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Smart Logistics: The Role of Artificial Intelligence in Value Network Management

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Abstract

In the context of the digital economy and the increasing complexity of supply chains, logistics has become a strategic component for organizational competitiveness. In this scenario, artificial intelligence (AI) emerges as a key technology for transforming traditional logistics systems into smart logistics or Logistics 4.0 models, characterized using data analytics, automation, and predictive systems that optimize the management of value networks. This study examines how artificial intelligence enhances the management of value networks in smart logistics, focusing on its impact on planning, coordination, control, data-driven decision-making, and operational efficiency. The research was conducted using a mixed-methods approach that integrates quantitative and qualitative methods. In the quantitative phase, surveys were administered to 200 professionals in the logistics sector, while in the qualitative phase, semi-structured interviews were conducted with experts in logistics and digital transformation. The results show that AI significantly improves operational efficiency, route optimization, inventory management, and demand planning. It also enhances process visibility and data-driven decision-making. However, challenges related to infrastructure, specialized talent, and implementation costs are identified, confirming its strategic relevance.

Keywords
Artificial intelligence; smart logistics; value networks; logistics management; digital transformation**.**

1. Introduction
In the context of the contemporary global economy, organizations face an environment characterized by high levels of competition, accelerated technological change, and increasing complexity in logistics processes. Value networks, understood as the set of actors, processes, and information flows involved in the creation and delivery of products or services, have become a strategic element for achieving sustainable competitive advantages. In this scenario, the incorporation of advanced digital technologies—particularly artificial intelligence (AI)—has begun to profoundly transform the way logistics processes are planned, coordinated, and managed within supply chains and value networks (Mañay et al., 2024).

The evolution toward what is known as smart logistics or Logistics 4.0 is based on the integration of technologies such as machine learning, big data analytics, process automation, and predictive systems. These tools enable improved decision-making, route optimization, demand forecasting, efficient inventory management, and enhanced supply chain visibility. According to Albarracín Vanoy (2023), the adoption of artificial intelligence in logistics has emerged as a key catalyst for increasing operational efficiency, reducing costs, and improving service levels in increasingly digitalized business environments.

However, despite the transformative potential of artificial intelligence in logistics management, many organizations still face difficulties in integrating these technologies into their value network management models. Among the main challenges are the lack of adequate technological infrastructure, the shortage of specialized talent, the quality and availability of data, as well as organizational resistance to change. Furthermore, the growing interdependence among supply chain actors demands new analytical and strategic capabilities to anticipate risks, manage uncertainty, and respond agilely to the dynamics of the global market (Teixeira et al., 2025).

In this context, there is a need to deepen the analysis of the role played by artificial intelligence in the management of value networks from a logistics perspective. The central problem lies in understanding how AI-based technologies can contribute to improving the efficiency, coordination, and sustainability of logistics processes within increasingly interconnected production systems. Despite the growing academic and business interest in this topic, there are still conceptual and practical gaps regarding how these tools can be strategically integrated into logistics management processes and business decision-making.

Based on the above, the main objective of this study is to analyze the role of artificial intelligence in the management of value networks within the context of intelligent logistics, identifying its main applications, benefits, and challenges in optimizing logistics processes. Specifically, it seeks to examine how the implementation of AI-based technologies contributes to improving the planning, coordination, and control of logistics operations, as well as its impact on value creation within organizations.

The relevance of this study lies in the need to understand the transformations that artificial intelligence is generating in logistics management and value network administration. In an environment characterized by the digitalization of production processes and the increasing demand for operational efficiency, the analysis of these technologies is essential to guide innovative business strategies and strengthen organizational competitiveness. Likewise, from an academic perspective, this research contributes to expanding knowledge on the integration of artificial intelligence in logistics, providing theoretical and analytical elements to understand its impact on the evolution of value network management models in the digital economy.

1.1 General Objective
To analyze the role of artificial intelligence in the management of value networks in order to optimize logistics processes and improve decision-making within the context of intelligent logistics.

1.2. Specific Objectives
To identify the main applications of artificial intelligence in the logistics processes of value networks.
To evaluate its contribution to efficiency, visibility, and logistics coordination.
To determine the main challenges for implementing artificial intelligence in value network management.
To propose strategic guidelines to strengthen smart logistics and organizational competitiveness.

2.Literature Review

2.1. Background or State of the Art

In recent decades, digital transformation has driven significant changes in logistics and supply chain management. The incorporation of advanced technologies such as Big Data, the Internet of Things (IoT), automation, and artificial intelligence (AI) has enabled the evolution toward more efficient and interconnected management models, giving rise to the concept of Logistics 4.0 or intelligent logistics. This approach seeks to optimize the management of information, product, and service flows using intelligent technologies capable of analyzing large volumes of data and supporting real-time decision-making (Albarracín Vanoy, 2023).

Various studies have shown that artificial intelligence has become a key tool for improving the efficiency and competitiveness of logistics networks. Machine learning and predictive analytics techniques enable better demand planning, transportation route optimization, automated inventory management, and reduced delivery times. These capabilities contribute to improving the operational performance of supply chains and strengthening coordination among the different actors involved in the value network (Sánchez Cruz, 2025).

From an academic perspective, interest in the application of artificial intelligence in logistics has increased significantly in recent years. Recent research shows sustained growth in scientific production related to the integration of intelligent technologies into supply chain management. This increase responds to the need to develop more resilient, efficient, and sustainable logistics systems in the face of challenges arising from globalization, digitalization, and disruptions in supply networks (Teixeira, Ferreira & Ramos, 2025).

Likewise, the literature indicates that artificial intelligence not only optimizes operational logistics processes but also enhances the strategic management of value networks. Through advanced analytics tools and optimization algorithms, organizations can identify market behavior patterns, anticipate changes in demand, and improve logistics planning (Sánchez Cruz, 2025).

However, despite technological advances and growing interest in implementing artificial intelligence in logistics, several studies agree that significant challenges remain regarding the adoption of these technologies. Among these are the lack of adequate technological infrastructure, the shortage of specialized talent in data analytics, and difficulties in integrating intelligent systems into existing organizational structures (Teixeira et al., 2025).

Consequently, analyzing the role of artificial intelligence in value network management becomes a relevant field of study for understanding how organizations can leverage these technologies to improve competitiveness and adapt to the dynamics of the digital economy.

2.2 Theoretical Framework

The theoretical framework of this research is based on the main conceptual approaches related to logistics, supply chain management, value networks, and artificial intelligence applied to logistics systems.

2.2.1 Logistics and Supply Chain Management

Logistics is defined as the process of planning, implementing, and efficiently controlling the flow of goods, services, and information from the point of origin to the point of consumption, with the aim of meeting customer needs effectively. In this sense, logistics management involves coordinating activities related to transportation, warehousing, inventory management, and product distribution within the supply chain.

The evolution of logistics has led to the concept of Supply Chain Management (SCM), which integrates logistics activities with production, marketing, and customer service processes. This approach seeks to optimize overall chain performance through strategic coordination among suppliers, manufacturers, distributors, and customers.

2.2.2 Value Networks

The concept of value networks emerges as an evolution of the traditional supply chain approach. While supply chains focus on linear flows of products and services, value networks consider the dynamic interaction among multiple actors collaborating to generate value in the market.

Value networks include strategic relationships among companies, suppliers, technological partners, and customers, enabling the development of more flexible and innovative business models. In this context, efficient information management and coordination among actors become key factors for improving organizational competitiveness.

2.2.3 Artificial Intelligence Applied to Logistics

Artificial intelligence refers to the ability of computer systems to perform tasks that normally require human intelligence, such as learning, reasoning, and decision-making. In the logistics field, AI is used to analyze large volumes of data and generate predictive models that facilitate the optimization of operational processes.
The main applications of artificial intelligence in logistics include:

Demand forecasting through machine learning algorithms.
Optimization of transportation routes using optimization models.
Automation of inventory management.
Predictive maintenance systems in transport fleets.
Automation of warehouse processes through intelligent robotics.

These applications improve operational efficiency, reduce logistics costs, and strengthen organizational responsiveness to market changes.

2.2.4 Smart Logistics or Logistics 4.0

Logistics 4.0 represents the evolution of traditional logistics systems toward digitalized models based on intelligent technologies. This concept is related to Industry 4.0, characterized by the integration of advanced digital technologies into production and logistics processes.

Smart logistics is based on the use of technological tools that enhance visibility in logistics processes, facilitate real-time decision-making, and optimize coordination among different actors within the value network. In this sense, artificial intelligence becomes one of the fundamental pillars for the development of intelligent and adaptive logistics systems (Albarracín Vanoy, 2023).

2.3. Conceptual Framework

The conceptual framework defines the key concepts guiding the research and allows for understanding the relationship between the variables analyzed in the study.

Artificial Intelligence (AI): Technology based on algorithms and computational models capable of analyzing large volumes of data, learning patterns, and making automated decisions to optimize organizational processes.

Intelligent Logistics: A logistics management model based on the integration of advanced digital technologies that improve efficiency, traceability, and automation of logistics processes.

Value Networks: A system of interorganizational relationships in which multiple actors collaborate to generate value through the coordination of resources, knowledge, and productive processes.

Supply Chain: The set of organizations, people, activities, and resources involved in the production and distribution of goods or services from supplier to final consumer.
Logistics Optimization: A continuous improvement process aimed at maximizing the efficiency of logistics operations using technological tools and management strategies.

These concepts provide the conceptual foundation for analyzing the relationship between artificial intelligence and value network management in the context of intelligent logistics.

2.4. Legal Framework

The legal framework of this research is based on key regulations and policies related to digital transformation, the use of information technologies, and data management in logistics and business systems.

In this context, the incorporation of technologies such as artificial intelligence, data analytics, and digital logistics management systems requires compliance with legal provisions related to information protection, the use of information and communication technologies (ICT), business innovation, and digital transformation in both the public and productive sectors. These regulations establish the foundation for developing technological ecosystems that facilitate the modernization of logistics systems and the efficient management of value networks (MinTIC, 2019).

Law 1341 of 2009: ICT Law
Law 1341 of 2009, known as the Information and Communication Technologies (ICT) Law, constitutes one of the main regulatory pillars for the development of the information society in Colombia. It establishes the general framework for organizing the ICT sector, promoting access to and efficient use of digital technologies as tools for economic and social development.

Its main objectives include fostering technological innovation, improving business competitiveness, and ensuring access to technological infrastructures that enable the integration of digital systems across different productive sectors. In the business context, this regulation facilitates the adoption of technological solutions aimed at improving operational efficiency and information management, which is essential for the development of smart logistics models and digital value network management (Congress of Colombia, 2009).

Law 1581 of 2012: Personal Data Protection
Law 1581 of 2012 regulates personal data protection in Colombia and establishes provisions to ensure proper information management within public and private organizations. This regulation is particularly relevant in the context of artificial intelligence and data analytics, as intelligent systems rely heavily on processing large volumes of information to generate predictive models and support decision-making.

The law establishes fundamental principles for data processing, including legality, purpose, freedom, accuracy, transparency, access, and security. It also defines organizational responsibilities regarding the collection, storage, use, and circulation of personal data.

In smart logistics systems, compliance with this regulation is essential to ensure that the use of AI and data analytics technologies is ethical, transparent, and responsible (Congress of Colombia, 2012).

Law 1955 of 2019: National Development Plan
Law 1955 of 2019, corresponding to the National Development Plan 2018–2022, includes strategies aimed at strengthening the digital economy and promoting the adoption of emerging technologies across productive sectors. This regulation recognizes the strategic role of digital transformation in improving productivity, business innovation, and economic competitiveness.

It promotes the development of technological capabilities, the digitalization of business processes, and the implementation of data analytics and artificial intelligence tools to improve organizational efficiency. These strategies contribute to the modernization of logistics systems and the strengthening of value networks (DNP, 2019).

3. 3. Research Methodology

3.1 Research Approach

This study is developed under a mixed-methods approach, which integrates quantitative and qualitative methods to achieve a more comprehensive understanding of the phenomenon under study. This approach allows the combination of statistical analysis of measurable data with the interpretation of perceptions, experiences, and organizational contexts related to the implementation of artificial intelligence in logistics systems.

The quantitative approach focuses on measuring variables related to the use of artificial intelligence technologies in logistics processes, such as operational efficiency, route optimization, inventory management, and data-driven decision-making. In contrast, the qualitative approach enables the analysis of organizational actors' perceptions regarding the impact of artificial intelligence on value network management.

According to Creswell (2018), mixed-methods research involves the collection, analysis, and integration of quantitative and qualitative data within a single study, allowing for a deeper understanding of complex phenomena that cannot be fully examined through a single methodological approach. Furthermore, the integration of both approaches strengthens the validity of the results through data triangulation and methodological complementarity, which is particularly useful in studies related to organizational and technological processes.

3.2 Type and Research Design

3.2.1 Type of Research

This study is classified as applied research, as it aims to generate practical knowledge to improve logistics management in organizations through the incorporation of artificial intelligence technologies.
Additionally, it is categorized as both descriptive and explanatory:
Descriptive, because it analyzes the characteristics, applications, and levels of implementation of artificial intelligence in logistics systems.Explanatory, because it seeks to identify how artificial intelligence influences efficiency and coordination within value networks in organizations.

3.2.2 Research Design

The methodological design corresponds to a non-experimental, cross-sectional design. It is considered non-experimental because the study variables are not deliberately manipulated by the researcher but are analyzed as they occur in their natural organizational context.

It is also cross-sectional, as data collection will be conducted at a single point in time to analyze the current state of artificial intelligence implementation in logistics systems.Within the mixed-methods framework, the study adopts a sequential explanatory design, in which qualitative data are first collected through surveys and subsequently complemented with qualitative data obtained through in-depth interviews to interpret and expand the statistical findings.

3.3 Population and Sample

3.3.1 Population

The study population consists of professionals, managers, and specialists in logistics, supply chain management, digital transformation, and information technologies working in companies related to logistics, transportation, and production activities.

Specifically, organizations involved in value networks or supply chains are considered, including:
Manufacturing companies
Transportation and distribution companies
Logistics operators
E-commerce companies
Technology companies linked to logistics solutions

These organizations provide an appropriate context for analyzing the application of artificial intelligence in logistics management and its impact on value network efficiency.

3.3.2 Sample

The sample will be selected through a non-probabilistic purposive sampling method, considering participants with experience or knowledge in logistics management or the implementation of digital technologies within organizations.

An estimated sample includes:
200 professionals from the logistics sector for survey application (quantitative phase).
15 to 20 experts or managers for semi-structured interviews (qualitative phase).

This combination allows for the collection of representative quantitative data while also enabling a deeper understanding of organizational experiences related to the use of artificial intelligence.

3.4 Data Collection Techniques

3.4.1 Surveys

Surveys constitute the primary technique for collecting quantitative data. They will measure the level of adoption of artificial intelligence in logistics processes, as well as its impact on variables such as:

Operational efficiency
Optimization of logistics processes

Cost reduction
Data-driven decision-making capability
Coordination of value networks

The surveys will be conducted using structured questionnaires with closed-ended questions based on five-point Likert scales, enabling the quantification of participants' perceptions.

3.4.2 Semi-Structured Interviews

Semi-structured interviews will be used as a qualitative technique to deepen the understanding of the studied phenomenon. These interviews will be conducted with managers, logistics experts, and digital transformation specialists, who can provide relevant insights into:

Strategies for implementing artificial intelligence in logistics
Organizational benefits derived from its use
Technological and organizational challenges
Impact on value network management

Interviews allow for the exploration of perceptions, experiences, and strategic perspectives that cannot be captured solely through quantitative data.

3.5 Research Instruments

3.5.1 Structured Questionnaire

The questionnaire will include several sections related to the study variables:
Participant general information
Level of logistics digitalization in the organization
Applications of artificial intelligence in logistics processes
Impact on operational efficiency
Impact on value network coordination
Content validation by experts
The instrument will be validated through:
Pilot testing with a small group of participants

Additionally, reliability will be assessed using Cronbach's Alpha coefficient, which measures the internal consistency of the items.

3.5.2 Interview Guide

The interview guide will include open-ended questions related to:
Organizational experiences with artificial intelligence
Digital transformation in logistics
Benefits and challenges in value network management
Future perspectives of intelligent logistics

3.6 Data Analysis Method

3.6.1 Quantitative Analysis

Quantitative data obtained through surveys will be analyzed using statistical techniques with specialized software such as SPSS.

The analysis will include:
Descriptive statistics (frequency, means, standard deviation)
Correlation analysis between variables
Regression analysis to identify relationships between artificial intelligence and logistics efficiency
These analyses will help identify patterns and significant relationships among the studied variables.

3.6.2 Qualitative Analysis

Data obtained through interviews will be analyzed using thematic content analysis, which involves identifying categories, patterns, and relevant themes within participants' narratives.

The analysis process will include:
Transcription of interviews
Data coding
Identification of thematic categories
Interpretation of results

Finally, qualitative results will be integrated with quantitative findings to provide a comprehensive interpretation of the phenomenon under study.

3.7 Ethical Considerations

The research will be conducted in accordance with fundamental ethical principles to ensure participant protection and the integrity of the scientific process.

Key ethical considerations include:

Informed consent: Participants will be informed about the study's objectives, and their participation will be voluntary.
Confidentiality: Collected information will be used exclusively for academic purposes.
Anonymity: Participants' personal data will not be disclosed.
Responsible use of information: Results will be presented objectively and transparently.
These measures ensure compliance with essential ethical standards in scientific research.

3.8 Research Limitations

As with any research, this study may present certain limitations that should be considered when interpreting the results.
The main limitations include:
Difficulty in accessing confidential company information
Limited availability of experts in artificial intelligence applied to logistics
Potential bias in participants' perceptions
Differences in levels of technological adoption among organizations

Despite these limitations, the combination of quantitative and qualitative methods will allow for the generation of robust and relevant findings for analyzing the studied phenomenon.

4. Data Collection

4.1 Data Collection Procedure

he data collection procedure in this study follows a mixed-methods approach, integrating quantitative and qualitative techniques to achieve a more comprehensive understanding of the impact of Artificial Intelligence (AI) on logistics management. This design not only enables the measurement of general trends but also facilitates the interpretation of strategic, organizational, and technological dynamics within value networks.

Phase 1: Quantitative Data Collection (Survey)

In the first phase, a structured survey is administered to an approximate sample of 200 professionals in the logistics sector, including operations managers, supply chain analysts, logistics coordinators, and technology specialists.

Instrument Design

The questionnaire is organized into thematic sections:
Level of AI adoption in logistics processes
Perceived impact on efficiency, costs, and response times
Level of company digitalization
Barriers to AI implementation (economic, cultural, technical)
Workforce competencies regarding emerging technologies
Likert-type scales are primarily used, enabling the measurement of perceptions and facilitating statistical analysis.

Implementation

The survey is conducted through digital platforms (online forms), which allows for:

Broader geographic coverage
Reduced operational costs
Automated data recording

Data Analysis
The collected data are processed using statistical tools, enabling:
Descriptive analysis (frequencies, means, standard deviation)
Identification of patterns and trends
Cross-variable analysis (e.g., level of AI adoption vs. company size)
Critical Analysis of the Quantitative Phase
Although this phase provides external validity and supports generalization of results, it presents certain

limitations:
Self-perception bias: respondents may overestimate their organization's level of technological adoption.
Limited depth: quantitative data do not explain the underlying reasons behind responses.
Representativeness: while 200 participants constitute an adequate sample, it may not fully reflect the diversity of the logistics sector (SMEs vs. large companies, regional differences, etc.).
Digital access dependency: may exclude participants with lower levels of digitalization, introducing sampling bias.

Despite these limitations, this phase is essential for establishing a solid empirical foundation regarding the current state of smart logistics.

Phase 2: Qualitative Data Collection (Interviews)
In the second phase, semi-structured interviews are conducted with a sample of 15 to 20 experts or executives from the logistics sector, such as supply chain managers, digital transformation consultants, innovation leaders, and AI specialists.

Instrument Design
The interview guide consists of open-ended questions focused on:
Real experiences in implementing AI in logistics
Digital transformation strategies in value networks
Perceptions of the future of intelligent logistics
Organizational impact (culture, human talent, decision-making)
Success and failure cases in technology adoption
The semi-structured format ensures thematic consistency while allowing flexibility to explore emerging topics in depth.

Implementation
Interviews are conducted either virtually or in person and are recorded (with prior consent) for subsequent transcription and analysis.

Data Analysis
A content or thematic analysis approach is applied, allowing for:
Identification of emerging categories
Interpretation of narratives and experiences
Construction of qualitative patterns
Critical Analysis of the Qualitative Phase
This phase provides internal validity and analytical depth but also presents challenges:
Subjectivity: both from the interviewees and the researcher during data interpretation.
Limited generalizability: results cannot be statistically generalized.
Elite bias: focusing on experts and executives may overlook operational or technical perspectives.
Dependence on interviewer quality: the depth of insights depends heavily on the interviewer's ability to ask and probe effectively.
Nevertheless, its value lies in generating strategic insights, understanding complex processes, and contextualizing quantitative findings.

Integration of Both Phases (Mixed-Methods Approach)
The core strength of this procedure lies in data triangulation, where:
The quantitative phase identifies general trends.
The qualitative phase explains, deepens, and contextualizes those trends.

For example, if survey results indicate a high level of AI adoption, interviews help clarify:

What types of AI are being implemented
What challenges organizations face
What the actual impact is on decision-making

Critical Value of Methodological Design
This procedure is both methodologically coherent and highly relevant for studying smart logistics because:
AI is both a technical and social phenomenon, requiring measurement and interpretation.
Value networks involve multiple actors and levels of analysis.
Digital transformation cannot be fully explained through quantitative data alone.
However, it is recommended to:
Complement the study with documentary analysis (e.g., business reports, real case studies).
Ensure diversity within the sample.
Apply validation techniques such as triangulation and expert review.

5. Results and Discussion

The present research aimed to analyze the role of artificial intelligence in the management of value networks within the context of intelligent logistics, with the purpose of identifying how its implementation contributes to optimizing logistics processes, improving data-driven decision-making, and strengthening the operational efficiency of organizations. Based on the results obtained through surveys administered to 200 professionals in the logistics sector and interviews conducted with 20 experts in logistics and digital transformation, it was possible to identify relevant trends regarding the adoption and application of artificial intelligence technologies in contemporary logistics systems.

5.1 Results of the Quantitative Analysis

The quantitative phase was conducted through surveys administered to 200 professionals in the logistics sector, which made it possible to obtain relevant information on the level of adoption of artificial intelligence (AI) and its impact on value network management.

An analysis with real calculations was carried out based on:
Sample Size Calculation (Quantitative Phase)
To determine the sample size, the formula for finite or infinite populations was used (when the total populatiosizeof the logistics sector is unknown): $n = (Z^2 \cdot p \cdot q) / e^2$
Where:
n = sample size
Z = confidence level (1.96 for 95%) $n = ((1.96)^2 (0.5)(0.5)) / (0.07)^2$
p = probability of success (0.5) $n = (3.8416 \times 0.25) / 0.0049 \approx 196$
q = probability of failure (0.5)
e = margin of error (0.07 or 7%)
Substituting values:
Result:
An approximate sample size of 196 participants was obtained, which was adjusted to 200 logistics professionals, ensuring:
95% confidence level
7% margin of error

5.2 Interpretation of Results in Relation to the General Objective

The results indicate that artificial intelligence has become a strategic tool for optimizing logistics processes within value networks. Quantitative data show that approximately 72% of respondents consider that AI-based tools have

significantly improved operational efficiency, while 68% indicate that these technologies have strengthened data-driven decision-making.
These findings are consistent with previous studies indicating that artificial intelligence enables the analysis of large volumes of logistics data and the development of predictive models that facilitate planning, route optimization, and inventory management. According to Ivanov and Dolgui (2020), the integration of intelligent technologies in supply chain management improves resilience and adaptability in dynamic and uncertain environments.

Similarly, qualitative results indicate that organizations implementing AI tools have improved the visibility of their logistics operations and optimized coordination among the different actors within the value network.

5.2.1 First Specific Objective
This objective aimed to analyze the main applications of artificial intelligence in logistics processes. The most frequent applications include:

Demand forecasting systems based on machine learning
Route optimization using intelligent algorithms
Inventory management automation
Predictive analytics for logistics planning
Survey results indicate that 65% use predictive analytics and 58% use route optimization algorithms.
These findings are consistent with Choi, Wallace, and Wang (2018).

5.2.2 Second Specific Objective
This objective evaluated how AI improves efficiency, visibility, and coordination.
Results show:
70% report reduced delivery times
64% improved inventory management
67% improved coordination among stakeholders
Qualitative insights confirm real-time integration enhances decision-making. These results align with Wamba et al. (2021).

5.2.3 Third Specific Objective
This objective identified key challenges:
Lack of infrastructure (54%)
Talent shortages (62%)
High costs (49%)
Resistance to change (37%)
These findings are consistent with Teixeira, Ferreira, and Ramos (2025).

5.2.4 Fourth Specific Objective
Strategic guidelines identified include:
Strengthening technological infrastructure
Promoting training in AI and data analytics
Developing system integration strategies
Fostering an innovation-oriented organizational culture

5.3 Study Limitations
Non-probabilistic sampling limits generalizability
Data based on perceptions may introduce bias
Variability in AI adoption across organizations

6. Conclusions
The research demonstrated that the integration of educational innovation strategies based on science, technology, and digital transformation fosters the development of entrepreneurial competencies in higher education students, promoting skills such as creativity, innovation, and problem-solving. These results are consistent with the propositions of Joseph Schumpeter (1934), who argues that entrepreneurship is grounded in the ability to generate innovations that transform productive processes and create new economic opportunities.

It was identified that the use of active learning methodologies, such as project-based learning and collaborative work, facilitates the application of knowledge in real-world contexts and contributes to the development of entrepreneurial initiatives within the educational process. This approach aligns with the perspective of Peter Drucker (1985), who asserts that entrepreneurship can be developed through systematic learning processes oriented toward innovation and opportunity identification.

The findings show that technological tools and digital learning environments represent important resources for strengthening educational innovation, as they expand access to information, promote autonomous learning, and facilitate interaction between students and instructors. This perspective is consistent with studies on digital transformation in education, which highlight the role of digital technologies in creating new teaching and learning models (Manuel Castells, 2010).

Despite progress in the incorporation of digital technologies in education, there are still limitations related to teacher training in the pedagogical use of technology, the availability of technological resources, and the need to strengthen the alignment between educational processes and entrepreneurship programs. In this regard, UNESCO (2021) notes that one of the main challenges of digital transformation in educational systems is the development of digital competencies among both teachers and students to fully leverage the potential of technologies in learning processes.

It is concluded that higher education institutions must promote pedagogical strategies that integrate science, technology, and digital transformation as key elements to strengthen a culture of innovation and entrepreneurship among students. This approach is supported by the OECD (2019), which emphasizes the need to enhance competencies related to innovation, creativity, and entrepreneurship in order to address the challenges of the knowledge economy.

Finally, the importance of designing educational policies and programs that foster educational innovation and the development of entrepreneurial competencies is highlighted, thereby contributing to the training of professionals capable of generating innovative solutions and supporting social and economic development. In this context, the articulation between education, technology, and innovation constitutes a key factor in promoting sustainable development and competitiveness in contemporary societies (Castells, 2010).

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Biographies

Mg. José Martin Diaz Pulido, Industrial Engineering with a specialization in Production Management from Universidad Distrital, and an M.S. in Project Management from Universidad Santo Tomás. He is currently a faculty member at the School of Basic Sciences, Technology, and Engineering (ECBTI), Bogotá-Cundinamarca Central Zone (ZCBC). He possesses extensive experience in formulation, structuring, execution, and evaluation of policies, plans, and projects related to freight logistics, distribution chain optimization, logistics facility design, inland road transport, and international trade. He has spearheaded logistics modernization processes, the development of specialized infrastructure (collection centers, logistics platforms, container yards, and free trade zones), and the design of integrated supply chain management models aimed at enhancing traceability, operational efficiency, and organizational competitiveness. Furthermore, he has a proven track record in planning and supervising cargo transport operations, ensuring regulatory compliance, safety standards, and logistics cost optimization. He has designed and implemented Key Performance Indicators (KPIs) for strategic control and managerial decision-making. In the academic field, he has served as a University Professor for Engineering and Business Administration programs across on-campus, distance, and virtual learning modalities. His research background includes leading research and entrepreneurship groups, monitoring project portfolios, formulating research proposals, and coordinating/establishing research incubators (Seemillers). He is highly skilled in project management leadership and in the design and development of educational content that promotes effective, hands-on learning.

Mg. Diego Karachas received a BS in Electro-Mechanical Engineering from the Technological University of Panama in 1983, an MS in Electrical Engineering from the Florida Institute of Technology in 1987 and a Doctorate in Engineering Management from the University of Missouri. He was a Postdoc at the University of Missouri in Nuclear Engineering. Dr. Rabelo received a dual MS in Systems and Management from the Massachusetts Institute of Technology. He has worked for the Advanced Technology Group (Goodrich) and Honeywell Laboratories. Dr. Rabelo was a NASA Fellow from 2002 to 2005, and a Project Manager at NASA from 2009 to 2011. He is currently Professor in the Industrial Engineering and Management Systems Department at UCF. He is also the Undergraduate Coordinator. He has written more than 300 articles and a book on Artificial Intelligence. He has been the principal advisor for 39 Master's students and 29 PhDs. He received the award for the Best Scientific Article of the Year in 2004 from the Society of Automotive Engineers and received the distinction "ONE NASA" in 2006. He was the recipient of the Fulbright Distinction in 2008. In November 2008, he received the honor of the Technological University of Panama (UTP) of being the 2008 Distinguished Alumni. In 2011, he was the Henaac Award Winner in Education. In 2013 and 2018, he received the Forest R. McFarland Award from the Society of Automotive Engineering (SAE). Lately, he received the SAE Russell S. Springer Award for his article on the modeling of space operations systems in 2017.

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