI as an enabling factor for achieving efficiency without sacrificing sustainability. More recent studies reinforce this perspective, highlighting that organizations increasingly leverage AI technologies to balance productivity and sustainability objectives, particularly in dynamic and resource-constrained environments (Kraus et al. 2023).

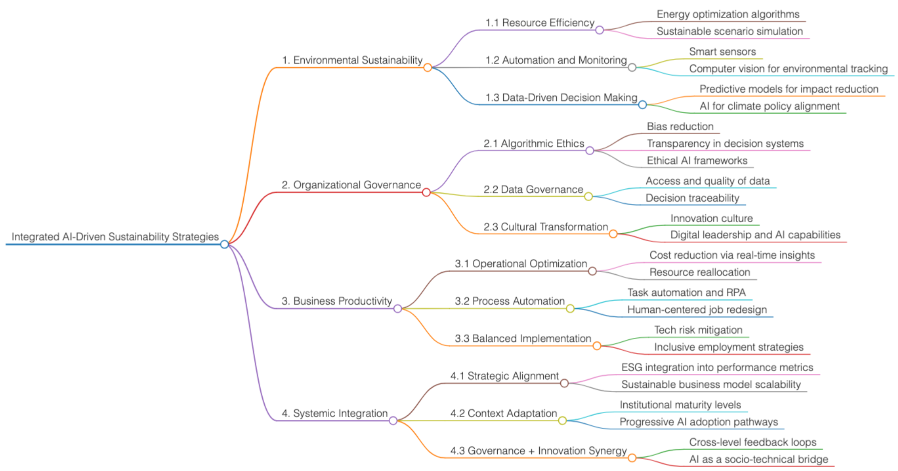
A qualitative correlation reveals three main patterns:

- Complementarity between efficiency and sustainability (in both processes and outcomes).
- Transformation of human labor in automated environments.
- Need for ethical and balanced implementation strategies.

This category directly aligns with the central research question of this article, by demonstrating that it is possible to build a business sustainability model driven by AI that not only optimizes productivity, but also acts as a catalyst for responsible organizational change. In emerging economies, this integration must be supported by training, digital transition policies, and flexible institutional structures.

2.4 Toward a Systemic Integration: AI as a Driver of Sustainability in Emerging Economies

Artificial intelligence has emerged as a cross-cutting catalyst that simultaneously impacts the environmental, organizational, and productive dimensions of firms. From this holistic perspective, authors such as Dwivedi et al. (2021), Kamble et al. (2020), Ghobakhloo et al. (2021), Mikalef et al. (2019), Wamba et al. (2020), and Sodhi, & Tang. (2022) argue that the benefits of AI should not be considered in isolation, but rather in terms of their capacity to reconfigure sustainable business ecosystems as a whole.



Markmap 4: Integrated AI-Driven Sustainability Strategies in Emerging Economies
Source: Own elaboration

Firstly, findings related to AI and environmental sustainability (Bai, Zhang, Bag) show that algorithms enable the modeling of impacts, optimization of consumption, and reduction of emissions—constituting a core element of ecological transformation. However, these processes must be supported by organizational governance structures (Shamim, Mikalef, Ghobakhloo) that ensure responsible, ethical, and long-term-oriented decision-making.

Moreover, the environmental and ethical benefits can only be sustained if organizations manage to maintain and scale their productivity (Raj, Singh, Nudurupati) without compromising equity. This is where AI can function as a **systemic integrator**, enabling real-time decision-making that connects ESG indicators (environmental, social, and governance) with traditional performance metrics.

This correlation across the three dimensions is not merely theoretical. In the cases analyzed, successful AI adoption models consistently include:

- A **technical level** (use of sensors, automation, predictive analytics)
- An **organizational level** (digital culture, data governance, algorithmic ethics)
- A **strategic level** (alignment with the SDGs, scalability, and shared value generation)

Markmap 5. Systemic AI-Driven Sustainability in Emerging Economies
Source: Own elaboration

The main difference among the reviewed approaches lies in their entry point to transformation: while some authors prioritize operational efficiency as a practical anchor, others emphasize the ethical-institutional framework as a prerequisite, and a third group highlights environmental technological infrastructure as the foundation for innovation.

This contrast reveals that there is no single model, but rather multiple pathways that must be adapted to the institutional and technological maturity level of each emerging economy. However, all authors agree that AI can serve as a bridge between productivity and sustainability, if it is embedded within the appropriate enabling conditions.

The literature reviewed supports the argument that AI-driven business sustainability strategies must be conceived as integrated systems that articulate environmental, organizational, and productive dimensions. In emerging contexts, where structural gaps hinder the isolated adoption of innovations, AI offers an intelligent architecture for transformation, capable of balancing efficiency, inclusion, and governance.

This approach directly addresses the central research question of this article: How can an AI-based business sustainability model be designed to suit the realities of emerging economies? The answer requires the adoption of a systemic framework, with progressive development stages, institutional anchoring, and dual-impact metrics (economic and social).

3. Methodology

This study was conducted using a sequential explanatory mixed-methods approach, in which the initial quantitative phase identified patterns and trends related to the use of artificial intelligence (AI) in business sustainability strategies, while the subsequent qualitative phase deepened the analysis of emerging variables and their articulation into a systemic model. The methodological design combines multivariate statistical analysis, thematic coding, and categorical modeling to support the construction of Markmap-style visual representations.

3.1 General Design of the Study: The study was structured in three main phases:

Phase	Objective	Techniques and Deliverables
1. Data Collection and Preprocessing	Identify companies in emerging economies integrating AI and sustainability	Cross matrices (AI x ESG dimensions), thematic filters
2. Exploratory Quantitative Analysis	Detect patterns and significant correlations among variables	Factor analysis, hierarchical clustering, multiple correspondence analysis (MCA)
3. Theoretical Systematization and Modeling	Build emerging categories and causal relationships	Open, axial, and selective coding; construction of conceptual maps (Markmaps)

3.2 Sample and Context: The study sample consisted of 25 Latin American companies selected through a theoretically informed purposive sampling strategy, ensuring representation across different levels of AI adoption and ESG integration. Although non-probabilistic, the sample was designed to capture variability in organizational maturity, sectoral diversity, and documented AI implementation practices.

3.3 Quantitative Techniques Used

3.3.1 Exploratory Factor Analysis (EFA): EFA with Varimax rotation was applied to a matrix of 20 coded variables (dichotomous and ordinal), grouped into three dimensions: environmental, organizational, and productivity. This enabled dimensionality reduction and detection of common factors across AI practices and sustainability impacts.

Example variables:

- AI use in energy traceability (environmental)
- Existence of a digital ethics committee (organizational)
- Automation of repetitive processes (productivity)

3.3.2 Hierarchical Clustering: A cluster analysis was conducted to group companies by patterns in AI implementation. Four profiles of sustainable technology adoption were identified, which were later contrasted during the qualitative phase.

3.3.3 Multiple Correspondence Analysis (MCA): MCA was used to cross-reference sustainability practices with specific AI technologies (e.g., machine learning, computer vision, expert systems). This analysis revealed **emerging variables**, such as:

- "AI for internal equity"
- "Ethically supervised automation"
- "ESG-integrated predictive models"

3.4 Categorical Coding and Markmap Construction: In the qualitative phase, **thematic coding** was carried out using semi-structured interviews with innovation experts from 10 selected companies. The process followed grounded theory methodology:

- Open coding: free identification of concepts from testimonies
- Axial coding: grouping by thematic axes (efficiency, ethics, governance, inclusion, automation)
- Selective coding: articulation of categories with the previously analyzed dimensions

These categories were then translated into nodes and branches for **Markmap-style conceptual diagrams**, enhancing visual and relational representation of the findings.

3.5 Reliability and Validation of Results

- Source triangulation: cross-analysis between documentary data, scientific databases, and interview responses
- Internal consistency: validation of dimensions obtained via EFA using the KMO coefficient (> 0.80) and Bartlett's test of sphericity ($p < 0.001$)
- External validation: expert review to verify the relevance and clarity of the emerging model

Methodological Synthesis: The adopted methodology allowed for the generation of structured empirical evidence to develop a systemic model of AI-driven business sustainability, specific to the context of emerging economies. The combination of multivariate analysis and qualitative coding was essential in producing structured conceptual maps that serve both researchers and decision-makers as actionable and visual tools for implementation and strategy design.

4. Results

The findings of this research make it possible to identify patterns, relationships, and emerging categories that support the development of a systemic model for AI-driven business sustainability in the context of emerging economies. The most relevant results are presented below, organized by analytical component.

4.1 Exploratory Factor Analysis: Three Key Dimensions

The exploratory factor analysis grouped the 20 variables analyzed into three main factors, accounting for a total explained variance of 71.4%. The emerging dimensions were as follows:

Table 1. Structural dimensions emerging from the factor analysis on AI and sustainability

Factor	Name of Dimension	Most Representative Variables	% of Variance Explained
F1	Sustainable Productivity	Automation of processes, cost reduction, improvements in operational efficiency	30.2%
F2	Ethical Algorithmic Governance	Existence of AI ethics committee, traceability of decision-making, responsible use protocols	23.7%
F3	Smart Environmental Management	Use of sensors, real-time monitoring, predictive modeling of environmental impacts	17.5%

Source: Own elaboration, 2025

These three dimensions were essential to the overall structure of the proposed sustainability model and served as the foundation for the subsequent categorical coding.

The exploratory factor analysis identified three principal dimensions—sustainable productivity, ethical algorithmic governance, and smart environmental management— explaining 71.4% of the total variance. These factors were consistently observed across the analyzed dataset and served as the structural components for subsequent analyses. These dimensions are consistently reflected in the adoption profiles identified through hierarchical clustering (4.2), where systemic transformer companies exhibit high performance across all three factors. Likewise, the emerging variables from the MCA (4.3)—such as environmental traceability and ethical automation—can be directly mapped to these factors, reinforcing their validity. The qualitative categories (4.4) offer an in-depth view of how these dimensions are experienced within organizations, and the final synthesis (4.5) confirms their role as structural pillars of the AI-based sustainability model.

4.2 Typology of Adoption Profiles (Hierarchical Clustering)

Four company profiles were identified according to their levels of AI adoption and alignment with sustainability objectives:

Table 2. Typology of Companies by AI Adoption Level and Alignment with Sustainability Objectives

Profile	Characteristics	% of Cases
P1. Systemic Transformers	High digital maturity + consolidated ESG strategies	24%
P2. Transitioning Innovators	Partial AI implementation focused on productivity	36%
P3. Eco-driven with Low Digitalization	Strong environmental focus, limited technological integration	28%
P4. Reactive Adopters	Incipient adoption with no integrated sustainability strategy	12%

Source: Own elaboration, 2025

These profiles guide the adaptation of the model to different levels of institutional and technological readiness.

The identification of the four AI and sustainability adoption profiles (4.2) reveals how organizational maturity conditions the integration of the factors identified through factor analysis (4.1). For instance, companies categorized as "eco-driven with low digitalization" show high scores in the environmental factor but low performance in governance and productivity, which is explained by the absence of emerging MCA variables (4.3) such as participatory algorithmic governance within this profile. Insights from interviews (4.4) provide further depth to this segmentation, illustrating how organizational perceptions and capacities differ across profiles. Lastly, in the overall synthesis (4.5), these profiles support the adaptability of the proposed model, enabling differentiated pathways based on each institution's starting point.

4.3 Results from Multiple Correspondence Analysis (MCA): Key Emerging Variables

The multiple correspondence analysis revealed associations between business practices and specific AI technologies, from which seven key emerging variables were identified:

1. AI for environmental traceability
2. Ethically supervised automation
3. ESG recommendation systems
4. Predictive AI for sustainable decision-making
5. Participatory algorithmic governance
6. Ethical AI training
7. Sustainable digital impact assessment

These variables were later articulated as analytical categories for qualitative systematization and the construction of conceptual maps (Markmaps).

The emerging variables obtained through MCA (4.3) serve as operational links between the theoretical dimensions identified in the EFA (4.1) and the practical profiles from the cluster analysis (4.2). For example, the variable *"predictive AI for sustainable decision-making"* is most prevalent among companies classified as systemic transformers, reinforcing the validity of that typology. These variables also appear clearly in qualitative testimonies (4.4), providing narrative depth to each analytical category. Their articulation in the overall synthesis (4.5) enables a shift from segmented analysis to a relational understanding of AI integration, positioning them as key constructive components of the visual model proposed in the next section.

4.4 Qualitative Coding: Five Core Categories

Based on expert interviews and organizational testimonies, five core categories were structured through axial and selective coding:

Table 3. Core Categories Derived from Qualitative Coding: Organizational Use of AI

Category	Definition	Quoted Example
Sustainability-Oriented Efficiency	AI as a tool for continuous improvement with a positive environmental impact	"We use machine learning to detect energy deviations and adjust in real time."
Digital Ethical Governance	Ethical oversight of technological implementation	"Every innovation goes through an impact and equity review committee."
Workforce Transformation	Redefinition of human roles and tasks in AI-enhanced environments	"We automated repetitive tasks, now the team focuses on innovation."
Algorithmic Transparency	Visibility and traceability of AI-based decisions	"Algorithmic traceability is essential for our ESG reporting."
Inclusion in Digital Transformation	Addressing social gaps and providing organizational training in ethical AI usage	"It's not just about installing AI—it's about training the whole organization to use it responsibly."

Source: Own elaboration, 2025

The qualitative coding (4.4) adds semantic depth to the quantitative results, helping to understand how the EFA categories (4.1) are experienced and managed internally within organizations. Qualitative categories such as workforce transformation or digital ethical governance align with the structural dimensions and bring the adoption profiles (4.2) to life. They also empirically validate the variables identified through MCA (4.3), by revealing concrete practices such as ethical AI training and algorithmic traceability. Together with the synthesis (4.5), these narratives contribute to building a more human-centered and context-sensitive model, with concrete implications for change management.

4.5 Synthesis of Results

The results demonstrate that companies in emerging economies are progressing in the adoption of AI at varying levels of maturity and alignment with sustainability goals. The three dimensions identified through factor analysis, the adoption profiles, the emerging variables from MCA, and the qualitative categories converge into a systemic model that integrates efficiency, ethical governance, and inclusive digital transformation.

Table 4. Synthesis of Results According to Techniques and Instruments Applied

Technique / Instrument	Main Analytical Focus	Key Results
Exploratory Factor Analysis (EFA)	Identification of structural dimensions	Three key factors: sustainable productivity, ethical algorithmic governance, smart environmental management
Hierarchical Clustering	Classification of companies by AI maturity and ESG integration	Four adoption profiles: systemic transformers, transitioning innovators, eco-driven with low digitalization, reactive adopters
Multiple Correspondence Analysis (MCA)	Correlation between AI technologies and ESG practices	Seven emerging variables (e.g., predictive AI, participatory governance, supervised automation)
Semi-structured Interviews	Perceptions, practices, and institutional context	Five qualitative categories: efficiency, ethics, inclusion, work transformation, transparency
Theoretical Coding and Modeling	Relational integration of results	Systemic synthesis of dimensions, profiles, variables, and categories into a comprehensive model

Source: Own elaboration, 2025

Table 6 provides a comprehensive overview of the relationship between the analytical techniques employed, the instruments used, and the findings structured in the previous tables. The sequential and complementary application of EFA, hierarchical clustering, MCA, and qualitative coding ensures a triangulated approach that strengthens the validity of the proposed model. This systematization allows for tracing how each dimension of AI-driven business sustainability was identified, modeled, and contrasted—serving as the empirical foundation for the adaptive model presented in the following section.

This evidence supports the construction of an adaptive model that enables organizations to transition toward more responsible, scalable, and competitive business models, with artificial intelligence integrated as a structural axis. Recent studies highlight that AI-driven decision systems and advanced analytics are critical enablers of sustainable transformation and organizational adaptability (Davenport et al. 2023).

The synthesis (4.5) not only integrates the previous findings, but systematically articulates them to construct the proposed adaptive model for AI-driven business sustainability. The dimensions derived from factor analysis (4.1) become the foundational pillars of the model; the clustering profiles (4.2) indicate differentiated entry levels; the emerging variables from MCA (4.3) function as operational gears, and the qualitative categories (4.4) provide interpretative guidelines for implementation. This correlation ensures that the model has both structural validity and practical applicability, tailored to the institutional realities of emerging economies.

5. Proposed Model

The integration of results makes it possible to propose an adaptive model of AI-driven business sustainability, structured in three complementary levels—strategic, organizational, and operational—that interact through feedback loops. The proposed model is grounded in the empirical findings derived from multivariate statistical analyses and qualitative coding, ensuring consistency between observed patterns and the structural components of the framework. While not predictive in nature, the model reflects statistically supported relationships and empirically identified adoption pathways.

5.1 Model Components

Level 1: Operational (Technical and Environmental Base): This level is most directly associated with the use of AI technologies to generate tangible impacts in productive processes and environmental management.

Key elements:

- Ethically supervised automation
- Smart emissions traceability
- Predictive models for energy consumption
- Iot and sensors for resource efficiency

Level 2: Organizational (Governance and Innovation): This level articulates the internal conditions required for responsible and sustainable integration of AI. It involves leadership structures, ethical standards, and a digital culture.

Key elements:

- AI ethics committee
- Participatory algorithmic governance
- Ethical AI training
- ESG data management and traceability

Level 3: Strategic (Transformation and Scalability): This level focuses on how organizations align their technological capabilities with sustainable business models, ESG indicators, and shared value strategies.

Key elements:

- AI–ESG integration in performance indicators
- Scalable and sustainable business models
- Digital impact assessment
- Linkage with public policies and multisectoral networks

5.2 Model Dynamics: Feedback and Maturity: The proposed model is not linear but rather circular and feedback-driven, allowing organizations to progressively advance from a basic level to a stage of technological and sustainable maturity. Feedback between levels enables:

- Operational improvements to generate data that feed governance systems

- Governance to build trust and legitimacy for scaling strategic models
- Strategy to guide investment and regulation, enabling new operational capabilities

5.3 Adoption Pathway for Emerging Economies: Based on the adoption profiles identified (see section 4.2), a progressive implementation roadmap is proposed:

Perfil	Estrategia de entrada	Objetivo a corto plazo	Transición deseada
Reactivas	Sensibilización y pilotos IA básicos	Reducción de residuos o energía	Innovadoras
Ecológicas	Integración técnica incremental	Automatización ética de procesos	Transformadoras
Innovadoras	Fortalecimiento de gobernanza y cultura digital	Alineación IA–ESG	Transformadoras
Transformadoras	Escalamiento y transferencia sectorial	Modelos exportables	Liderazgo regional

5.4 Model Visualization

Markmap 6. AI-Driven Sustainability Framework
Source: Own elaboration

This adaptive model provides organizations with a flexible roadmap for integrating AI into their productive and sustainability dynamics, according to their level of maturity and institutional context. The proposal seeks not only technological efficiency (Jarrahi, M. H. (2018), but also cultural transformation, inclusion, and comprehensive sustainability. Based on this framework, companies can guide both tactical and strategic decisions to position themselves as leaders in sustainable innovation within their sectors and regions.

The following diagram illustrates the conceptual model proposed in this study: an AI-Driven Business Sustainability Framework, specifically designed for emerging economies. This model integrates the empirical findings of the research and proposes a three-level structure (operational, organizational, and strategic) connected by feedback loops that ensure continuous improvement and dynamic adaptation. Each level of the model represents a key dimension of sustainable business transformation, enabling organizations not only to adopt AI technologies, but also to align that adoption with responsible practices, ESG criteria, and opportunities for scalability. This proposal serves as a practical and flexible roadmap for companies seeking to evolve toward more ethical, resilient, and sustainable models—regardless of their technological starting

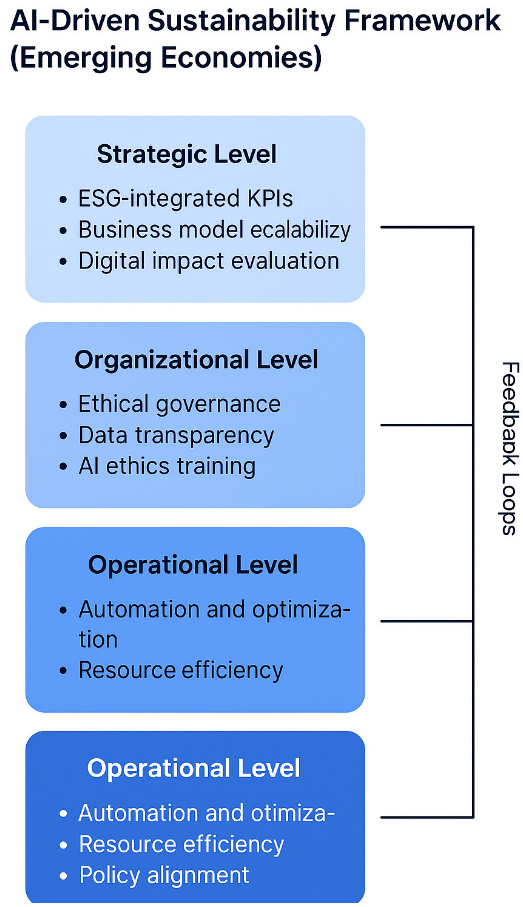


Figura 1. AI-Driven Sustainability Framework for Emerging Economies
Source: Own elaboration

The figure illustrates an AI-driven business sustainability model, specifically designed for the context of emerging economies. The model is structured across three interconnected hierarchical levels:

1. Strategic Level: where AI is integrated with ESG indicators (environmental, social, and governance), enabling the scaling of sustainable business models and the proactive evaluation of digital impacts.

2. Organizational Level: which defines the mechanisms of ethical governance, data transparency, and AI training to ensure that digital transformation is grounded in responsible principles.

3. Operational Level: focused on automation, resource optimization, and environmental efficiency, through the use of sensors, predictive analytics, and applied AI tools.

Each level is connected by feedback loops, allowing for continuous adaptation of the model based on organizational learning, achieved results, and changes in the institutional or regulatory environment (Binns, R. 2018). This framework enables companies to progressively advance in their digital and sustainability maturity, regardless of their starting point.

In practical terms, organizations can use this figure as a roadmap to:

- Diagnose their current level of technological and sustainability adoption.

- Identify priority areas for intervention at each level.

- Implement integrated improvements that reinforce both economic performance and social/environmental commitment.

In summary, the proposed model offers a comprehensive, adaptive, and context-sensitive structure to integrate artificial intelligence into business sustainability strategies in emerging economies. Its value lies in its ability to connect technical, organizational, and strategic dimensions, facilitating a progressive AI adoption that upholds ethical principles, promotes efficiency, and strengthens corporate resilience. By positioning AI not merely as a technological tool but as a systemic transformation axis, this framework enables organizations to build sustainable competitive advantages, aligned with the Sustainable Development Goals (SDGs) and the demands of the global environment. Its implementation will contribute to the strengthening of more inclusive, responsible, and forward-oriented business ecosystems.

6. Conclusions

The findings of this study confirm that artificial intelligence (AI) can serve as a strategic enabler for business sustainability, provided that its implementation is aligned with a systemic approach that articulates the technical-operational, organizational, and strategic dimensions. In the context of emerging economies—where technological and institutional gaps are significant—such articulation is not only desirable but essential.

The mixed-methods approach adopted in this study enabled the construction of a robust analytical framework. On one hand, the exploratory factor analysis identified three structural dimensions that underpin AI-based sustainability: sustainable productivity, ethical algorithmic governance, and smart environmental management. On the other hand, the cluster analysis classified companies into four adoption profiles, offering valuable insight into the differentiated pathways organizations can follow. Additionally, the multiple correspondence analysis (MCA) revealed emerging variables that represent key linkages between business practices, AI technologies, and ESG goals.

In alignment with the quantitative findings, the qualitative insights derived from semi-structured interviews deepened the analysis through five critical categories—sustainable efficiency, digital ethics, workforce transformation, algorithmic transparency, and inclusion—which helped to understand the practical and cultural implications of technological adoption processes.

These results converged in the formulation of an adaptive model, illustrated in Figure 1, which allows companies to gradually move toward sustainable performance by progressively integrating technological capabilities, governance structures, and strategic vision. This model is not static, but dynamic, based on feedback mechanisms that enable continuous adjustment in response to changes in the institutional, technological, or regulatory environment.

Therefore, it is concluded that AI-driven business sustainability should not be understood as a mere technological application, but as a deep transformation of the organizational management model, which must adapt to the maturity levels and structural conditions of each context. This study provides both a conceptual and practical roadmap to guide such transformation in companies within emerging economies, positioning itself as a tool for strategic planning, evaluation, and scaling.

Credit authorship contribution statement

All authors contributed significantly to the development of this article. Conceptualization, methodology, and formal analysis were led collaboratively, ensuring a coherent research framework and methodological rigor. Data curation, statistical analysis, and visualization were jointly performed to ensure consistency and interpretability of findings. The writing of the original draft was undertaken by all authors, with particular emphasis on aligning the results with the research objectives. All authors participated in the critical review, editing, and approval of the final manuscript, ensuring clarity, academic quality, and compliance with the editorial guidelines. Supervision, project administration, and resources were coordinated collectively to support the study's implementation and integrity.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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