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AI-Enhanced Manufacturing in Latin America: Opportunities, Challenges, Applications, and Regulatory Policy Frameworks for Intelligent Production Systems

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Abstract

As artificial intelligence (AI) reshapes production, its integration into manufacturing offers gains in precision, efficiency, and sustainability. Globally, AI supports additive, subtractive, and forming processes through optimization, monitoring, defect detection, and design innovation. In Latin America, however, adoption is limited and uneven, with most evidence from surveys, policy reports, and pilot projects rather than large-scale implementations. This review addresses that gap by examining the global landscape of AI in manufacturing and the specific conditions influencing its adoption in the region. The study is guided by the question: What structural conditions are required to enable successful and sustainable AI integration in Latin American manufacturing? To answer, it applies the Triadic Integration Framework, which identifies three pillars: digital infrastructure, policy and governance, and socio-industrial capacity. The analysis highlights barriers, including fragmented regulation, skills shortages, cybersecurity risks, and cost–benefit uncertainties, while also pointing to opportunities in various industrial sectors. To translate insights into practice, a phased roadmap is proposed, outlining short-term, medium-term, and long-term actions, along with the responsible stakeholders and the necessary resources. As an integrative review, the study synthesizes existing knowledge to build a framework, defining directions for future research, emphasizing that successful adoption requires technical progress, inclusive governance, and regional coordination.

Keywords: artificial intelligence; smart manufacturing; additive manufacturing; AI governance; manufacturing policy; Latin America; digital transformation; ethical AI; industrial policy; sustainable manufacturing

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1. Introduction

Artificial intelligence (AI) is rapidly transforming industrial manufacturing systems, enabling unprecedented levels of automation, process-specific customization, and efficiency. In particular, the integration of AI into manufacturing processes is reshaping how industries approach design and production, leading to a new era of intelligent, adaptive, and data-driven production that promotes a swift transition from Industry 4.0 to Industry 5.0 [1–5]. AI techniques, such as deep learning, reinforcement learning, and generative models, have already demonstrated their capacity to optimize key aspects of manufacturing processes, including process, material, and geometry parameters [6–9]. Through machine learning (ML) algorithms, these technologies enhance process control, reduce material waste, and improve product quality by learning from large datasets and dynamically adjusting production parameters [8–12].

While advanced economies are building integrated AI-driven manufacturing ecosystems, Latin America's adoption of these technologies remains fragmented. Countries such as Brazil, Mexico, Chile, Peru, Costa Rica, and Argentina have made significant advancements in their national AI strategies [3,13]. However, these initiatives are often poorly coordinated with broader industrial and manufacturing policies, resulting in fragmented implementation and limited systemic impact [3,14]. In this sense, small and medium enterprises (SMEs) in the manufacturing sector face particular challenges, including limited access to capital, insufficient human resources, and low technological readiness [1,3,4,15–17].

Recent evidence shows that the Latin American smart manufacturing market reached USD 25.1 billion in 2024 and is projected to grow to USD 59.9 billion by 2033, at a compound annual growth rate of 9.1%. This expansion is largely driven by the potential expected from integrating AI solutions to improve efficiency, facilitate predictive maintenance, enhance quality control, and collaborate with global technology providers [18]. Recent evidence underscores that AI adoption in Latin America's manufacturing sector is accelerating. According to the IBM Global AI Adoption Index 2023, 67% of IT professionals in the region reported that their organizations had accelerated AI adoption over the past two years, which is above the global average of 59% [19]. At the same time, the full index report indicates that 47% of large firms in Latin America are already implementing AI solutions, 40% are still in the exploration stage, and only 15% have not yet adopted AI [20]. The most common applications include digital labor (39%), IT process automation (36%), and marketing and sales (35%). Emerging use cases are also found in healthcare diagnostics, environmental risk analysis, and sustainability initiatives. Nevertheless, significant barriers persist, particularly the shortage of skilled professionals (37%), data complexity (33%), and cost constraints (23%), which continue to hinder the scaling of AI solutions in manufacturing.

From the global perspective, several reviews highlight that while the implementation of AI has led to tangible improvements in sustainability and efficiency in energy-intensive sectors [15,21,22], the lack of coordinated governance, investment in digital infrastructure, and regional regulatory frameworks remains a significant obstacle [2,14,23,24]. Meanwhile, advanced applications such as digital twins, metaverse-based industrial simulations, and generative AI for product innovation are progressing rapidly in the Global North [2–4,15]. Some AI technologies are accessible for a wide range of activities; however, their formal and standardized implementation in Latin America remains limited. Systemic barriers, including high costs, insufficient digital infrastructure, technological illiteracy, institutional resistance, and workforce skills gaps, have hindered the widespread adoption of digital solutions, particularly among small and medium-sized enterprises (SMEs) [25–27]. Additionally, the Technology and Innovation Report from the United Nations indicates that the Latin America and Caribbean region is among the countries with low institutional capacity for AI adoption and development, reinforcing the rationale for proposing a tailored framework [28].

Despite these barriers, opportunities are emerging. The potential of AI to support smart, efficient, and context-aware manufacturing processes worldwide is evident in multiple sectors relevant to Latin America, including cement [12,21,29–31], food and agriculture [15,24], textiles [32,33], and metal transformation and processes [22,34–36]. Furthermore, institutions and research communities in the region are contributing to the global AI discourse, particularly in areas such as sustainable production, cybersecurity, and industrial IoT [1,17,23,31].

A key consideration is that AI-enhanced and optimized industrial systems require more than technical development: robust governance structures are essential to balance innovation with inclusivity, transparency, and sustainability [2,14,17,23,24]. These frameworks must consider data governance, ethical AI deployment, public–private partnerships, education and reskilling programs, and alignment with national development goals [3,14,37–42].

This paper addresses a specific gap in the scientific literature: the uneven adoption of AI in Latin American manufacturing despite global advancements. The underlying reason is that the existing literature remains fragmented, with studies focusing either on technological aspects or on policy and governance, but rarely examining their interaction in the regional context. Both recent systematic review protocols [43,44] and foundational methodological references [45] emphasize the importance of structured approaches when addressing literature fragmentation. Furthermore, evidence from Latin American studies highlights persistent technological, economic, and institutional barriers that complicate adoption, underscoring the need for integrative frameworks [46,47]. To address this shortcoming, our study examines the intersection of technical capabilities, policy frameworks, and socio-industrial conditions, providing an integrative analytical framework that synthesizes these domains and offers a roadmap for aligning AI-driven manufacturing innovations with inclusive and sustainable industrial development in the region.

This study adopts an integrative literature review approach, combining peer-reviewed publications with institutional and policy reports to capture both academic and governance perspectives on AI in manufacturing in Latin America. While not a systematic review in the strict PRISMA sense, the search process followed structured criteria across multiple databases (Scopus, WoS, IEEE Xplore, Scielo, Google Scholar) and applied explicit inclusion and exclusion filters to ensure relevance.

This study is designed as an integrative literature review. Its purpose is to consolidate fragmented evidence, propose an analytical framework, and generate future research questions. Thus, the paper is structured as follows: Section 2 describes the methodology and search strategy, outlining the databases, keywords, and inclusion/exclusion criteria employed. Section 3 examines the technical foundations of AI in manufacturing, including its application across additive, subtractive, and forming processes; the roles of sensing and data acquisition; the main AI paradigms; and representative industrial applications. Section 4 analyzes the Latin American context through the Triadic Integration Framework, addressing three structural pillars: digital infrastructure, policy and governance, and socio-industrial capacity. This section also discusses specific challenges, including regulatory gaps, skill shortages, cybersecurity vulnerabilities, cost–benefit uncertainties, and regional disparities. Section 5 presents the proposed roadmap for action, outlining short-, medium-, and long-term recommendations, along with associated stakeholders and resource requirements. Finally, Section 6 presents the conclusions, highlighting the implications of the findings and outlining future research directions to support the adoption of inclusive, sustainable, and innovation-ready AI in the region.

2. Methodology

2.1. Literature Search Strategy

This study adopted a systematic literature review to examine the integration of AI in manufacturing within Latin America. The search was initiated in Scopus, using keywords that combined three domains: (i) artificial intelligence ("AI", "machine learning", "deep learning"), (ii) manufacturing and Industry 4.0 ("manufacturing", "smart manufacturing", "intelligent production systems", "Industry 4.0"), and (iii) Latin America (both regional and country-specific terms such as Brazil, Mexico, Argentina, and Chile). The time frame was set between 2010 and 2025 to capture the emergence of national AI strategies and Industry 4.0 policies in the region.

As the search in Scopus revealed only a limited number of region-specific studies, the scope was expanded to include Web of Science, IEEE Xplore, and Scielo, ensuring coverage of both international and regional academic outputs. In addition, Google Scholar was used as a supplementary tool to identify relevant grey literature, particularly institutional and policy reports from the OECD, UNDP, CEPAL, PARLATINO, and national governments, which provide essential insights into regulatory and industrial developments in Latin America.

Inclusion criteria required that publications be produced between 2010 and 2025, written in English, Spanish, or Portuguese, and explicitly address AI applications in manufacturing or policy frameworks relevant to Latin America. Exclusion criteria excluded studies unrelated to manufacturing, those outside the Latin American context, or those published before 2010 (see Figure 1).

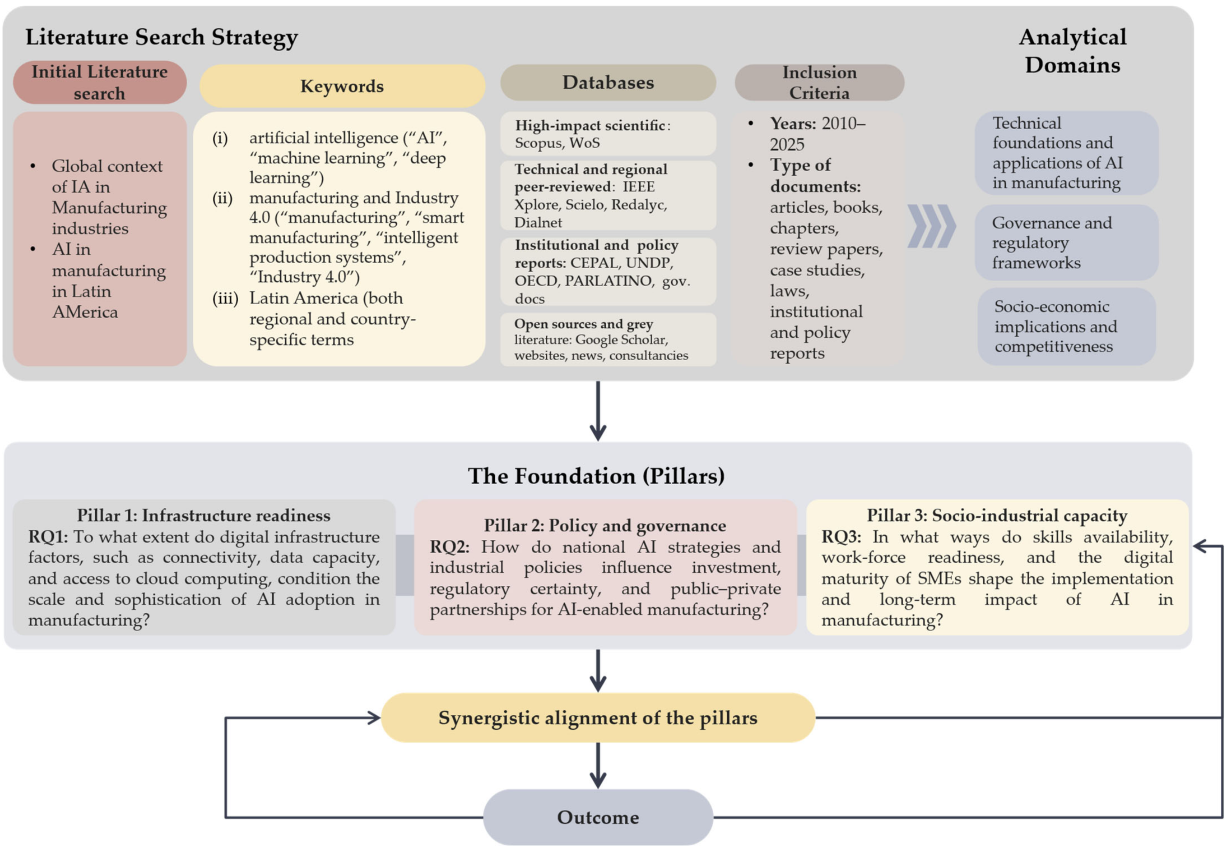

Figure 1. Literature search strategy and analytical framework. The review integrates academic and policy sources and organizes them into three analytical domains: (i) technical foundations, (ii) governance, and (iii) socio-industrial capacity, synthesized in the Triadic Integration Framework.

2.2. Analytical Domains of the Review

The literature identified through this process was reviewed and thematically organized into three analytical domains: (i) technical foundations and applications of AI in manufacturing, (ii) governance and regulatory frameworks, and (iii) socio-economic implications and competitiveness. This approach ensured the incorporation of academic research, institutional reports, and policy documents, including national strategies and legislative initiatives, allowing for a comprehensive understanding of the opportunities and challenges associated with AI adoption in Latin American manufacturing.

Nevertheless, a noticeable gap remains between the potential of AI technologies and their uneven adoption in the region's manufacturing sector. This suggests that integration is not merely a matter of technological availability but also depends on broader systemic conditions.

2.3. Research Problem and Questions

To address this issue, the review is guided by the following central research question:

What structural conditions are required to enable the successful and sustainable integration of AI into Latin American manufacturing?

From this central question, three research questions were derived, aligned with the analytical domains of the review:

- RQ1: Infrastructure readiness—To what extent do digital infrastructure factors, such as connectivity, data capacity, and access to cloud computing, condition the scale and sophistication of AI adoption in manufacturing?
- RQ2: Policy and governance—How do national AI strategies and industrial policies influence investment, regulatory certainty, and public–private partnerships for AI-enabled manufacturing?
- RQ3: Socio-industrial capacity—In what ways do skills availability, workforce readiness, and the digital maturity of SMEs shape the implementation and long-term impact of AI in manufacturing?

In addition to addressing the central research question and its three derivative sub-questions, the review also mapped the global applications of AI across different manufacturing processes (additive, subtractive, and forming). This step provided the necessary technical foundations to answer the first component of the study, how AI is currently applied in manufacturing techniques worldwide, before focusing on the specific challenges and structural conditions for adoption in Latin America.

To synthesize the research questions and provide an analytical lens for the review, this study adopts the Triadic Integration Framework. The framework asserts that AI adoption in manufacturing is shaped by the interaction of three interconnected domains, which together establish the conditions for successful and sustainable implementation.

2.4. The Research Model: The Triadic Integration Framework for AI Adoption

The analysis of AI adoption in manufacturing is complex, requiring a framework that captures its multifaceted nature. To this end, and to synthesize the research questions, this study adopts the Triadic Integration Framework as its analytical lens. This framework posits that successful and sustainable AI integration is shaped by the synergistic interaction of three interconnected domains: digital infrastructure, policy and governance, and socio-industrial capacity.

This framework is not conceived in isolation but is grounded in and synthesizes established theories of technology adoption. Its structure is inspired by the well-known Technology–Organization–Environment (TOE) framework [48], which categorizes influencing factors into technological, organizational, and environmental contexts. The three pillars were selected because they represent the most critical and recurring thematic domains identified in the literature on technological innovation:

- Digital Infrastructure (representing the technological context) emphasizes the foundational role of technological readiness, including connectivity, data capacity, and cloud computing access, as a non-negotiable prerequisite for deploying sophisticated AI applications [49].
- Policy and Governance (representing the environmental context) highlights how external factors, such as national strategies and regulatory certainty, create the necessary ecosystem for investment and risk mitigation [50].
- Socio-Industrial Capacity (representing the organizational context) focuses on the human and organizational dimensions, such as skills availability and the digital maturity of SMEs, which are consistently identified as the most significant determinants of long-term success [51,52].

Furthermore, the framework incorporates a feedback loop, recognizing that the outcomes of AI adoption inform subsequent adjustments across all three domains, ensuring the model reflects the dynamic and iterative nature of technological integration [53]. By adopting this synthesized framework, this review provides a structured yet holistic basis for analyzing the interdependent barriers and facilitators of AI adoption in the Latin American manufacturing context.

The Triadic Integration Framework was selected not as a causal model to be statistically validated within this review, but as a necessary analytical lens to organize a fragmented and multidisciplinary field of study. Its three pillars, digital infrastructure, policy, and governance, and socio-industrial capacity, were inductively identified as the most salient and recurring thematic domains in the literature. The framework's purpose is to provide structure for synthesis and to illuminate the proposed connections between domains that future research can now operationalize and test.

Logical Sequence of the Model

The Triadic Integration Framework is structured as a sequential logic that reflects the evolution of AI adoption in manufacturing within Latin America. The framework begins by identifying the three foundational pillars that condition adoption (technological infrastructure, policy and governance, and socio-industrial capacity). It then highlights the importance of their synergistic alignment, since isolated progress in one domain is insufficient without coordination across the others. When alignment occurs, it generates measurable outcomes in terms of industrial upgrading, productivity, and sustainability. Finally, the framework incorporates a feedback loop, recognizing that the results of adoption, whether successful or limited, inform subsequent adjustments in infrastructure, policy, and workforce development. This logical sequence allows the framework to serve not only as a descriptive model, but also as a diagnostic tool to assess strengths, weaknesses, and opportunities in the region's path toward AI-enabled manufacturing.

- The Foundation (The Three Pillars)

The model is based on three core pillars that create the necessary conditions for adoption. Technological infrastructure refers to the hardware of adoption, including broadband penetration, cloud service availability, supercomputing capacity, and IoT connectivity in factories. Policy and governance represent the rulebook, encompassing national AI strategies, data privacy regulations, intellectual property rights, industrial standards, and ethical guidelines. Socio-industrial capacity encompasses the human and organizational dimensions, including the supply of skilled talent, the digital maturity of manufacturing firms (particularly small and medium-sized enterprises, or SMEs), and their financial and absorptive capacities to integrate advanced technologies.

- The Mechanism (Synergistic Alignment)

The framework emphasizes that the mere existence of these pillars is not sufficient. Adoption depends on their alignment. For instance, a government policy that funds digital upskilling programs (pillar 2) directly strengthens the workforce (pillar 3). Similarly, a firm's investment in AI talent (pillar 3) can only be fully leveraged if robust digital infrastructure (pillar 1) is in place. Conversely, even strong infrastructure remains underused without coherent policies that foster trust and encourage investment (pillar 2). Alignment is thus the mechanism that transforms potential into concrete adoption.

- The Outcome (AI Adoption and Impact)

When the three pillars are simultaneously developed and effectively aligned, they create an enabling ecosystem that facilitates the successful integration of AI. The outcomes extend beyond isolated pilot projects, generating tangible impacts such as higher productivity, improved product quality, greater energy and resource efficiency, stronger competitiveness in global value chains, and the creation of high-value jobs.

- The Feedback Loop

The model also recognizes adoption as a dynamic and iterative process. The outcomes of AI adoption, whether positive or negative, provide feedback that informs future actions. Successful adoption justifies further investment in infrastructure, leads to policy refinement, and incentivizes more workforce training—thereby reinforcing all three pillars. By contrast, failures expose structural misalignments, such as regulatory gaps or infrastructure deficiencies, which can then be addressed to improve readiness for subsequent adoption efforts.

In summary, the Triadic Integration Framework serves as a diagnostic and interpretive tool. It highlights that strong and coordinated development of infrastructure, policy, and socio-industrial capacity is essential for fostering AI adoption in Latin American manufacturing. This framework enables researchers and policymakers to identify weaknesses in the system and design comprehensive interventions that extend beyond a purely technical focus.

3. Technical Foundations of AI in Manufacturing

3.1. Types of Manufacturing Process

Manufacturing processes are generally classified into subtractive, additive, and forming techniques. These processes shape materials by applying energy such as mechanical force, heat, or light, to alter the physical structure of a workpiece. Each requires precise control of process parameters to ensure product quality, and many benefit from real-time monitoring and adaptive process control [10,54–57].

Subtractive manufacturing removes excess material from a solid workpiece to achieve the desired geometry, characterized by high precision, a superior surface finish, and strict dimensional tolerances. Typical tools used in subtractive manufacturing include cutting tools, milling heads, and grinding discs [58]. It plays a crucial role in the production of ultra-precision machine tools (UPMTs), which achieve submicron or nanometer accuracy, enabling the manufacture of complex, high-performance components in the aerospace, optics, and semiconductor industries [56].

Compared to some emerging manufacturing technologies, it is often more efficient for mass production due to faster processing speeds and well-established tooling systems. Moreover, this technique relies on a high-precision monitoring and measurement system integrated into the machinery, improving the quality of the final product [59]. Nonetheless, challenges such as tool wear, caused by abrasion, adhesion, chemical, and thermal effects, continue to limit performance [60,61]. Effective control of parameters such as feed rate, cutting speed, tool geometry, and coolant flow, supported by signals including cutting force, vibration, and surface roughness, is crucial to ensure quality and process stability [11].

Among the main limitations of subtractive manufacturing are thermal errors, which significantly affect machining accuracy and are costly to mitigate using traditional methods [62]. Machine tools also consume substantial energy across various states, including idle, runtime, production, and states such as basic, cutting, and ready, requiring strategies such as tool optimization, energy efficiency models, the use of efficient machine tools, the selection of appropriate tools, and the application of AI [63]. Another persistent challenge is predicting the replacement time of tools, particularly in machining composites. Here, advanced approaches such as digital twins integrated with AI offer promising solutions to improve monitoring, optimize energy use, and extend tool life [51,64–66].

Two types of machining are recognized within subtractive manufacturing: conventional and non-conventional machining [67]. Conventional methods rely on chip removal to shape the material and include processes such as milling (end and face), turning, drilling, and grinding, all widely used for their robustness and versatility [63,68–71]. In contrast, non-conventional machining techniques are used to create complex shapes with difficult-to-machine materials precisely. Among the most notable non-conventional machining techniques are laser beam machining (LBM) [67], electrical discharge machining (EDM) [72], chemical machining (CM) and electrochemical machining (EM), jet machining (JM), and ultrasonic machining (UM) [67].

Forming manufacturing plastically shapes materials into a desired geometry without material removal, making it one of the most traditional production methods [73]. It is frequently applied for limited production runs of tailored components with intricate geometries and high surface quality at competitive cost. Critical variables, such as pressure, temperature, and tooling, significantly impact performance and can be optimized through parametric studies to enhance quality, productivity, and material utilization [74]. Parts obtained by forming often show favorable properties, including high strength-to-weight ratios and refined surface finishes [75]. However, precise control is essential to avoid defects such as cracking (common in aluminum alloys), thinning, wrinkling, or bursting, which typically result from errors in parameters, material quality, or tool design [74].

Widely applied forming techniques include stretch forming, which uses pre-tensioning and stretching to produce complex sheet metal parts [75], and hydroforming, which relies on high pressures to shape components from materials such as high-strength steels and aluminum alloys [74]. Another advanced approaches are Reconfigurable Multipoint Forming (RMF), which employs adjustable dies and elastic cushions to create complex 3D parts [75], and electromagnetic forming, a large-scale deformation process that can be combined with stretching [73].

Additive manufacturing (AM) completes the classification of manufacturing methods, enabling the layer-by-layer construction of complex geometries while minimizing raw material waste and reducing the need for additional tooling or assemblies [59]. Beyond shape freedom, AM can be combined with generative design and topology optimization to fabricate biomimetic and lightweight components. It is highly versatile in materials, ranging from polymers and resins to ceramics and metal alloys [76].

Among the key advantages of AM are its ability to rapidly produce complex structures with minimal material waste and its versatility in design, which enables the fabrication of biomimetic components with high strength-to-weight ratios. AM is particularly advantageous for spare parts, small production batches, customized products, and on-demand manufacturing [68]. However, challenges remain, including low precision, surface irregularities, and variability in mechanical properties. Defects such as porosity, non-homogeneous microstructures, solidification cracking, residual stresses, and distortion often require post-processing steps, such as CNC machining, to improve geometric tolerance and surface finish, as in hybrid manufacturing [59].

AM technology is divided into seven principal categories according to the ISO/ASTM 52900:2021 [76]: Jetting (BJT), Directed Energy Deposition (DED), Material Extrusion (MEX), Material Jetting (MJT), Powder Bed Fusion (PBF), Sheet Lamination (SHL), and Vat Photopolymerization (VPP) [77].

BJT was developed initially in 1995 by a team from the Massachusetts Institute of Technology [78]. This technique involves spreading the powder material over the printing surface using a roller and then binding the powder with an adhesive [78,79]. Once the adhesive is applied, the build platform is lowered to construct the next layer [80]. The process typically uses powdered materials, such as metals or sand [79]. Despite its advantages, the process faces several limitations, including a high probability of defects, which are generally caused by the variety of starting materials and challenges in quality control. Additionally, the two-step process makes it more susceptible to errors [78].

DED was initially developed in the 1990s [80]. To function correctly, this technology requires a concentrated thermal energy source, such as a laser, to simultaneously melt and deposit materials [79]. Stable operation requires controlled conditions such as inert atmospheres or vacuum chambers to ensure proper melting and solidification, as well as careful tuning of parameters like laser power, spot size, and feed rate. DED is widely applied for the repair and remanufacturing of high-value components, but its main limitation is precision, which is strongly affected by melt pool dynamics (temperature, width, and solidification time), impacting the final product's quality [79,80].

MEX was initially developed in the 1980s [80]. In this technique, the printing material is extruded through a heated print head, which melts it before deposition [79]. This process is repeated as the filament is extruded layer by layer onto the build platform, forming the intended structure [76,80]. It mainly uses low-melting polymers, thermoplastics, and composites, with ABS and PLA being the most common due to their widespread applications in biomedical and aerospace fields [76,77,80]. Other materials, such as HDPE, are also employed for their mechanical performance [81]. The most popular variant, Fused Deposition Modeling (FDM/FFF), is widely adopted because of its simplicity, affordability, and lack of special operating requirements, making it highly accessible in education, research, and entrepreneurship [76,77,80,82]. This technique has been widely adopted by the public due to its ease of use and affordability [77,80]. Furthermore, unlike other AM methods, this technique does not require special conditions during operation, such as controlled atmospheres or vacuum chambers. This makes it particularly accessible for educational, research, and entrepreneurial settings [82]. However, MEX is limited by slow printing speeds, relatively low resolution, and anisotropic mechanical properties caused by its layer-by-layer nature. Ongoing improvements aim to achieve better print quality by optimizing parameters such as layer height, extrusion speed, nozzle diameter, and print speed [80].

MJT was developed in the 1990s [56]. This AM technique involves depositing droplets of printed material onto the build surface using thermal or piezoelectric mechanisms. Once deposited, the material is cured with ultraviolet light. Due to the nature of the process, a support structure is required during printing, which must be removed after manufacturing [79,80]. Widely used materials in this technique include waxes and photopolymers, which are selected for their appropriate viscosity, rapid solidification, and compatibility with curing and jetting systems [80]. It commonly employs waxes and photopolymers chosen for their viscosity, rapid solidification, and compatibility with curing systems. MJT offers high precision, smooth surface finishes, and efficient material use, making it suitable for fine details and complex geometries. However, it requires support structures, has a restricted material palette, and print quality is highly dependent on fluid properties. Moreover, the closed chambers used in MJT complicate real-time monitoring, and process parameters such as print orientation, nozzle cleaning, and layer thickness must be carefully optimized [80].

PBF is an AM technique that uses a thermal energy source, such as a laser or an electron beam, to selectively melt powder particles spread over a build platform [79,80]. This process is repeated layer by layer until the part is fully consolidated [80]. Within this category, several specialized techniques exist, such as Selective Laser Sintering (SLS), Direct Metal Laser Sintering (DMLS), and Electron Beam Melting (EBM). Each depends on the type of material used and the required specifications of the final product [79,80].

Commonly used materials with this technique include aluminum, titanium, and cobalt, as well as ceramics and certain polymers. All of them are used in fine powder form [80]. Selective Laser Sintering (SLS) often employs polymers such as polyamide 11 and 12 (PA-11 and PA-12), polystyrene (PS), thermoplastic polyurethane (TPU), and thermoplastic elastomers. PBF enables the fabrication of strong, geometrically complex parts and often operates without the need for support structures, thereby reducing material waste. However, it faces significant challenges, including porosity from incomplete melting, residual stresses, high energy demand under vacuum or inert conditions, and difficulties in in situ monitoring. Optical systems are particularly susceptible to high temperatures, material evaporation, and changes in reflectivity, while polymers may degrade and warp, complicating the control of final mechanical properties [77,80].

SHL is an AM technology that was introduced in the 1980s [80]. This technique is based on the construction of parts layer by layer through the bonding of thin sheets of material. This process involves engraving the desired shape onto each sheet using a laser and then joining them together using ultrasonic welding or adhesives [79,80]. To perform this method, various types of materials presented in rolled sheet form, laminates, are employed, including metal [78], paper, and polymers [80]. SHL offers material flexibility and does not require support structures, which reduces consumption. However, it is limited by slow build speed, high material waste, and challenges in real-time monitoring due to closed chambers and poor optical conditions, which complicate process control [80].

VPP is a method that involves depositing resin material on a build platform, which is then solidified using ultraviolet (UV) light [80]. The first VPP technology to be commercialized was stereolithography (SLA) in the 1980s [77,78]. The most widely used materials in VPP are liquid photopolymeric resins [79,80]. Photopolymers account for approximately 50% of the AM market share. A key advantage of VPP lies in its ability to fabricate detailed and complex structures. In contrast to other AM methods, VPP is constrained by the build size and results in reduced part strength. Another challenge is in situ monitoring, which is hindered by material shrinkage, the evolution of thermal and chemical composition, and solute redistribution and segregation [77]. Additionally, VPP necessitates the use of a support structure [80]. On the other hand, monitoring methods such as thermography have limitations due to the difficulty of establishing precise calibration and the variation of emissivity with temperature [78].

The review of manufacturing processes revealed a broad and diverse technological landscape that is continually evolving. Within this context, common needs were identified, such as precise control of multiple parameters to ensure both the aesthetic and functional quality of the final product [10,54–57].

These needs arise from the limitations associated with various processes, such as ultraprecision machining [56] and powder bed fusion [77,79,80]. Issues like tool wear [60], energy consumption [63], difficulties in effective in situ monitoring, and the occurrence of defects are significant challenges. These limitations, along with the complex nature of these manufacturing processes, make them ideal candidates for the application of AI and ML [11,60]. For the effective performance of these models, it is crucial to identify which parameters need to be monitored and the availability of data for their training [67,80].

This section aims to establish a clear technical basis for manufacturing processes, to serve as a reference framework for identifying specific research challenges to be addressed through AI [59]. The following sections examine how AI algorithms can transform these challenges into opportunities for optimization and predictive capabilities.

3.2. AI Potential for Manufacturing Processes

The integration of AI into manufacturing processes represents a significant strategic investment whose success is often contingent on the organization's existing digital infrastructure. Specifically, a well-implemented Enterprise Resource Planning (ERP) system provides the essential data backbone and process integration necessary to scale AI initiatives beyond isolated pilots. The factors that determine successful ERP adoption, such as high-quality data and business process reengineering, are the same enablers for effective AI. For instance, AI models for predictive maintenance or parameter optimization rely on the clean, standardized data ensured by a successful ERP implementation, while reengineered processes create the streamlined workflows that AI can optimally automate and enhance [83].

With this foundational relationship in mind, the specific applications of AI across manufacturing domains can be examined. AI is increasingly integrated into manufacturing systems, enabling machines to learn and optimize processes more efficiently [84]. Its main applications include process optimization and real-time monitoring [59,68]. To illustrate its versatility, the following sections discuss AI applications across major manufacturing approaches, moving from traditional subtractive methods to advanced additive techniques.

Subtractive manufacturing is one area where AI has a significant impact, supporting tasks that improve various aspects of the process. Among its most important applications is tool condition monitoring and prediction (TCM), which allows us to maximize tool life and minimize the risk of equipment damage or injury [85,86]. This monitoring capability is largely driven by data analysis from force, temperature, vibration, and acoustic emission sensors to detect tool wear and predict its remaining life [60,87]. Predictive maintenance enables the optimization of tool performance and contributes to extending its useful life [11,60]. It is worth noting that image processing techniques are also crucial for tool monitoring [87,88].

AI is also used to optimize parameters such as cutting speed, depth, and feeding. This improves efficiency, reduces costs, and contributes to improved final product quality [11,58]. A clear example of this is its application in laser machining, where it is used to predict and optimize aspects such as roughness and removal rate [67,89]. Moreover, AI contributes to reducing energy consumption and machining efficiency [11,90]. Altogether, these applications demonstrate that in subtractive manufacturing, AI plays a key role in monitoring and optimizing processes, making them more efficient and autonomous [84].

Forming manufacturing represents another key area of AI application, where AI is used to manage complex data and optimize processes to produce a final product with complex shapes and improved properties [11]. In this technique, AI assists in predicting and optimizing parameters such as injection pressure, material temperature, and cooling time to ensure the production of high-quality parts [69,91]. Typical defects in this process include flow lines, weld lines, delamination, sink marks, burns, and deformations [91,92].

The methods used for this function range from Artificial Neural Networks (ANNs) to genetic algorithms (GA) [75,93]. In addition to parameter optimization, AI is also applied in the design and optimization of molds, including the development of conformal cooling channels (CCC), which follow the shape of the part to generate more efficient cooling. This application can significantly reduce the number of mold design iterations [69]. In the stretch forming process, AI helps to prevent errors such as distortion and axial springback by optimizing the forming path, stretch length, and bending angle [75]. In hydroforming, AI enables process optimization by altering the load path and helping to overcome limitations in material selection [74].

AM presents a promising field for the application of AI, offering new opportunities to optimize key parameters, enabling overall performance improvements [79,82]. For instance, in BJT, one of the main applications of AI is high-speed in situ monitoring through X-ray imaging, which allows the analysis of the dynamics of binder droplet generation and deposition. This enhances the reliability of the geometry and final product quality [80]. This contributes to a better understanding and optimization of the powder material spreading process, as its ability to distribute uniformly is crucial for proper process performance. Inconsistencies, such as empty patches or irregular packing, can lead to structural defects, including pores and cracks. Similarly, integrated early detection systems enable real-time automatic adjustment of process conditions. This improvement enhances efficiency and significantly reduces waste, thereby improving the quality of the final product [94].

In the case of DED, AI has been focused on improving parameters such as laser power, spot size, and feed rate. This results in a higher-quality final product [95]. Machine Learning models can be used to respond to specific process conditions, contributing to the optimization of the resulting microstructure [82]. On the other hand, for MEX, ML algorithms, particularly ensemble techniques such as CatBoost, XGBoost, GBM, and LGBM, enable highly accurate predictions of mechanical properties, including tensile strength (UTS), in 3D-printed PLA parts [76]. Furthermore, machine learning can predict stiffness, energy absorption capacity, and damping of structures [11,82]. In the case of DED, AI has been focused on improving parameters such as laser power, spot size, and feed rate. This results in a higher-quality final product [95]. Machine Learning models can be used to respond to specific process conditions, contributing to optimizing the optimization of the resulting microstructure [82]. On the other hand, for MEX, ML algorithms, particularly ensemble techniques such as CatBoost, XGBoost, GBM, and LGBM, enable highly accurate predictions of mechanical properties, including tensile strength (UTS), in 3D-printed PLA parts [76]. Furthermore, machine learning can predict stiffness, energy absorption capacity, and damping of structures [11,82]. In the case of DED, AI has been focused on improving parameters such as laser power, spot size, and feed rate. This results in a higher-quality final product [95]. Machine Learning models can be used to respond to specific process conditions, contributing to optimizing the optimization of the resulting microstructure [82]. On the other hand, for MEX, ML algorithms, particularly ensemble techniques such as CatBoost, XGBoost, GBM, and LGBM, enable highly accurate predictions of mechanical properties, including tensile strength (UTS), in 3D-printed PLA parts [76]. Furthermore, machine learning can predict stiffness, energy absorption capacity, and damping of structures [11,82]. In the case of DED, AI has been focused on improving parameters such as laser power, spot size, and feed rate. This results in a higher-quality final product [95]. Machine Learning models can be used to respond to specific process conditions, contributing to optimizing the optimization of the resulting microstructure [82]. On the other hand, for MEX, ML algorithms, particularly ensemble techniques such as CatBoost, XGBoost, GBM, and LGBM, enable highly accurate predictions of mechanical properties, including tensile strength (UTS), in 3D-printed PLA parts [76]. Furthermore, machine learning can predict stiffness, energy absorption capacity, and damping of structures [11,82].

AI, in conjunction with experimental design methods such as the Taguchi method, enables the optimization of process parameters, including printing speed, layer thickness, and infill density, to improve the surface quality and mechanical properties of the final product. Within this framework, Physics-Informed Machine Learning (PIML) models have demonstrated the ability to predict phenomena such as warping and layer adhesion by integrating fundamentals of heat transfer and material flow [7]. Machine learning (ML)-based systems have been developed to detect defects in real-time, such as stringing (unwanted material threads), surface roughness, porosity, and lack of adhesion between layers [80].

For MJT, the integration of AI presents new opportunities to optimize the process and enhance the quality of the final product. One of the most impactful applications of artificial intelligence in MJT is the prediction and optimization of mechanical properties, along with the reduction in defects caused by variations in material behavior. Physics-informed machine learning (PIML) enables the prediction of surface finish and dimensional fidelity. This is achieved by incorporating fluid dynamics equations that describe the material's behavior during injection and curing. This is particularly relevant in MJT, since the surface quality of the final part depends primarily on parameters such as fluid viscosity, droplet size, and curing conditions [77].

AI also facilitates real-time monitoring of 3D surface topography to identify process deviations, including non-uniform droplet formation, surface irregularities, and insufficient interlayer bonding. These data, collected through high-resolution imaging and sensor fusion, feed machine learning algorithms integrated in closed-loop feedback systems that autonomously adjust jetting parameters. This data, obtained through high-resolution imaging and sensor integration, is processed by machine learning algorithms embedded in real-time, closed-loop control systems to automatically adjust jetting parameters. Furthermore, adaptive AI-based control can dynamically fine-tune parameters, such as droplet volume and deposition velocity, in response to real-time variations in material viscosity or temperature, thereby increasing process stability and part uniformity [80,82].

The potential of AI in PBF lies in optimizing the quality of the result, minimizing defects such as porosity, cracks, or lack of fusion that can compromise the mechanical properties of the final product, through process monitoring and control with machine learning [7]. For instance, deep learning autoencoders can detect anomalous patterns and anticipate production failures up to six hours in advance, thereby reducing unnecessary consumption of critical resources, such as materials and time [10]. Another application of AI is in powder bed monitoring, where it enables real-time assessment of powder spreading quality and detection of anomalies such as uneven material distribution or insufficient coverage. This is possible through machine learning techniques that optimize the spreading process and enhance the mechanical properties of the final product [94]. A critical application of AI in PBF is parameter optimization, where machine learning identifies key parameters that influence fatigue performance and defect formation, including laser power, scanning speed, layer thickness, and preheating temperature [96,97].

According to this literature review, few concrete applications of AI or ML have been found for SHL. This is the AM technology with the fewest specific studies that employ artificial intelligence and machine learning techniques, constituting a clear area with opportunities for future research [98].

Despite this, there are applications of artificial intelligence in laminated structures in general. One of these is damage assessment in laminated composite structures, where supervised and unsupervised applications are used to diagnose failures and monitor structural health (SHM). These methods enable the early detection, localization, and quantification of defects, such as delamination, voids, and matrix cracks, that occur either during fabrication or operational service. Among the tools used for this purpose are Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and autoregressive models [99,100].

A notable case is the optimization of complex industrial operations, such as furnace control in steel manufacturing. This approach aims to enhance productivity by ensuring consistent quality, reducing energy and silicon consumption, and predicting failures through the standardization of best practices. These optimizations can be attractive in environments where efficiency and reliability are critical [101]. Additionally, unsupervised machine learning techniques, such as 1D Convolutional Autoencoders (1D CAE) and Gaussian Mixture Models (GMM), have been applied to monitor drilling operations in laminated stacks composed of aeronautical-grade aluminum and carbon fiber-reinforced polymers (CFRP). These models enable the automated identification of material changes, signal segmentation, and the detection of anomalies or low-quality holes [70].

AI plays a role across multiple stages of the VPP process. In the pre-design phase, AI supports computer-aided design, image processing, and the selection of suitable materials and printing parameters. During the printing stage, AI is applied to method selection, failure detection, real-time process monitoring, and defect control. Once the printing is completed, artificial intelligence is used for post-process quality inspection. The final part analysis enables the optimization of parameters such as layer thickness and exposure time [77].

Machine learning models have also been used to monitor, predict, and mitigate emissions of volatile organic compounds (VOCs), a potentially harmful byproduct of VPP technology [102]. The use of machine learning in quality control is considered a promising approach for predicting outcomes in VPP. These models can predict the effects of in situ photochemical reactions, such as shrinkage and segregation, which impact the behavior of the resin and the quality of the final part. Machine learning models, such as Physics-Informed Machine Learning (PIML), allow for precise prediction of surface quality and dimensional accuracy. They achieve this by utilizing fluid dynamics equations that account for droplet coalescence and solidification events [77].

3.3. Applications of Artificial Intelligence in Manufacturing

3.3.1. Overview of AI Capabilities in Manufacturing

AI has become a cornerstone of smart manufacturing, particularly within the context of Industry 4.0 and Industry 5.0 [5,103,104]. Its integration into manufacturing processes enables enhanced process control, real-time decision-making, quality assurance, predictive maintenance, and sustainability [60]. However, the successful implementation of these technical capabilities often hinges on the organization's ability to manage them through integrated systems. Drawing directly on the framework developed by Beusch et al. [105], a company's strategic posture can be analyzed using the two key dimensions from their integrated control systems typology: (1) the intensity of internal interactive control use for sustainability (e.g., intensive management dialogues focusing on data and initiatives), and (2) the strategic focus on external sustainability demand drivers (e.g., regulatory changes or customer demand for green products). This framework suggests that the greatest strategic value is realized when AI is not just a tool for internal efficiency, aligning with a "value chain-driven sustainability focus", but is leveraged to "reconceive products and markets," moving the company toward the ideal "integrated sustainability strategy" quadrant identified by Beusch et al. [105].

This trend is also emerging in Latin America, although adoption remains at an early stage. For instance, in Brazil, 16.9% of manufacturing firms with more than 100 employees already report using AI technologies, with applications spanning administration (73.8%), product development (65.9%), production (56.4%), and logistics (48.4%) [106]. Furthermore, some other empirical studies offer evidence of AI adoption in manufacturing across Latin America. In Argentina and Brazil, case studies of SMEs reveal the introduction of AI-enabled quality control systems, automation of production workflows, and applications in customer–supplier management, all aimed at improving efficiency and competitiveness. However, these firms report critical barriers such as shortages of specialized personnel, inadequate technological infrastructure, limited financing, and even cultural resistance to technological change in family-owned businesses [107]. Poveda-Valverde [108] further analyzed 14 studies on Latin American SMEs, identifying four manufacturing-specific cases in Mexico, Brazil, Argentina, and Colombia, where AI is being applied to production-line automation, predictive analytics for inventory management and fault detection, and AI-enabled quality control [107]. The remaining studies focus on retail, finance, and utilities, underscoring the relatively limited but growing body of empirical evidence on AI adoption in manufacturing across the region. This study highlights the heterogeneity of adoption and the limited number of documented industrial cases, as well as the persistent barriers, budget limitations, infrastructure gaps, and shortages of specialized human capital, as critical obstacles to scaling AI in manufacturing.

Moreover, Gonzalez-Tamayo et al. [109] analyzed surveys of 490 SMEs across Argentina, Costa Rica, Ecuador, Mexico, and Uruguay, showing that while many firms express a strategic commitment to digitalization, actual adoption depends largely on their digital maturity and the extent of workforce training in digital skills. This finding is consistent with other evidence from the region, which highlights that infrastructure gaps, limited financing, and shortages of specialized personnel continue to hinder SMEs' ability to move beyond experimentation and scale AI applications in manufacturing. While these studies offer valuable insights, they remain limited to a small number of cases and countries. A broader regional perspective is offered by Vergara-Villegas et al. [110], who review applications of AI for Industry 4.0 across Mexico, Colombia, Ecuador, Argentina, Chile, and Brazil. Their findings document industrial pilots in robotics and automation, AI-assisted AM, predictive analytics for process optimization and maintenance, as well as IoT-enabled real-time monitoring. Although most of these initiatives remain at the pilot stage, they demonstrate that AI implementation in manufacturing is no longer a theoretical possibility but an emerging reality in Latin America.

Despite these advances, persistent barriers, including insufficient digital infrastructure, high implementation costs, and limited access to financing, continue to hinder broader regional adoption. Building on this context, it is important to examine the underlying technical foundations of AI in manufacturing. At the core of many of these capabilities is ML, a subset of AI that enables systems to learn from data and improve performance without explicit programming. Within ML, deep learning has emerged as a powerful approach for solving complex problems that involve vast amounts of high-dimensional data. For example, cyber-physical systems in manufacturing use deep learning to monitor and adjust process variables, such as temperature, print speed, or laser power, thereby enabling the transition from reactive to autonomous and adaptive control [111].

To better understand how AI is applied in manufacturing, it is essential to distinguish between its main learning paradigms:

- Supervised Learning: Algorithms learn from labeled data (i.e., input-output pairs), making it ideal for tasks such as predicting product quality, tool wear, or machine failures. It is widely used in predictive maintenance and defect classification.

- Unsupervised Learning: These algorithms discover hidden patterns in unlabeled data, such as clustering similar process behaviors or detecting anomalies without prior examples. Applications include dimensionality reduction and anomaly detection.
- Reinforcement Learning (RL): RL models learn by interacting with an environment and receiving feedback in the form of rewards or penalties. This approach is increasingly used in production scheduling, autonomous control of machinery, and adaptive planning under uncertainty [111].
- Generative AI: These models learn to generate new data resembling the training set and are increasingly applied in generative design, process simulation, and synthetic data generation for training other ML models in data-scarce contexts. These paradigms are depicted in Figure 2.

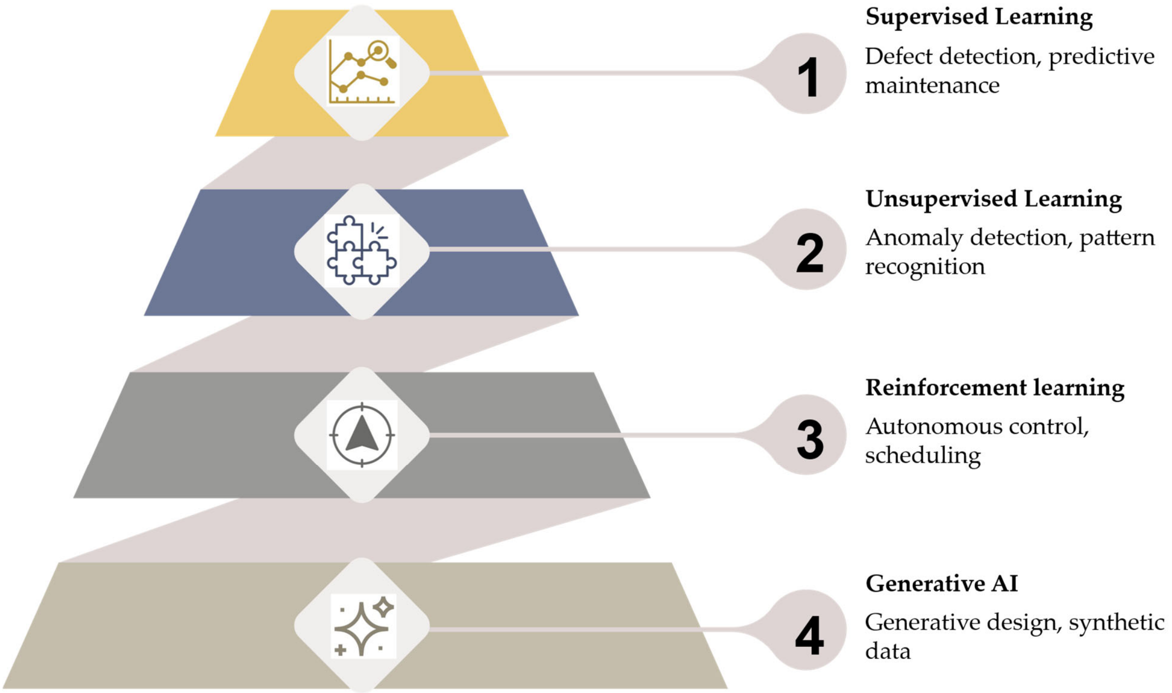

Figure 2. AI paradigms in smart manufacturing, from supervised and unsupervised learning to reinforcement learning and generative AI. Each layer represents an increase in complexity and autonomy, supporting prediction, anomaly detection, adaptive control, and design generation.

Building on these paradigms, the integration of AI into manufacturing can be understood as a pipeline that links the physical layer of production with data-driven intelligence and operational outcomes. At the foundation, different manufacturing processes (additive, subtractive, and forming) generate complex operational data. This information is captured through sensing and data acquisition systems, which provide the inputs required for machine learning models and AI algorithms. These computational layers enable predictive, adaptive, and optimization capabilities, ultimately driving practical applications such as defect detection, property prediction, and process monitoring. This progression, from processes to sensing, from sensing to learning, and from learning to application, illustrates how AI transforms manufacturing into an adaptive, intelligent, and data-driven environment. This integrated view is illustrated in Figure 3.

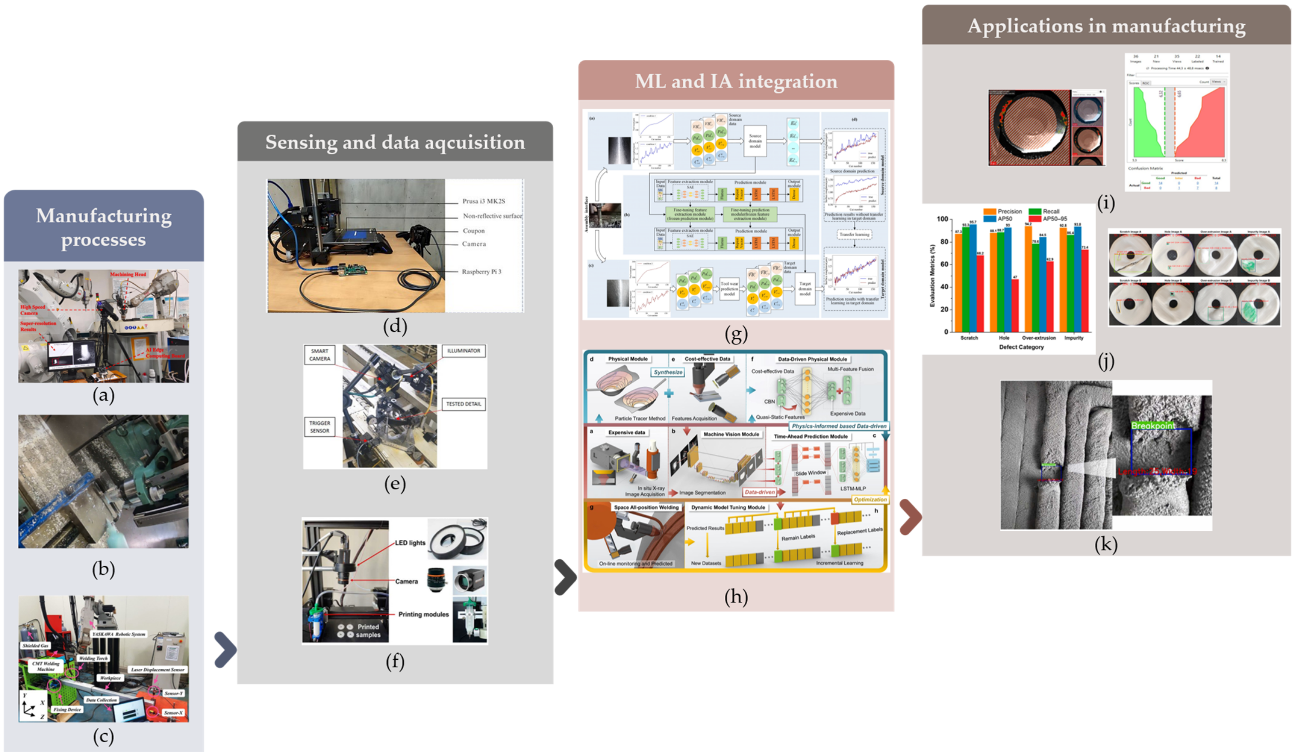

Figure 3. Pipeline of AI integration in manufacturing. The diagram synthesizes representative examples from the literature, illustrating how AI applications emerge from the interaction between manufacturing processes (additive, subtractive, and forming): (**a**) [112], Copyright (2024), with permission from Elsevier, (**b**) [113], and (**c**) [114]; sensing and data acquisition systems: (**d**) [115] Open Access CC-BY 4.0, (**e**) [116], Open Access CC-BY 4.0, (**f**) [117], Open Access CC-BY 4.0, machine learning and AI integration: (**g**) [118], Open Access CC-BY 4.0, and (**h**) [119] Open Access CC-BY 4.0; and practical applications such as defect detection, property prediction, and process monitoring: (**i**) [116], Open Access CC-BY 4.0, (**j**) [117], Open Access CC-BY 4.0, and (**k**) [120], Copyright (2024), with permission from Elsevier.

3.3.2. Process-Level Applications

- Process optimization

Artificial intelligence is increasingly used to optimize key process parameters across various manufacturing techniques, with the goal of improving efficiency, reducing costs, and enhancing product quality [121]. In subtractive manufacturing, machine learning algorithms enable the dynamic tuning of parameters such as cutting speed, feed rate, and depth of cut, thereby reducing tool wear and improving surface finish.

During the forming process, AI-driven models are utilized to optimize injection pressure, material temperature, and cooling time, thereby ensuring dimensional accuracy and preventing defects [122]. In forming processes, particularly injection molding, AI-driven models are applied to optimize parameters such as injection pressure, melt temperature, and cooling time, ensuring dimensional accuracy and preventing defects. Gim et al. developed a hybrid optimization framework integrating Artificial Neural Networks (ANNs), Explainable AI (XAI), and the Non-dominated Sorting Genetic Algorithm II (NSGA-II). The two ANN models predict in-mold conditions and product quality, while SHAP values (a method of XAI) identify the most influential process variables. The NSGA-II then finds Pareto-optimal solutions that maximize quality while minimizing cycle time. This resulted in a 22.6% improvement in part quality compared to the baseline [123].

Deep learning has emerged, leveraging massive volumes of data gathered on equipment, and its processing through product decision-making information systems enables the adoption of groundbreaking techniques for condition-based maintenance. By harnessing data-driven modeling, cyber-physical process monitoring systems will transform manufacturing into an intuitive and automated process, leading to the decentralization of production processes. This optimization enables the adjustment of temperature, print speed, and laser power to achieve higher quality prints [63]. Thanks to the recent development of many machine learning techniques, solving complex problems has become more feasible; however, they cannot be easily examined after implementation to understand their logic [122]. A deep neural network is a model that uses different ML techniques to receive several inputs and predict one or more outputs [88]. These algorithms process vast amounts of data, learning intricate patterns and features critical for accurate biometric recognition.

Convolutional neural networks have been extensively utilized for facial recognition, significantly enhancing the system's ability to accurately identify individuals despite variations in lighting, angles, and expressions. This capability is crucial in industrial settings where environmental conditions can be unpredictable. Despite its drawbacks associated with interpretability and extrapolation, its potential is nearly limitless, as its performance largely depends on the quantity and quality of data, as well as the design of its architecture. It has been studied how the integration of ML in manufacturing processes, such as those in steel mills specializing in steel production and semiconductor production, can improve the development of these industrial sectors [124].

Furthermore, Ma et al. applied XGBoost and the Strengthened Elitist Genetic Algorithm to minimize product weight deviation in molded parts. Their model achieved a deviation of just 0.22%, demonstrating the precision of combining gradient-boosted trees with evolutionary search techniques [125].

It is also used in various types of AM, such as DED, where it focuses on improving laser power, spot size, and feed rate; MEX, optimizing print speed, layer thickness, and infill density; and PBF, focused on optimizing laser power, scan speed, layer thickness, and preheating temperature. These models often use deep learning or ensemble ML methods to capture the nonlinear relationships between parameters and product quality outcomes [122].

- Process Monitoring and Control

Another critical application of AI is real-time process monitoring and state prediction. In subtractive manufacturing, AI is widely used in tool condition monitoring (TCM) systems. These systems analyze sensor data, including cutting force, vibration, and temperature, to assess the wear state of cutting tools and predict potential failures before they occur [90]. This application is also utilized in several types of AM, including PBF, through deep learning autoencoders that can identify anomalous patterns and anticipate production errors before they occur, thereby saving resources [63]. Furthermore, it is also used in VPP to identify print failures, for real-time monitoring, and for defect control.

One of the most promising applications of deep learning in manufacturing is in anomaly detection for quality assurance. In AM, where high customization and low-volume production render traditional inspection inefficient, autoencoders (a type of unsupervised deep neural network) are trained on non-defective data to learn normal patterns. During production, new data is compared to this baseline, and reconstruction errors serve as indicators of potential defects. In AM, especially PBF, deep autoencoders are used to analyze 2D image data and identify anomalies in surface quality. For instance, Kreutz et al. implemented an autoencoder-based system to detect surface anomalies in 3D-printed footwear using RGB image segments, achieving an ROC AUC score of 0.87, demonstrating the viability of such systems even at early implementation stages [126].

For injection molding, Tayalati et al. developed a hybrid anomaly detection method combining Long Short-Term Memory (LSTM) autoencoders with Statistical Process Control (SPC) to monitor melt cushion pressure profiles. The system identified temporal anomalies in injection dynamics, enabling timely intervention to prevent pressure instability and defective output [127].

Another noteworthy approach applied a stacked autoencoder (SAE) with XGBoost to detect faults in non-return valves by extracting features from pressure, torque, and displacement signals. This model achieved a 99.6% accuracy rate in real-time fault classification [128]. Rønsch et al. introduced an acoustic-based monitoring method using Gaussian models and autoencoders to detect latch lock failures and lubrication degradation in molding equipment. Their approach supports condition-based maintenance, avoiding catastrophic breakdowns [129]. Moreover, CNNs trained on thermal images obtained via infrared thermography have been applied to predict warpage, mass, and tensile strength in polymer components. This approach achieved an average error of less than 5%, demonstrating the effectiveness of image-based deep learning for non-invasive, real-time quality prediction [129].

Digital twins and cyber-physical systems further enhance monitoring capabilities by combining sensor data with simulation models for anomaly detection and process feedback. These systems use neural networks and physics-informed models to predict deviations and simulate corrective actions in real time.

- Prediction and Optimization of Final Product Properties

AI plays a critical role in predicting and optimizing the properties of final products in manufacturing processes. In subtractive manufacturing, image processing and deep learning techniques such as CNNs have been applied to predict surface roughness, one of the most critical indicators of part quality. In forming processes, machine learning algorithms are used to predict mechanical properties, such as hardness and yield strength, based on process parameters and material behavior. For AM, particularly in MEX, ensemble learning models like CatBoost, XGBoost, Gradient Boosting Machines (GBM), and LightGBM have been demonstrated to provide high prediction accuracy for tensile strength, elongation, and modulus of elasticity [11,82]. In Powder Bed Fusion (PBF), machine learning models are used to determine the optimal process window by correlating process parameters, such as scan speed, laser power, and layer thickness, with properties like fatigue resistance and part density. ANNs can help predict part density with a 20% reduction in calibration time for PBF of titanium alloys [75]. In Vat Photopolymerization (VPP), AI models integrate fluid dynamics with ML to anticipate print outcomes such as dimensional accuracy and surface smoothness.

- Design optimization and Resource Efficiency

AI enables optimal design, reducing waste and conserving resources. Regarding subtractive manufacturing, AI is used to reduce energy consumption, improving machining efficiency [130]. For forming manufacturing, it plays a crucial role in mold design and optimization, including the design of CCC, which reduces the number of mold design iterations.

AI contributes significantly to design innovation and resource efficiency by reducing material waste, energy consumption, and the number of manual iterations in tooling and production planning [67]. In subtractive manufacturing, energy-efficient machining is achieved through machine learning models that optimize key cutting parameters such as cutting speed, feed rate, and depth of cutting. Advanced deep learning approaches, such as deep neural networks, random forests, and hybrid models combining convolutional neural networks with continuous wavelet transforms have demonstrated high performance in predicting surface quality, energy usage, and chatter behavior. For example, CNN-CWT models enable real-time chatter detection during milling, allowing manufacturers to proactively intervene and thereby reduce tool damage and material waste. In forming processes, particularly in injection molding, design optimization focuses on mold cooling structures.

The integration of AI with simulation tools allows for the development of CCC, which enhances cooling uniformity, reduces cycle time, and lowers energy requirements. Machine learning algorithms are used to evaluate heat transfer efficiency and flow dynamics, supporting hybrid manufacturing strategies where optimized CCC designs are produced using metal AM [68]. In AM, AI plays a key role in both design refinement and resource efficiency. In Powder Bed Fusion (PBF), machine learning models trained in real-time process data can predict deviations in melt pool dimensions, laser energy absorption, and spatter behavior. These insights enable corrective actions before defects develop, minimizing waste and build failures. A recent advancement includes the use of ML algorithms to predict and mitigate volatile organic compound (VOC) emissions during the curing process, enhancing both sustainability and workplace safety [131]. Figure 4 illustrates some of the AI-driven applications identified in the current literature.

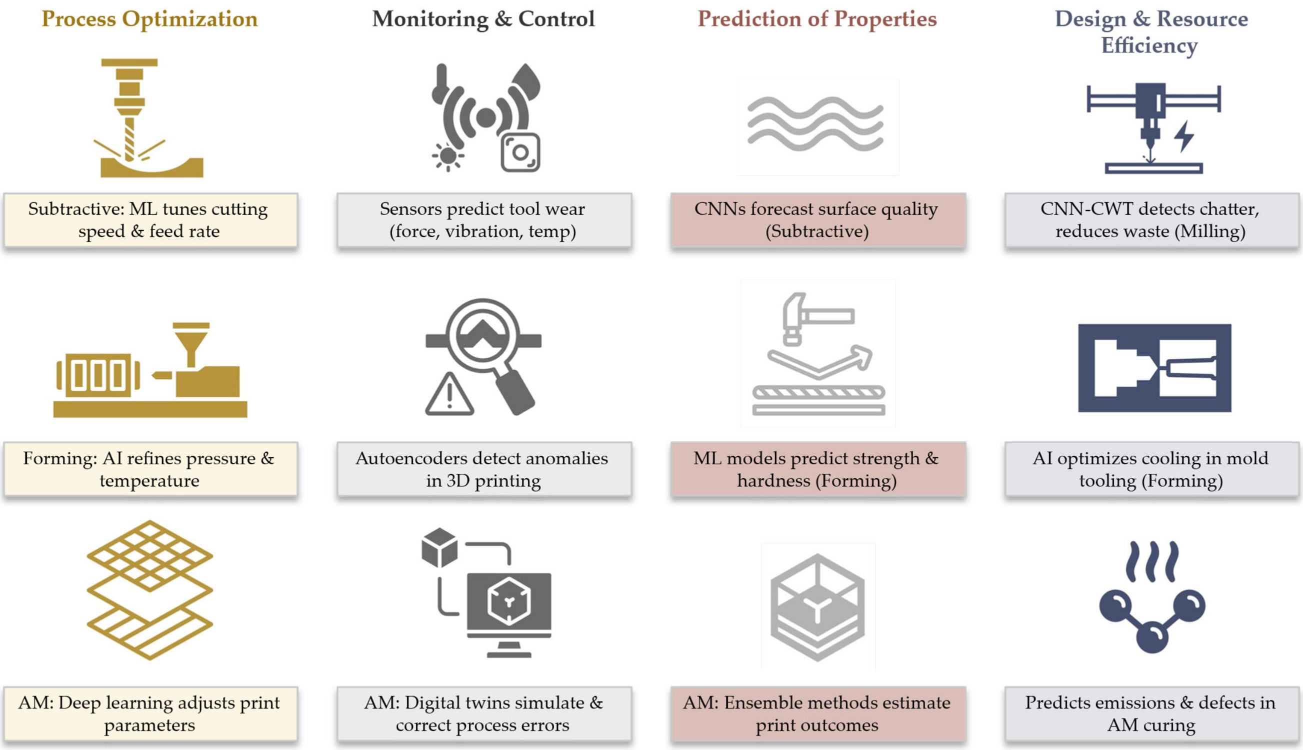

Figure 4. AI-Driven Applications Across the Manufacturing Process: From Parameter Optimization to Sustainable Design. The diagram was developed by the authors as a conceptual synthesis of the systematic literature review (see Sections 3.3.1 and 3.3.2), summarizing recurring applications of AI across subtractive, forming, and additive manufacturing processes. Categories were derived from reviewed studies and illustrate how AI supports optimization, monitoring, prediction, and design/resource efficiency.

4. Policy and Regulatory Landscape in Latin America

The integration of AI and other technologies into manufacturing systems is not only a technical shift but also a policy challenge, particularly in Latin America, where governance structures often lag behind technological change [27,132–135]. As AI-driven manufacturing gains momentum worldwide, countries in the region are beginning to address the complex regulatory, ethical, and socio-economic implications of this transformation. Despite this, other regions, such as the Global North, still lack robust legislation, which raises concerns regarding ethical principles and actionable approaches [136]. The definitions and regulatory frameworks that have already been established provide a pathway for integration within the manufacturing industry, compared to Latin American industries [137,138].

This section provides an overview of national AI strategies and policy initiatives in Latin America, focusing on how governments are responding to the rise of AI-enhanced manufacturing. Drawing on recent literature and official documents, this paper aims to examine both the opportunities and the regulatory fragmentation that shape the regional landscape. Special attention is paid to the challenges of data governance, transparency, labor dynamics, and the need for harmonized frameworks that align AI adoption with national development and sustainability goals.

4.1. Current Status of AI and Manufacturing Policies

Latin American countries have begun to articulate national strategies and legislative initiatives to govern the development and deployment of AI, though the pace and scope of these efforts vary significantly across the region. Countries like Brazil, Chile, and Colombia have adopted formal national AI strategies, while others, such as Mexico, are still in the process of developing legislation. Meanwhile, countries like Argentina, Peru, and Costa Rica have yet to establish comprehensive frameworks.

Brazil's Estratégia Brasileira de Inteligência Artificial (EBIA), launched in 2021, represents a significant step toward structured governance, supported by draft legislation on ethical AI and integration with innovation laws [139–143]. Chile's national AI policy emphasizes the economic, ethical, and educational dimensions of AI adoption. Its participation in international frameworks, such as the Digital Economy Partnership Agreement (DEPA), reinforces its commitment to multilateral cooperation [144]. Colombia's CONPES 3975 has positioned the country as a regional leader in the ethical governance of AI through its regulatory sandbox model and active data protection authority [139].

By contrast, countries without formal strategies, such as Argentina, Uruguay, and Costa Rica, primarily participate in international governance forums, having ratified conventions like Convention 108 for data protection [144,145]. Meanwhile, Panama is contributing to regional efforts through the Modelo de Ley de Inteligencia Artificial para América Latina y el Caribe, a Latin Parliament (PARLATINO)-led initiative that aims to harmonize regulatory frameworks across the region [146].

From a broader policy analysis perspective, Athayde and Vergara [13] noted that AI regulation in Latin America tends to prioritize ethical considerations, such as transparency and the protection of fundamental rights, over competition policy, contrasting with many frameworks in the Global North. This rights-based approach reflects the region's sensitivity to historical inequalities and institutional asymmetries.

In terms of manufacturing, recent studies highlight the positive impact of AI on the Global Value Chain (GVC) positioning of developing economies. Liu et al. [147] found that the adoption of AI in manufacturing contributes significantly to productivity gains and innovation potential, thereby reinforcing the need for policies that support the integration of AI into industrial strategies. However, as highlighted in recent reviews, many national strategies still lack comprehensive mechanisms to address the social and regulatory implications of integrating AI into sustainable manufacturing practices [3,14].

Complementary to AI policies, some governments are developing frameworks specifically tailored to AM and broader digital manufacturing practices. For example, regulatory frameworks are evolving to ensure the safe use of AM technologies, particularly in high-stakes sectors like aerospace and healthcare [148–150]. These efforts involve standardizing materials and implementing quality assurance protocols. Moreover, digital transformation strategies are increasingly encouraging manufacturers to adopt tools such as data analytics, automation, and digital twins, promoting a transition toward smart, interconnected production systems [5,36,40,66,151,152].

Furthermore, policies are also addressing the economic implications of AM, emphasizing the need for sustainable practices and the potential for AM to reduce waste and energy consumption in manufacturing [4,153–155], leading to a sustainable industry, within the framework of Industry 5.0 principles [5,104,156].

Together, these policy developments illustrate both progress and persistent gaps in Latin America's preparedness for AI-enhanced manufacturing. While strategic efforts are underway, a cohesive and inclusive governance approach remains essential to align technological innovation with long-term development and sustainability goals. Table 1 depicts an overview of the current state of Latin American national AI strategies.

Table 1. Overview of national artificial intelligence strategies and governance initiatives in selected Latin American countries. The table summarizes whether a formal AI strategy exists, the name of the strategy or initiative, key regulatory or institutional developments, and relevant sources.

Country	National AI Strategy	Name of Law/Initiative	Regulatory or Institutional Advances	Manufacturing/Industry 4.0 Provisions	Source
Brazil	Yes (since 2021)	Estratégia Brasileira de Inteligência Artificial (EBIA)	Public consultations, draft bills on ethical AI, and integration with innovation law.	EBIA explicitly created AI centers for Indústria 4.0 applications in manufacturing productivity and SMEs.	[139–143]
Chile	Yes (2021)	Política Nacional de Inteligencia Artificial	Strategy focused on economy, ethics, and education. Active in DEPA.	Notes industrial applications within the economy pillar, but no binding provisions for manufacturing.	[144]
Colombia	Yes (2019)	CONPES 3975—Política Nacional para la Transformación Digital e IA	Regulatory sandbox for AI ethics and data protection. Data privacy authority is active.	CONPES highlights the adoption of Industry 4.0 (including IoT, Big Data, and AI) in production/logistics.	[139,157]
Mexico	In development	Draft bills inspired by the EU AI Act	Legislative discussions: proposal to create Agencia Nacional de Inteligencia Artificial (ANIA)	Multiple bills are under debate; no explicit provisions for manufacturing have been introduced to date.	[139,158]
Uruguay	No formal strategy	N/D	Ratified Convention 108, active in DEPA and regional digital governance.	No manufacturing-specific measures.	[144,145]
Argentina	No national strategy	N/D	Signed Convention 108+. Engaged in human rights frameworks around AI.	Limited Industry 4.0 programs at the provincial level, not tied to the AI national policy.	[139,144]
Peru	No	N/D	Fragmented regulatory approach via consumer law, digital justice, and data protection.	No explicit manufacturing provisions identified.	[139]

Table 1. *Cont.*

Country	National AI Strategy	Name of Law/Initiative	Regulatory or Institutional Advances	Manufacturing/Industry 4.0 Provisions	Source
Costa Rica	No	N/D	Participates in regional initiatives on digital governance and cybersecurity.	Manufacturing is not addressed in current initiatives.	[144]
Panama	No national strategy	Modelo de Ley de Inteligencia Artificial para América Latina y el Caribe	PARLATINO-led initiative for regional harmonization of AI governance, with participation from Panama and the Technological University of Panama (UTP) researchers.	The draft mentions industrial/logistics AI applications, but it is not yet binding.	[146]

As illustrated in Table 1, explicit provisions linking AI strategies to manufacturing are rare in Latin America. Brazil stands out with its Estratégia Brasileira de Inteligência Artificial (EBIA), which has explicitly created AI research centers aimed at supporting Industry 4.0 applications, particularly in SMEs and enhancing productivity [159]. This initiative positions Brazil as one of the few countries in the region where regulation has incorporated a direct industrial dimension. Similarly, Colombia's CONPES 3975 [160] highlights the role of IoT, Big Data, and AI in production and logistics, and included a regulatory sandbox to test ethical and data protection aspects of AI under the supervision of the national data authority. Despite these advances, both cases remain limited in scope, as their industrial provisions are still in the early stages of implementation and have not yet had a systemic impact on national manufacturing ecosystems. As shown in Table 1, explicit provisions linking AI strategies to manufacturing are rare in Latin America.

In contrast, Chile's Política Nacional de Inteligencia Artificial [161] integrates industrial applications only indirectly through its economic pillar, without binding measures for manufacturing adoption. Mexico has debated multiple draft bills inspired by the EU AI Act, including the proposal for a National AI Agency (ANIA), but no explicit provisions for manufacturing have been enacted to date. Meanwhile, Uruguay, Argentina, Peru, Costa Rica, and Panama either rely on general digital governance and human rights instruments, such as Convention 108 and 108+, or on regional initiatives like PARLATINO's model law, without incorporating concrete manufacturing policies.

These examples demonstrate that while national AI strategies in Latin America increasingly reference economic modernization, only Brazil and Colombia have formally acknowledged Industry 4.0 within their regulatory frameworks. Even so, the absence of binding and sector-specific provisions highlights the broader problem of regulatory fragmentation, leaving manufacturing firms without tailored incentives or governance mechanisms to support the adoption of AI.

4.2. Challenges in Governance

4.2.1. Regulatory Lag and Policy Fragmentation

The integration of AI into manufacturing processes presents significant opportunities for enhancing production efficiency and sustainability. However, the governance of these technologies in Latin America faces substantial challenges, particularly due to regulatory lag and policy fragmentation [27,134]. As AI technologies evolve rapidly, existing regulatory frameworks often struggle to keep pace, resulting in gaps that can hinder innovation and the ethical deployment of these technologies [162,163].

One of the primary challenges is the fragmentation of policies across different countries in the region. Each nation has its own regulatory landscape, which can create inconsistencies and complicated compliance for businesses operating in multiple jurisdictions [139]. This fragmentation can lead to a lack of coherent strategies for AI governance, making it difficult to address common issues such as data privacy, ethical use, and the socio-economic impacts of AI technologies [38,132,155,164,165].

This fragmentation is not only visible at the national level but also on the regional scale. Several initiatives, such as the Digital Economy Partnership Agreement (DEPA), which includes Chile [166], PARLATINO [146], and Mercosur [167], have sought to establish common frameworks; however, their influence on manufacturing policy remains limited. DEPA, facilitates cooperation on digital trade, cross-border data flows, and interoperability standards, indirectly shaping industrial ecosystems by promoting digital infrastructure. PARLATINO has developed a Modelo de Ley de Inteligencia Artificial para América Latina y el Caribe, which includes references to industrial and logistics applications, though it has not yet been translated into binding national legislation. Mercosur has only recently initiated discussions on AI as part of its broader digital integration agenda, with preliminary mentions of Industry 4.0. These initiatives reflect growing recognition of AI's strategic role but also highlight the absence of a coherent regional framework capable of driving AI adoption in manufacturing.

It also has concrete consequences for industrial adoption. In the absence of sector-specific regulation and coordinated industrial policies, manufacturing firms, particularly SMEs, lack incentives, funding mechanisms, and clear compliance pathways to implement AI solutions. Although Brazil's EBIA and Colombia's CONPES highlight Industry 4.0 applications, neither provides binding mechanisms that support SMEs in overcoming cost and infrastructure barriers. As a result, governance gaps exacerbate existing industrial weaknesses, leaving firms without the institutional support necessary to transition from isolated AI pilots to widespread adoption.

Moreover, the regulatory lag refers to the slow adaptation of laws and policies to the rapid advancements in AI and AM technologies. This delay can result in outdated regulations that do not adequately address the risks and challenges posed by these innovations. For instance, ethical concerns related to AI decision-making processes and the potential for algorithmic bias are often not sufficiently covered by existing laws, leaving significant gaps in accountability and oversight [168,169].

To effectively harness the benefits of AI-optimized manufacturing, it is crucial for Latin American countries to develop harmonized regulatory frameworks that promote innovation while ensuring adherence to ethical standards and maintaining public safety. This requires regional cooperation and the establishment of joint regulatory bodies that can facilitate consistent enforcement and address cross-border challenges [170,171].

Therefore, addressing the challenges of regulatory lag and policy fragmentation is crucial for creating a conducive environment for AI-optimized manufacturing in Latin America. By implementing integrated frameworks that align technological advancements with national development goals, policymakers can create a future-ready and equitable approach to AI deployment in the region.

Beyond regulatory frameworks, preparedness indicators also provide insights into the potential for AI adoption in manufacturing. The Latin American Artificial Intelligence Index [172] evaluates 19 countries on dimensions such as technological infrastructure, human capital, research capacity, and governance. According to ILIA, Chile, Brazil, and Uruguay lead the region, showing comparatively higher readiness to integrate AI into industrial and manufacturing processes. This heterogeneity in readiness levels underscores the importance of tailoring regulatory and industrial policies to national capabilities.

4.2.2. Issues of Data Privacy, Intellectual Property, and Algorithmic Transparency

Integrating AI into manufacturing processes presents significant governance challenges, particularly concerning data privacy, intellectual property, and algorithmic transparency. They are critical, as they can significantly impact the successful implementation of AI-optimized manufacturing processes and technologies in Latin America.

The rapid adoption of AI technologies raises substantial concerns regarding data privacy [157,173]. As organizations increasingly rely on AI for decision-making, the ethical management of personal and sensitive data becomes paramount. Studies indicate that privacy and data protection issues are significant ethical challenges in AI applications, necessitating robust governance frameworks to ensure compliance with privacy standards and protect individuals' rights [133,174].

The intersection of AI and manufacturing processes also complicates intellectual property (IP) rights. The creation of new materials and processes through AI can lead to disputes over ownership and patentability. The lack of clear regulations regarding AI-generated innovations poses risks for businesses and can stifle innovation. It is essential to develop adaptive IP frameworks that can accommodate the unique characteristics of AI technologies while promoting fair competition [36,165].

Transparency in AI algorithms is crucial for building trust among stakeholders. The opacity of AI decision-making processes can lead to biases and unfair outcomes, particularly in sectors such as manufacturing, where precision is crucial. Ensuring that AI systems are explainable and accountable is vital for ethical governance. This includes implementing standards for algorithmic transparency and establishing oversight mechanisms to monitor AI applications [162,175].

Addressing these governance challenges requires a collaborative approach involving policymakers, industry leaders, and civil society. By fostering dialogue and developing comprehensive regulatory frameworks, stakeholders can ensure that the benefits of AI-optimized AM are realized while safeguarding ethical standards and public trust.

4.2.3. Cybersecurity Challenges in AI and ML for Manufacturing

The growing integration of AI and ML into manufacturing processes has provided several improvements in manufacturing systems, making them more connected and efficient [11,121]. However, this digitalization of manufacturing operations entails significant cybersecurity challenges [11,59,176]. Some of the key risks for these systems include malicious external attacks, such as malware intrusions and breaches of sensitive industrial data [11]. In addition to adversarial manipulation of data streams from critical sensors, which compromises process security [176]. These cybersecurity breaches can lead to diverse consequences at various levels, including the loss of information confidentiality, misappropriation of intellectual property, and degradation of product quality [90,177].

A practical response to these risks involves adopting a robust security measure in the design and operation of AI-based manufacturing systems. To address the risks described above, the security of communication networks must be strengthened by incorporating ML algorithms that resist external manipulation and developing application programming interfaces (APIs) that allow the integration of AI models [90]. In addition, establishing robust security protocols is essential; it is important to establish security protocols that guarantee the integrity and confidentiality of shared data [178].

The literature agrees on the need to advance research within the cyber-physical systems community to address these emerging risks. Therefore, it is essential that cybersecurity be viewed not just as a technical add-on, but as a key element in building trust, resilience, and sustainability in manufacturing driven by artificial intelligence [176].

4.3. Ethical and Social Considerations

4.3.1. Inclusion, Labor Displacement, Environmental Sustainability, and Digital Equity

Integrating AI and manufacturing processes raises significant ethical and social considerations that must be addressed to ensure the responsible deployment of these technologies. These considerations include inclusion, labor displacement, environmental sustainability, and digital equity.

The deployment of AI in Industry can exacerbate existing inequalities if not managed properly. It is crucial to ensure that diverse voices are included in the development and implementation of AI technologies. This involves engaging marginalized communities and ensuring equitable access to the benefits of AI-enhanced manufacturing processes. Research emphasizes the importance of social diversity, equity, and inclusion as key factors in mitigating risks associated with AI technologies [179–181].

The automation of manufacturing processes through AI can lead to significant labor displacement. As AI systems become increasingly capable, there is a risk that traditional manufacturing jobs may become obsolete. This necessitates the development of strategies to retrain and upskill workers, ensuring they can transition into new roles created by the evolving technological landscape. Studies highlight the need for interdisciplinary approaches to address the socio-economic implications of automation [182,183].

AI has the potential to enhance the sustainability of manufacturing processes by optimizing resource use and reducing waste. However, the environmental impact of AI technologies themselves, including energy consumption and electronic waste, must be carefully considered. Ethical frameworks should guide the integration of AI in ways that promote environmental stewardship and align with the Sustainable Development Goals [164,184].

The digital divide poses a significant challenge in the equitable deployment of AI technologies. Access to AI tools and training is often limited to certain demographics, which can perpetuate existing inequalities. Ensuring that all communities have access to the necessary resources and education to engage with AI technologies is essential for fostering digital equity [154,185].

While AI-optimized manufacturing holds great promise for enhancing efficiency and sustainability, it is imperative to address the ethical and social implications associated with its deployment. Policymakers, educators, and industry leaders must collaborate to create frameworks that promote inclusion, mitigate labor displacement, ensure environmental sustainability, and foster digital equity. By doing so, they can support a future-ready and equitable approach to AI-enhanced manufacturing in Latin America.

4.3.2. Challenges and Opportunities for SMEs in AI Implementation in Industrial Manufacturing

SMEs play a critical role in the industrial manufacturing landscape of Latin America. Their adoption of artificial intelligence faces unique challenges but also presents significant opportunities for innovation and competitiveness [108]. But it takes risks and challenges to implement in SMEs, such as:

- Unlike large corporations, SMEs often lack the capital required to invest in advanced AI technologies, infrastructure, and skilled personnel. High upfront costs can slow down adoption.
- Access to trained AI specialists and data scientists is limited, particularly in emerging economies, making it difficult for SMEs to build internal capabilities [3].

- AI systems require large volumes of high-quality data. SMEs may lack the digital maturity to collect, store, and process data effectively, which limits the performance of AI applications.

In the same space, the multiple opportunities for the implementation of this system in SMEs should be taken into consideration:

- AI can help SMEs reduce production costs, minimize waste, and improve efficiency, making them more competitive against larger players.
- AI-driven tools can enable SMEs to offer personalized products and adapt more quickly to shifting market demands, which is often an advantage of smaller-scale operations.
- Through AI-enhanced predictive analytics and supply chain optimization, SMEs can better integrate into global value chains and expand their reach.
- AI-powered resource management systems can help SMEs adopt cleaner production practices, aligning with environmental regulations and consumer expectations.

The successful implementation of AI in SMEs requires tailored strategies that address their structural limitations while leveraging their agility and adaptability. Public policies that support training, financial incentives, and digital infrastructure are crucial for ensuring that SMEs in Latin America can benefit equitably from AI-driven industrial transformation.

Recent studies indicate that while adoption of AI is on the rise, the region still faces significant barriers that hinder its full potential. A comprehensive analysis reveals that large organizations, particularly those with over 200 employees, are more likely to adopt AI technologies due to their greater financial and technical resources [46]. However, the overall adoption rate in manufacturing remains lower compared to sectors such as banking and healthcare, highlighting the need for targeted initiatives to accelerate AI implementation [48]. In Brazil, companies are increasingly leveraging AI for predictive maintenance and quality control, showcasing a commitment to enhancing operational efficiency [186]. Mexico has initiated various programs aimed at fostering AI development in manufacturing, supported by government policies and investments in technology [187]. Meanwhile, Chile is focusing on collaborative robotics and AI applications to improve manufacturing processes, reflecting a strategic approach to adopting advanced technologies [188]. The paper emphasizes the importance of coherent policy frameworks to support AI adoption. Countries like Brazil, Mexico, and Chile are developing national strategies to address ethical and socio-economic challenges; however, regulatory lags and structural inequalities continue to impede progress [189]. The need for regional coordination and inclusive policymaking is critical to ensure equitable technological transformation [190]. The findings suggest that to fully harness the potential of AI in manufacturing, stakeholders must address existing barriers and enhance collaboration among industry leaders, policymakers, and educational institutions. This includes increasing investment in research and development, strengthening academia-industry partnerships, and developing specific industrial policies to foster innovation [191]. In conclusion, while AI adoption in Latin American manufacturing is progressing, it is crucial to address the remaining challenges. By fostering a supportive environment for AI integration, the region can enhance its competitiveness and drive sustainable economic growth.

In recent years, several Latin American manufacturing companies have successfully implemented AI technologies, demonstrating measurable improvements in efficiency and productivity. One notable case is the application of AI algorithms in 50 manufacturing companies across Latin America, which resulted in an 11.6% improvement in predictive accuracy and significant increases in production efficiency [187]. This study highlights the potential for integrating behavioral economics with AI to optimize industrial processes, demonstrating how AI can enhance operational metrics across various manufacturing contexts.

Another example can be found in Brazil, where the adoption of Industry 4.0 technologies, including AI, has been linked to increased global competitiveness. The research indicates that Brazil's investment in AI and collaborative robotics has the potential to catalyze economic diversification, with significant implications for the manufacturing sector [186]. This case exemplifies the broader trend of leveraging AI to not only enhance production processes but also promote innovation and sustainability within the industry.

Additionally, a study focusing on Ecuador emphasizes the growing interest in AI adoption driven by favorable policies and economic conditions. Despite existing barriers, such as technological limitations and budgetary constraints, there is a strong anticipation for increased AI integration in project management and manufacturing processes over the next five years [46]. This case underscores the significance of supportive regulatory frameworks and investment in technology in facilitating the successful implementation of AI in the region.

These examples collectively validate the theoretical frameworks surrounding AI's transformative potential in manufacturing, underscoring the need for continued investment and policy support to effectively harness AI's capabilities.

A comparative overview of the current landscape of AI and digital infrastructure in Latin America reveals notable differences in connectivity, data capacity, and the availability of industrial AI technologies. Table 2 compares Latin American countries across several key dimensions, including digital connectivity, human capital, business digital adoption, government digitalization, access to high-performance computing (HPC), and the strength of their AI and startup ecosystems. Together, these indicators provide a picture of which countries are best positioned to lead in the digital economy and which ones still lag behind [188,189,192].

Brazil consistently ranks at the very top. It has the region's largest number of internet users, affordable connectivity, and a highly developed e-commerce and fintech sector worth more than $40 billion. Its government scores very high in cybersecurity readiness, and it hosts by far the most powerful HPC infrastructure in the region through the Santos Dumont supercomputer and the SINAPAD network. Additionally, Brazil ranks first in tech startups, boasting the largest number of AI companies, unicorns, and venture capital investments.

Mexico follows closely behind. It combines strong connectivity, relatively affordable broadband, and a large pool of educated workers with concentrated AI expertise. Its digital business sector is robust, with e-commerce revenues above $30 billion, and the government performs strongly in digital services and cybersecurity. Mexico also runs the ABACUS HPC center, which supports both academia and industry. In the startup world, Mexico ranks as second regionally, with a thriving ecosystem in fintech, logistics, and mobility.

Chile also scores very high in terms of connectivity. It actually offers the fastest and most affordable internet in the region. Its e-government services are efficient, and it is well known for the Start-Up Chile program, which makes it one of the top five startup ecosystems in Latin America. Chile's HPC capacity, through the NLHPC, supports scientific research across various sectors, including energy and agriculture.

Argentina also ranks in the top five, thanks to its relatively affordable internet, high rates of higher education, and a strong base of digital businesses. While its e-government still lags, Argentina's scientific HPC efforts (the Tupac cluster) and a growing AI startup community keep it well positioned. Colombia ranks in third position in the startup ecosystem, driven by a booming fintech scene and a growing AI talent base. Its internet speeds are competitive, and e-commerce is expanding quickly. The government is improving digital services, and the SC3UIS cluster supports local research efforts.

Table 2. Comparative overview of the current landscape of AI and digital infrastructure in Latin America [188,189,191–195].

Country	Connectivity & Data Access Indicators	Human Capital (Education, AI/Cyber Talent) [1]	Business Digital Use [2]	Digital Government [3]	HPC/Supercomputing Ecosystem [4]	AI & Startup Ecosystem [5]
Brazil	188M users, 170 Mbps, $1/GB	81% higher education, strong cyber workforce	$41B e-commerce, advanced fintech	Advanced, strong cybersecurity (96 pts)	Strongest HPC in the region (Santos Dumont 4.2 PF, SINAPAD)	Rank #1 in startup ecosystem; leads in AI startups, unicorns, and VC investment
Mexico	107M users, 79 Mbps, $4.8/GB	77% higher education, AI talent concentration	$34B e-commerce, solid fintech	Strong e-government (81 pts)	ABACUS (CINVESTAV) ~0.5 PF	Rank #2 in startup ecosystem; strong VC flows, AI startups in fintech & mobility
Chile	18M users, 266 Mbps, $0.7/GB	82% higher education	$7B e-commerce, dense fintech	Efficient e-government (68 pts)	NLHPC, highly used for academia	Top 5 ecosystems; strong public support (Start-Up Chile), AI in energy/agritech
Argentina	41M users, 88 Mbps, $1.5/GB	79% higher education	~$7B e-commerce, moderate fintech	Mid-level e-gov (49 pts)	Tupac cluster	Top 5 ecosystems; AI startups are growing despite macro instability
Colombia	40M users, 145 Mbps, $3.5/GB	77% higher education, AI skills expanding	~$8B e-commerce, growing banking	Mid-level e-gov (63 pts)	SC3UIS cluster	Rank #3 in startup ecosystem; booming AI fintech, government support
Uruguay	3M users, 156 Mbps, $1.6/GB	83% higher education, high wages	Small e-commerce, strong banking	Strong e-gov (75 pts)	Cluster-UY, open science model	Small but dynamic startup scene; AI startups in logistics and agritech
Costa Rica	5M users, 97 Mbps, $2.7/GB	75% higher education, high wages	Small e-commerce, strong banking	Mid-level (67 pts)	CeNAT HPC center	Niche ecosystem; AI startups in health tech & biotech
Peru	26M users, 167 Mbps, $2.1/GB	84% higher education, lower wages	~$6B e-commerce	Growing	No large-scale HPC	Emerging startup ecosystem, AI startups are still limited
Panama	3.5M users, 152 Mbps, $6.7/GB	72% school digital coverage, higher wages	Small e-commerce, weak fintech	Weak e-gov (33 pts)	RedCLARA hub (100 Gbps) but no major HPC	Nascent startup ecosystem, AI activity very low

[1] Human Capital (education, AI/cyber talent): Reflects workforce readiness for digital transformation. Rankings combine education levels (higher education, digital training), labor market value (wages), and the size of AI and cybersecurity talent pools. Higher scores = stronger capacity to train, attract, and retain skilled professionals. [2] Business Digital Use: Measure the extent to which businesses adopt digital technologies. Rankings consider e-commerce revenues, fintech activity, online banking penetration, digital marketing costs, and sectoral digitalization. Higher scores = more active and competitive use of digital tools across industries. [3] Digital Government: Measures the extent and quality of public digital services. Rankings are based on factors such as online service availability, average processing times, use of digital channels by citizens, and national cybersecurity scores. Higher scores = more efficient, secure, and widely adopted e-government. [4] High-Performance Computing (HPC): Reflects national access to supercomputing capacity. Rankings consider the existence of HPC centers, their computing power (measured in petaflops), and their integration with regional networks, such as RedCLARA. Higher scores = greater ability to support advanced research, AI training, and industrial innovation. [5] AI & Startups: Captures the strength of a country's innovative ecosystem. Rankings consider the number of AI startups, unicorns, and venture capital flows, as well as government support programs (e.g., Start-Up Chile). Higher scores = deeper ecosystems with more vibrant AI entrepreneurship and investment activity.

Uruguay is a relatively small country, but it excels in digital government and connectivity. Its collaborative HPC model, Cluster-UY, has supported over 100 theses and millions of computing hours in renewable energy and health research. While its startup ecosystem is smaller than that of Brazil's or Mexico's, Uruguay has carved out a niche in logistics and agritech AI. Costa Rica and Peru are mid-level performers. Costa Rica boasts a robust digital infrastructure and operates the CeNAT HPC center; however, its startup ecosystem remains small and specialized, with a focus on health tech and biotech. Peru has fast and affordable internet and high levels of education but lacks large-scale HPC and still has only a limited AI startup base.

Panama performs well in terms of connectivity speed but suffers from high costs and weak digital government services. While it does not operate its own HPC facilities, it plays a crucial role as a hub for RedCLARA, connecting the region to the U.S. and Europe via a 100 Gbps link. Its startup ecosystem, however, is still in its early stages.

Finally, countries such as Ecuador, Bolivia, Paraguay, Honduras, Guatemala, Nicaragua, Cuba, Venezuela, the Dominican Republic, and El Salvador remain at the bottom across most categories. They struggle with slower and more expensive internet, weaker human capital, limited digital business adoption, and a lack of HPC or startup presence. Most organizations depend heavily on regional networks, such as RedCLARA, to access advanced computing resources.

Ultimately, Latin America is divided into three clear groups: leaders (Brazil, Mexico, Chile, Colombia, Argentina, Uruguay), which combine strong infrastructure with thriving AI startup ecosystems; mid-level players (Peru, Costa Rica, Panama), which show good connectivity but weak HPC and startup activity; and laggards, which still face major gaps in digital infrastructure, human capital, and innovation ecosystems.

5. Bridging Technology and Policy: A Discussion on Strategic Opportunities

This study examined the intersection of AI and manufacturing in Latin America from three complementary perspectives: the technical capabilities of AI, the regulatory and governance landscape, and the specific challenges faced by the region's manufacturing sector. The analysis revealed that, although AI offers significant opportunities for enhancing productivity, quality control, predictive maintenance, and sustainable industrial practices, adoption in Latin America remains fragmented and uneven across countries. National AI strategies exist in several cases, yet they often lack integration with industrial policies, and SMEs continue to face barriers related to financing, infrastructure, and skills development. These findings highlight the need to frame the discussion not only around technological innovation but also around governance, regulatory harmonization, and socio-economic inclusion.

Within this broader context, regional economic projections underscore both the opportunities and the risks. According to the United Nations Development Programme (UNDP) [196], AI is projected to contribute up to 5.4% of Latin America's Gross domestic product (GDP) by 2030. Recent analyses emphasize that Latin America faces a dual challenge: to design its own regulatory frameworks while avoiding excessive technological dependency on external powers. Moreover, the overall AI market in the region was valued at USD 4.71 billion in 2024 and is expected to expand to USD 30.2 billion by 2033, with an annual growth rate of 22.9% [18]. These figures confirm both the strategic importance of AI adoption in manufacturing and the pressing need to address persistent inequalities in infrastructure, skills, and investment.

5.1. Addressing the Research Questions: Evaluating the Structural Conditions for AI in Latin American Manufacturing

The comprehensive analysis of literature, policy, and case studies presented in this review provides evidence-based answers to the three research questions that guided this work. Together, these responses outline the critical structural conditions required for the successful and sustainable integration of AI into Latin America's manufacturing sector.

RQ1: Infrastructure Readiness—To what extent do digital infrastructure factors, such as connectivity, data capacity, and access to cloud computing, condition the scale and sophistication of AI adoption in manufacturing?

The evidence strongly suggests that digital infrastructure is a fundamental prerequisite and a critical enabler for AI adoption. A comparative analysis, as described in Table 2, reveals a clear regional divide. Countries like Brazil, Mexico, and Chile, which perform better in terms of connectivity (bandwidth above 150 Mbps), affordable data costs (e.g., ~$1.5/GB in Argentina), and, crucially, access to supercomputing capabilities (e.g., Brazil's Santos Dumont cluster, Mexico's ABACUS), are also the ones leading in AI pilot projects and host the most vibrant startup ecosystems.

Conversely, nations with limited connectivity or prohibitive data costs (e.g., Panama at $6.7/GB) show only nascent adoption and very low AI activity. This is because AI applications in manufacturing, such as real-time process monitoring, predictive maintenance, and digital twins, are data-intensive and require low-latency transmission and robust processing power. Infrastructure thus acts as a critical enabler or a formidable impediment; without it, AI's potential remains theoretical and out of reach, especially for manufacturing SMEs.

RQ2: Policy and Governance—How do national AI strategies and industrial policies influence investment, regulatory certainty, and public–private partnerships for AI-enabled manufacturing?

Findings indicate that while the existence of national AI strategies is a positive step, their actual influence is severely limited by a lack of integration with concrete industrial policies and a fragmented regulatory landscape. Strategies were identified in Brazil (EBIA), Chile, and Colombia (CONPES 3975) (Table 1), but these are in early stages and predominantly focus on general ethical considerations and fundamental rights, with specific provisions for the manufacturing sector being rare and non-binding.

This policy fragmentation and regulatory lag (Section 4.2.1) create an environment of uncertainty for investors and firms, stifling the formation of robust public–private partnerships. For instance, although Brazil's EBIA establishes AI centers for Industry 4.0 applications, it does not provide clear funding mechanisms or fiscal incentives for SMEs to overcome cost barriers. The PARLATINO-led initiative (with Panama's participation) is a promising step toward regional harmonization that could address this weakness. In short, existing strategies have not yet generated the regulatory certainty or investment incentives needed to catalyze widespread adoption, functioning more as statements of intent than as effective action frameworks.

RQ3: Socio-Industrial Capacity—In what ways do skills availability, workforce readiness, and the digital maturity of SMEs shape the implementation and long-term impact of AI in manufacturing?

The analysis provides the strongest and most consistent support for the centrality of socio-industrial capacity as the most restrictive and determining pillar for long-term success. The most frequently cited barrier in the literature, confirmed by SME case studies (Section 4.3.2), is the shortage of specialized human capital (data scientists, AI engineers) and the low technological readiness of the existing workforce.

The review highlights that even in countries with relatively solid infrastructure, the skills gap throttles adoption. The ILIA 2024 index explicitly evaluates human capital, and countries with better scores in this area (Chile, Uruguay) show higher readiness for AI integration. Furthermore, the specific challenges faced by SMEs, financial constraints, cultural resistance to change, and insufficient size to absorb risk, underscore the "industrial" dimension of this capacity. The evidence is clear: without robust reskilling programs, specialized education, and knowledge-transfer mechanisms that strengthen socio-industrial capacity, advances in infrastructure and policy will have limited impact and will not be sustainable.

The answers to the three research questions validate the proposed Triadic Integration Framework, demonstrating that AI adoption in Latin American manufacturing is a multifaceted challenge requiring simultaneous and interconnected progress on three fronts:

- Infrastructure (RQ1) as the foundational technical enabler.
- Policy and Governance (RQ2) as the framework providing certainty, incentives, and direction.
- Socio-Industrial Capacity (RQ3) as the human and organizational engine that ultimately drives technology implementation and absorption.

The evidence suggests that, in the current phase, socio-industrial capacity (RQ3) acts as the most critical and restrictive pillar, often amplifying deficiencies in the other two domains. However, the model is dynamic. Projected growth of the regional AI market signals an opportunity where the deliberate strengthening of one pillar can catalyze progress in the others. Concerted investment in education and training (strengthening RQ3) can increase the return on infrastructure investments (RQ1) and create more effective demand for better-designed policies (RQ2). Therefore, the path to successful AI integration requires coordinated action that strengthens and, most importantly, deliberately aligns these three fundamental structural conditions.

5.2. The Need for Integrated Frameworks: Aligning Innovative Ecosystems with Policy Development

The need for integrated frameworks that align technological innovation with national development goals is critical. Policymakers are encouraged to adopt holistic approaches that consider the socio-economic context and promote transparency, inclusion, and adaptability in regulatory practices. This alignment can facilitate the responsible integration of AI into manufacturing processes, ensuring that it contributes positively to economic growth and social equity [134,135]. Recent studies emphasize that integrated frameworks should not only focus on technological advancements but also address the socio-economic disparities prevalent in the region. For instance, the development of policies that foster collaboration between government, academia, and industry can enhance the innovation ecosystem, ensuring that all stakeholders benefit from AI advancements [197,198].

Furthermore, harmonizing AI regulations across Latin American countries can foster a more cohesive approach to innovation, enabling the sharing of best practices and resources [132,199]. This is particularly important as fragmented regulatory environments can hinder the potential of AI technologies to drive economic growth and social progress. A comparative analysis of regulatory approaches in Latin America reveals that common concerns such as data privacy, ethical use, and the impact of AI on labor markets necessitate coordinated responses [132].

Additionally, addressing the ethical implications of AI deployment is essential. Policymakers must ensure that regulations are designed to protect fundamental rights while promoting innovation. This requires a careful balance between fostering technological growth and safeguarding public interests, which can be achieved through inclusive and adaptive regulatory frameworks [13,104]. Ethical considerations, including transparency, accountability, and the mitigation of algorithmic biases, are paramount in ensuring that AI technologies do not exacerbate existing inequalities [154,200,201].

Integrating AI into manufacturing industries in Latin America presents both opportunities and challenges. By adopting comprehensive and harmonized regulatory frameworks that prioritize ethical considerations and socio-economic inclusivity, policymakers can harness the transformative potential of AI while ensuring that its benefits are equitably distributed across society. The economic and regulatory perspectives on manufacturing highlight the importance of these frameworks [153]. Moreover, the role of AI in enhancing access and personalization in higher education is crucial for fostering innovation and addressing socio-economic disparities [202].

The integration of AI into manufacturing processes in Latin America has significant socio-economic implications, particularly concerning industrial GDP, productivity, and employment. As AI technologies enhance manufacturing efficiency, they can lead to increased productivity, which is a critical driver of industrial GDP growth. For instance, AI can optimize production parameters, thereby improving throughput and resource utilization, which are essential for boosting economic output [203,204].

However, the relationship between AI implementation and employment is complex. While AI can create new job opportunities in tech-driven sectors, it may also displace traditional manufacturing jobs, leading to a paradox where productivity increases do not translate into proportional employment growth [205,206]. This phenomenon is particularly evident in Latin America, where industrial employment has stagnated despite technological advancements [207]. The challenge lies in ensuring that the benefits of AI-driven productivity gains are equitably distributed across the workforce.

Moreover, the uneven development of AI capabilities across different countries in the region can exacerbate existing inequalities. Countries like Brazil, Mexico, and Chile are at the forefront of AI adoption; however, disparities in infrastructure, education, and investment can hinder the broader socio-economic benefits [188,190]. Policymakers must therefore focus on inclusive strategies that promote equitable access to AI technologies and training, ensuring that all segments of the population can benefit from the economic opportunities presented by AI-enhanced manufacturing.

Cross-regional evidence further illustrates that Latin America's challenges in AI adoption are not unique, but they manifest differently compared to other emerging regions. In sub-Saharan Africa, countries such as South Africa and Mauritius have advanced regulatory frameworks but still lag behind in technological infrastructure, which limits the integration of AI into manufacturing systems [208,209]. By contrast, Asian economies such as India, Vietnam, and Indonesia are leveraging stronger industrial ecosystems and targeted investments in digital skills to accelerate AI-enabled manufacturing, positioning themselves as competitive adopters of Industry 4.0 [208,210]. Latin America lies between these two trajectories: like Africa, it faces structural barriers of financing, skills shortages, and infrastructure gaps [107,108], but it also shares with Asia a growing number of policy roadmaps and industrial pilots, although these remain fragmented and underfunded [110]. This comparative perspective underscores that without coordinated strategies to scale pilot projects and strengthen digital capacity, Latin America risks both falling behind Asia's manufacturing competitiveness and experiencing forms of premature deindustrialization as global automation reshapes demand for its industrial output. For instance, in India, AI has been deployed in the automotive sector to optimize predictive maintenance and supply-chain management [210], while in South Africa, mining industries have implemented AI-driven monitoring systems to enhance operational safety and efficiency [208]. These cases illustrate that although challenges differ, both Asia and Africa are generating concrete industrial applications that contrast with Latin America's more fragmented pilot initiatives.

In conclusion, while AI has the potential to significantly impact industrial GDP and productivity in Latin America, careful consideration of its effects on employment and socio-economic inequalities is essential. Policymakers should strive for a balanced approach that promotes innovation while safeguarding jobs and fostering inclusive growth.

5.3. Stakeholder Engagement: The Role of Academia, Industry, and Civil Society in Shaping Regulation

The roles of academia, industry, and civil society in shaping regulations for AI-enhanced manufacturing in Latin America are critical for fostering an environment conducive to innovation while addressing ethical and socio-economic concerns. Each stakeholder group brings unique perspectives and expertise that can enhance the regulatory landscape.

Academia plays a pivotal role in generating knowledge and expertise related to AI and manufacturing processes [202,211–213]. Academic institutions are often at the forefront of research, providing evidence-based insights that can inform policy and regulatory frameworks. For instance, universities can conduct studies that assess the implications of AI technologies on manufacturing processes, thereby equipping policymakers with the necessary information to create informed regulations [214]. Furthermore, academia can facilitate dialogue among stakeholders, ensuring that regulations are grounded in scientific understanding and best practices [215].

Industry stakeholders play a crucial role in shaping regulations, as they possess valuable insights into the operational realities of AI and AM technologies. Their involvement in policy discussions can lead to regulations that are more aligned with technological advancements and market needs. However, there is a risk of regulatory capture, where industry interests may overshadow public welfare. Therefore, it is crucial to maintain a balance between industry input and public interest to ensure that regulations serve the broader community [216].

Civil society organizations play a crucial role in advocating transparency, ethical considerations, and the public interest in the regulatory process. They can help ensure that the voices of various community stakeholders are heard, particularly those who may be adversely affected by technological advancements. Engaging civil society in the regulatory dialogue can promote inclusivity and accountability in the governance of AI [217]. Moreover, civil society can mobilize public opinion and foster community engagement, which is essential for creating regulations that reflect the needs and values of society [218,219].

This analysis led to an understanding that the inclusion of AI into the manufacturing industrial sector in Latin America requires a collaborative approach that leverages the strengths of academia, industry, and civil society. This collaboration can help create a regulatory environment that fosters innovation while addressing ethical and socio-economic concerns, ultimately leading to a more equitable and sustainable future.

5.4. Regional Cooperation and Capacity Building: The Importance of Cross-Border Collaboration and Institutional Strengthening

There is a potential opportunity for countries in the region to collaborate on enhancing the adoption of AI in the manufacturing sector. By joining forces, especially through public–private partnerships and training programs, they can support the responsible use of these technologies. These kinds of collaborations can help close the tech gap and drive sustainable growth throughout the region [132,220].

Cross-border collaboration is increasingly recognized as a vital strategy for enhancing regional cooperation, particularly in the context of emerging technologies such as AI and AM. For instance, in Latin America, where regulatory frameworks are often fragmented, fostering collaboration among countries could lead to significant advancements in the adoption and optimization of AI-enhanced AM technologies. This collaboration can take various forms, including joint research initiatives, shared technological resources, and coordinated policy frameworks that address common challenges and opportunities.

One of the primary benefits of cross-border collaboration is the pooling of resources and expertise. By working together, countries can leverage their unique strengths and capabilities, leading to more innovative solutions and improved outcomes in manufacturing processes. For instance, collaborative efforts can facilitate the sharing of best practices in AI applications, thereby enhancing the efficiency and sustainability of manufacturing processes across the region [221,222]. Furthermore, such partnerships can help mitigate the risks associated with technological adoption by providing a support network for knowledge exchange and capacity building.

Institutional strengthening is another critical component of effective regional cooperation. Strong institutions are crucial for fostering an environment that enables collaboration, as they provide the necessary frameworks for governance, regulation, and policy implementation. In the context of AI-optimized AM, institutions can play a pivotal role in establishing standards, ensuring compliance, and fostering trust among stakeholders [223]. Moreover, robust institutions can facilitate dialogue between the public and private sectors, promoting public–private partnerships that are crucial for advancing technological innovation.

The challenges of regulatory lag and socio-economic disparities in Latin America further underscore the need for cross-border collaboration and institutional strengthening. By addressing these challenges collectively, countries can create a more equitable and inclusive environment for the deployment of AI-enhanced AM technologies. This approach not only supports technological advancement but also aligns with national development goals, ensuring that the benefits of innovation are widely shared [224,225].

Cross-border collaboration and institutional strengthening are essential for fostering a conducive environment for AI-enhanced manufacturing in Latin America. By working together, countries can enhance their technological capabilities, address regulatory challenges, and promote sustainable development. The findings from recent studies highlight the importance of these strategies in creating a future-ready manufacturing ecosystem that is both innovative and equitable. A Policy-Technical Integration Framework for Responsible AI in Manufacturing in Latin America is presented in Figure 5.

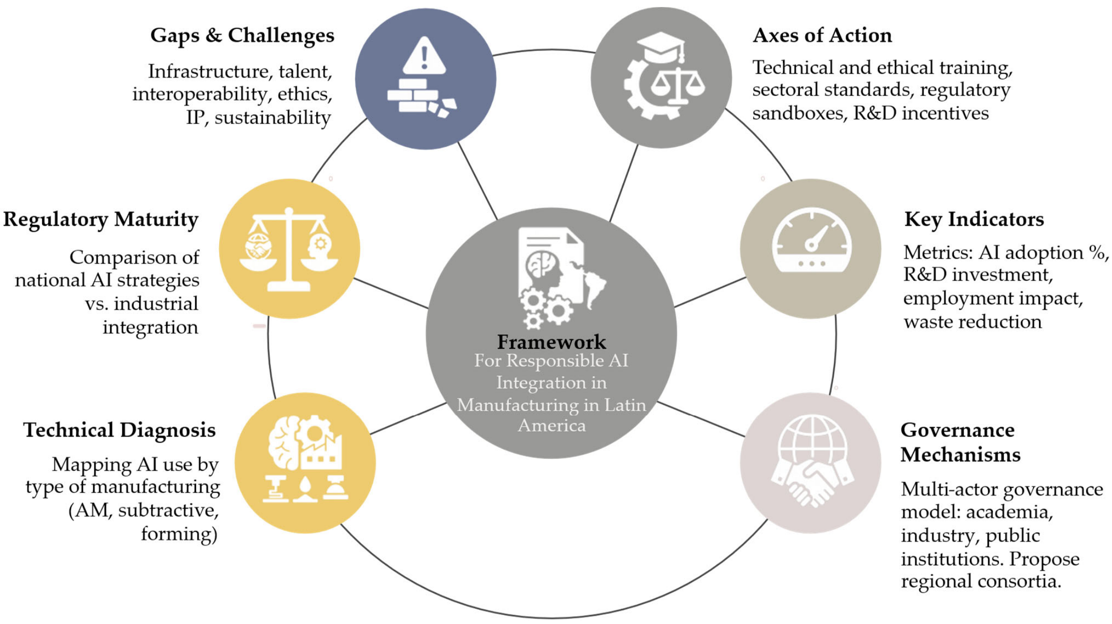

Figure 5. A Policy-Technical Integration Framework for Responsible AI in Manufacturing in Latin America. The framework outlines six interconnected components: technical diagnosis, regulatory maturity, challenges, action axes, indicators, and governance, to guide the ethical and effective adoption of AI across the region's manufacturing sectors.

5.5. Strategic Opportunities and Broader Impacts

Building on the triadic analysis, this section translates these insights into a strategic framework for action. The resulting model extends beyond theory to provide stakeholders with a clear set of prioritized interventions. For each initiative, the framework outlines the specific action, responsible stakeholders, required resources, and a measurable key performance indicator (KPI). This structure is designed to transform the analytical findings into actionable policy and industrial strategy.

The conceptual framework presented in Table 3 synthesizes the triadic analysis into a structured model for strategic intervention. It moves beyond identifying challenges to proposing causal logic for addressing them, illustrating that the pillars of infrastructure, policy, and socio-industrial capacity are not merely adjacent but deeply interdependent. The framework posits that the mechanism of impact for any single intervention is often contingent on progress in another pillar; for instance, the efficacy of regulatory sandboxes (Policy) is inherently limited without adequate digital infrastructure to facilitate participation, just as the benefits of subsidized connectivity (Infrastructure) cannot be fully realized without a skilled workforce (Capacity) to leverage it. This interconnectivity suggests that success hinges on coordinated, multi-stakeholder action rather than isolated initiatives. Furthermore, the formal integration of a feedback loop through an observatory transforms the model from a static plan into a dynamic system, emphasizing that policy must be adaptive and informed by real-time data on adoption metrics. Ultimately, this framework provides a testable hypothesis for regional development: that synchronized advancements across these four domains will create a compound effect, enabling a sustainable transition from small-scale pilots to systemic, industry-wide modernization.

Table 3. A Strategic Framework for AI Adoption in Latin American Manufacturing.

Strategic Priority	Recommended Action	Primary Stakeholders	Required Resources	Expected Outcome & KPI
Bridge the Infrastructure Gap	Develop national high-performance computing (HPC) hubs to enable SME access to advanced computing resources.	National Governments, Universities, Development Banks	Public funding, technical expertise	Increase in the number of SMEs using cloud/AI services by X%. Decrease in the data costs to <$2/GB.
Harmonize Policy	Adopt regional AI standards aligned with the PARLATINO model law.	Regional Bodies, such as Pacific Alliance, Mercosur, Ministries of Industry	Political capital, legal expertise	Number of countries adopting harmonized regulations. Increase in cross-border technology investment.
Build Socio-Industrial Capacity	Launch industry–academia "Digital Reskilling" certificate programs to train the workforce in AI literacy and manufacturing 4.0 skills.	Technical Universities, Industry Associations, Ministries of Education	Curriculum development, trainer funding	Increase in the number of workers certified in AI literacy per year. A decrease in the skills gap is reported in industry surveys.
Foster SME Adoption	Create regulatory sandboxes for AI testing and innovation in manufacturing.	Regulatory Agencies, Innovation Ministries	Legal frameworks for sandbox creation	Increase in the number of SMEs participating in pilot projects. % of pilots scaling to full implementation.

While the strategic framework in Table 3 specifies actions, stakeholders, resources, and KPIs, it also reflects the interdependence among the three pillars. For example, regulatory sandboxes (Policy) require adequate digital infrastructure, just as connectivity investments (Infrastructure) cannot yield results without workforce reskilling (Capacity). This highlights that the success of AI adoption depends on coordinated, multi-stakeholder action, reinforced by feedback mechanisms such as regional observatories.

5.5.1. Economic Potential and Competitiveness

The potential contribution of AI to manufacturing in Latin America is substantial, positioning the sector as a strategic arena for industrial modernization and economic diversification. Recent projections suggest that the regional AI market, valued at USD 4.71 billion in 2024, is expected to expand to USD 30.2 billion by 2033, with an annual growth rate of 22.9% [18]. In parallel, according to the UNDP, the aforementioned estimation that AI could add up to 5.4% to Latin America's GDP by 2030, equivalent to approximately USD 500 billion, although this potential remains significantly below the figure projected for North America (14.5%) [196,226].

For the manufacturing sector, these figures signal a dual opportunity: on one hand, to enhance productivity, quality assurance, and energy efficiency across industries such as automotive, aerospace, and food processing; and on the other, to foster resilience and sustainability in regional supply chains. Yet these opportunities will not be realized automatically. Structural barriers, including dependency on imported technologies, insufficient digital infrastructure, and limited financing for SMEs, continue to restrict the scaling of AI solutions [27,35,107,134,162,163]. Strategic alignment of industrial policies with AI adoption is therefore required to translate economic potential into broad-based competitiveness.

As previously highlighted by Gonzalez-Tamayo et al. [109], surveys of SMEs across Argentina, Costa Rica, Ecuador, Mexico, and Uruguay show that while there is growing commitment to digital transformation, such intention rarely translates into measurable outcomes without sufficient digital maturity and workforce training. In this section, we highlight how these findings underscore the importance of targeted policies and capacity-building programs, as SME readiness remains a crucial factor in the adoption of AI and Industry 4.0 solutions in the region. These findings suggest that the region's economic potential will remain underexploited unless investments in infrastructure are complemented by systematic capacity-building programs, ensuring that SMEs, the backbone of Latin American industry, can effectively scale AI applications from isolated pilots to systemic industrial upgrading.

Investing in HPC can significantly enhance the adoption of AI. For instance, Brazil's Santos Dumont and Mexico's ABACUS demonstrate how supercomputing can lead to significant breakthroughs in areas such as health, energy, and environmental solutions. Smaller countries could follow Uruguay's approach of collaboration, teaming up to share costs and strengthen their research capabilities. This way, they could speed up innovation across the region [192].

As highlighted in Section 3.3.2, concrete industrial experiences already demonstrate that AI is being applied to automation, predictive analytics, and AM across several countries. However, their economic impact remains marginal, as most initiatives are confined to pilot projects or small-scale implementations [107,108,110]. This creates tension between the macro-level potential projected by international organizations and the micro-level realities faced by firms, which are constrained by issues such as limited financing, inadequate skills, and inadequate infrastructure. Large corporations are better positioned to absorb the high capital intensity of AI adoption and thus capture benefits such as predictive maintenance, energy savings, and reduced scrap rates, while SMEs often struggle to move beyond experimental phases. Without tailored financial mechanisms, fiscal incentives, and workforce training, the region risks reinforcing structural inequalities rather than fostering inclusive competitiveness.

At the policy level, regional roadmaps identify manufacturing and agroindustry as priority areas for AI adoption, citing their potential to generate productivity spillovers and sustainable industrial upgrading [227]. Yet Latin America still lags behind Europe and Asia, where digital twins, smart factories, and integrated supply chains are already reshaping competitiveness [4,26,36,66,102,151,152,228]. This comparison highlights the urgency for governments in the region to move beyond experimentation and scale AI adoption through integrated industrial and digital strategies.

To close the gap in startup infrastructure, countries like Peru and Panama have strong digital capabilities but lack developed AI startup ecosystems. By aligning venture capital incentives with their existing strengths in connectivity and education, these nations can encourage growth and innovation [188].

It is essential to note that most macroeconomic estimates of AI's contribution to Latin American manufacturing are derived from market research reports and institutional publications [18,196], rather than peer-reviewed studies. By contrast, the academic literature has so far focused on micro-level analyses, documenting pilot projects and barriers in specific countries and firms [107,108,110]. This asymmetry highlights a significant research gap: while projections suggest the potential for AI to drive competitiveness and industrial upgrading, there remains limited empirical evidence on its measurable economic impact at the sectoral and regional levels. Addressing this gap through systematic, data-driven studies will be essential to evaluate whether AI adoption in manufacturing can deliver the promised gains in productivity, resilience, and global competitiveness.

These sources serve as illustrative evidence that contextualizes each of the Triadic Integration Framework pillars. For instance, IBM adoption statistics point to uneven levels of digital infrastructure, while Brazilian manufacturing cases highlight the interaction between industrial capacity and policy incentives. Their role in this review is to provide contextual grounding for the framework and to identify areas that future empirical studies should test more systematically.

Prioritizing affordability and equity is crucial in the digital landscape. Even in the most advanced countries, persistent gaps still exist in internet affordability and digital skills. It is essential for policymakers to focus on reducing costs and expanding digital education to foster inclusive growth and ensure equitable access to the benefits of AI for all individuals [189].

5.5.2. Employment, Skills, and SME Inclusion

While AI adoption in manufacturing offers significant gains in efficiency and competitiveness, its labor-market implications are complex. On one hand, automation of repetitive and routine tasks may displace workers in assembly lines and quality control, potentially intensifying the risks of job polarization already observed in industrial sectors. On the other hand, AI deployment generates new demand for roles in data engineering, robotics maintenance, predictive analytics, and supply chain optimization, creating opportunities for higher-skilled employment. The challenge for Latin America lies in whether education and training systems can adapt quickly enough to capture these opportunities while mitigating the risks of displacement. Some efforts have been made to incorporate AI into secondary and higher education levels in an effort to promote AI and ML-related competencies [229–231], as well as innovation and sustainability-related competencies [232–234].

SMEs, which represent the majority of manufacturing firms in the region, are particularly vulnerable. Limited access to financing, scarce digital infrastructure, and a shortage of skilled personnel restrict their ability to adopt AI solutions at scale [3,15–17]. Policy interventions should therefore prioritize human capital formation through modular training programs, dual education schemes, and partnerships between universities and industry. In parallel, governments could provide targeted tax incentives, credit guarantees, or digital extension services to support SME adoption of AI technologies. Without such mechanisms, the benefits of AI-driven manufacturing risk being concentrated in large firms, exacerbating structural inequalities within the industrial sector.

5.5.3. Sustainability and Circular Manufacturing

Beyond efficiency and productivity, AI integration in manufacturing has the potential to advance sustainability goals and support the transition toward circular production models. AI-driven process optimization can reduce energy consumption, minimize waste and scrap rates, and extend the lifespan of industrial equipment through predictive maintenance. In energy-intensive sectors such as metals, cement, and chemicals, these applications can significantly lower operational costs while contributing to national climate commitments. Such capabilities align directly with the principles of Industry 5.0, which emphasize resilience, human–machine collaboration, and environmental responsibility [60].

However, Latin American manufacturers have only begun to explore these sustainability-oriented applications. Most studies emphasize productivity and process optimization, while evidence directly linking AI adoption to sustainability outcomes such as waste reduction or emissions mitigation remains scarce. This gap reinforces the need for future research to align AI adoption with broader environmental objectives.

In most cases, the adoption of AI is concentrated in functions tied to productivity and cost reduction rather than environmental performance. To accelerate progress, governments and industry associations could define a baseline set of sustainability indicators, including energy intensity (kWh per unit produced), first-pass yield, and emissions per unit, specifically for AI-enabled manufacturing processes. By co-funding pilot projects and establishing benchmarking cohorts that allow firms to compare performance anonymously, policymakers can encourage the diffusion of green AI practices without compromising competitiveness. These measures would position AI not only as a driver of industrial modernization but also as a catalyst for advancing the region's commitments to sustainable development.

5.5.4. Governance, Digital Infrastructure, and Security

In today's digital landscape, Mexico and Brazil stand out as leaders in providing secure and efficient digital public services. However, many other countries are struggling to keep pace with these advancements. Developing robust digital government platforms is crucial for fostering public trust, attracting investment, and promoting the widespread adoption of artificial intelligence. For nations lagging behind, the challenge lies in overcoming these barriers to create a more effective and trustworthy digital infrastructure [189].

5.5.5. Political Tariffs and the Impact of AI Implementation in Manufacturing

The global manufacturing sector is increasingly shaped not only by technological transformations but also by shifts in international trade policies, including the imposition of new tariffs and trade barriers. These political measures intersect with the adoption of AI in manufacturing, creating both constraints and opportunities for industries in Latin America [235]. The introduction of new tariffs on imported machinery, electronic components, and digital technologies can increase the cost of acquiring AI-related infrastructure. For many manufacturers, particularly SMEs, this may slow down the integration of AI tools, such as robotics, sensors, and data-processing systems. Furthermore, tariffs on cloud computing services, semiconductors, or specialized hardware can limit access to the technological backbone required for AI deployment.

Conversely, AI technologies can serve to mitigate the negative effects of tariffs by enhancing operational efficiency and reducing dependency on imported inputs. For instance, AI-driven predictive maintenance and process optimization can lower production costs, offsetting the financial burden imposed by tariffs. Additionally, AI can help manufacturers identify alternative suppliers, optimize logistics routes, and redesign supply chains to reduce exposure to tariff-sensitive markets [236]. As trade disputes and tariff policies reshape global value chains, AI-enabled manufacturing provides opportunities for nearshoring and regional integration. Latin American countries, leveraging AI to enhance productivity, could become attractive alternatives for supply chain relocation. However, disparities in digital infrastructure and investment capacity across the region may exacerbate inequalities between countries that can adopt AI quickly and those that cannot [237]. The interaction between tariffs and AI adoption underscores the need for comprehensive industrial and trade policies. Governments must strike a balance between protective tariffs that support local industries and policies that encourage technological modernization. Incentives for AI adoption, subsidies for digital infrastructure, and international cooperation frameworks can help ensure that tariff policies do not unintentionally hinder innovation and competitiveness in the manufacturing sector. International Positioning and Comparative Perspective.

When viewed against other emerging regions, Latin America's progress in applying AI to manufacturing remains uneven and comparatively slow. For example, countries in Asia, such as India and China, have scaled AI-enabled predictive maintenance, digital twins, and smart supply chain management at a faster pace, supported by stronger industrial policies and greater investment in digital infrastructure. Similarly, some African economies, while smaller in scale, have developed regional centers of excellence to support SME digital transformation. This comparative lag highlights both the urgency and the opportunity for Latin America to define its own specialization niches rather than pursuing broad imitation of advanced economies.

Strategic positioning could focus on sectors where the region already has comparative advantages, such as food processing, agro-industrial machinery, and resource-based industries like mining and metals. In these areas, AI can generate significant value by enhancing energy efficiency, improving traceability, and boosting export competitiveness. Regional collaboration mechanisms, such as the Digital Economy Partnership Agreement (DEPA) and initiatives supported by the ECLAC and the Inter-American Development Bank (IDB), can help harmonize standards, reduce compliance costs, and foster cross-border innovation. At the same time, policymakers should address the risk of excessive dependency on imported technologies by promoting vendor-neutral platforms, open data standards, and selective participation in global regulatory frameworks, for instance, the EU AI Act. Such measures would not only strengthen Latin America's international positioning but also ensure greater sovereignty in the governance of AI-driven manufacturing.

5.6. A Roadmap for Action: Prioritized Initiatives for Stakeholders

To translate the insights from this analysis into tangible progress, a coordinated effort across all sectors of society is essential. The recommendations within this roadmap are derived not only from the analytical findings of this review but are also aligned with strategic priorities identified in key regional policy frameworks, such as the PARLATINO model law on AI [146], and are informed by empirical studies on digital transformation challenges faced by Latin American SMEs [107,109]. The following roadmap outlines specific, actionable recommendations categorized by timeframe and primary responsible stakeholders. A summary of this integrated plan is presented in Table 4.

Table 4. Integrated Action Roadmap for AI Adoption in Latin American Manufacturing.

Timeframe	Strategic Initiative	Primary Stakeholders	Key Performance Indicators (KPI)
Short-Term (0–18 m)	Establish National AI in Manufacturing Task Forces	National Governments, Ministry Leads	A task force is formed, and an initial strategy draft is published within 12 months.
	Launch Modular Digital Literacy Certificates	Technical Universities, Industry Associations	# of workers certified; # of training programs launched.
	Create Regulatory Sandboxes for SMEs	Regulatory Agencies, Innovation Ministries	# of SMEs participating in sandbox pilots.

Table 4. *Cont.*

Timeframe	Strategic Initiative	Primary Stakeholders	Key Performance Indicators (KPI)
Medium-Term (2–4 y)	Fund Regional AI Innovation Hubs	National/State Governments, Universities	# of hubs operational; # of companies served.
	Implement Fiscal Incentive Programs	Finance Ministries, Development Banks	$ value of tax credits/loans issued; # of SMEs applying.
	Develop Regional Data Sharing Frameworks	Regional Bodies, Data Protection Authorities	Framework adopted by X number of countries.
Long-Term (5+ y)	Integrate AI into Core STEM Education	Ministries of Education, Universities	Revised curricula in place at X% of secondary and tertiary institutions.
	Achieve Regional Regulatory Harmonization	Regional Political Bodies, National Legislatures	Signing of a regional agreement on AI standards.
	Establish an AI in Manufacturing Observatory	Multilateral Organizations, Research Universities	Observatory launched and annual report published.

5.6.1. Short-Term Actions (0–18 Months): Laying the Foundation

a. Establish National AI in Manufacturing Task Forces:
- Action: Create public–private task forces with representatives from industry associations, leading universities, and relevant ministries, such as Economy, Science and Technology, Labor, or national equivalent.
- Responsible Stakeholders: National Governments, Ministry Leads.
- Goal: To diagnose sector-specific needs, identify quick-win projects, and draft national AI-in-manufacturing strategy documents.

b. Launch Modular Upskilling and Reskilling Certificates:
- Action: Develop and deploy short, focused certificate programs in data literacy, AI fundamentals for managers, and basic IoT maintenance for technicians.
- Responsible Stakeholders: Technical Universities & Vocational Schools, Industry Associations, to define curriculum needs accordingly.
- Goal: To quickly build a baseline of digital competence within the existing manufacturing workforce.

c. Create Regulatory “Sandboxes” for Manufacturing:
- Action: Implement controlled environments where SMEs can test AI solutions, for instance, AI for predictive maintenance or quality control, with temporary regulatory flexibility.
- Responsible Stakeholders: National Regulatory Agencies, Innovation Ministries.
- Goal: To reduce the risk of adoption of SMEs and generate real-world data to inform sensible, evidence-based regulations.

5.6.2. Medium-Term Actions (2–4 Years): Building Capacity and Scaling

a. Fund Regional AI Innovation Hubs:
- Action: Establish physical hubs centered around key manufacturing regions (e.g., automotive in Mexico, aerospace in Brazil). These hubs should provide shared access to computing power, technical expertise, and collaboration space.
- Responsible Stakeholders: National Governments (funding), State Governments (hosting), Universities (operating).
- Goal: To create centers of excellence that serve as a resource for local industries, particularly SMEs, lowering the barrier to entry for AI experimentation.

b. Implement Fiscal Incentive Programs:
- Action: Introduce tax credits or soft loans for manufacturing firms, especially SMEs, that invest in certified AI technologies or employee digital upskilling.
- Responsible Stakeholders: Ministry of Economy, Finance Ministries, Development Banks.

- Goal: To directly offset the high initial costs of adoption and make investing in human capital financially attractive for companies.

c. Develop Regional Data Sharing Frameworks:

- Action: Collaborate on regional standards for industrial data governance that ensure security and privacy while enabling anonymized data pooling for training more robust AI models.
- Responsible Stakeholders: Regional Bodies, for instance, Pacific Alliance, Mercosur, among others, Data Protection Authorities.
- Goal: To overcome the problem of "small data" that individual companies face, fostering innovation without compromising proprietary or personal information.

5.6.3. Long-Term Actions (5+ Years): Sustaining Transformation

a. Integrate AI and Advanced Digital Skills into Core Education:

- Action: Revamp national STEM curricula from secondary to postgraduate levels to fully integrate AI, machine learning, and robotics, with a focus on manufacturing applications.
- Responsible Stakeholders: Ministries of Education, Accrediting Bodies, Universities.
- Goal: To future-proof the talent pipeline and ensure a steady supply of graduates ready to contribute to an intelligent production ecosystem.

b. Achieve Regional Regulatory Harmonization:

- Action: Fully align national AI strategies and manufacturing regulations across key Latin American markets, building on initiatives like the PARLATINO model law.
- Responsible Stakeholders: Regional Political Bodies, National Legislatures.
- Goal: To create a unified regional market that reduces compliance complexity for multinational manufacturers and strengthens the global positioning of the Latin American industry.

c. Establish a Latin American Observatory for AI in Manufacturing:

- Action: Create a permanent, multinational institution to continuously monitor adoption metrics, evaluate policy impacts, disseminate best practices, and update this strategic roadmap.
- Responsible Stakeholders: Multilateral Organizations (e.g., Inter-American Development Bank, Economic Commission for Latin America and the Caribbean, among others), Consortia of Research Universities.
- Goal: To ensure the region's strategy remains adaptive, evidence-based, and responsive to the rapid pace of technological change.

This structured approach moves beyond abstract recommendations, providing a clear sequence of actions for stakeholders to champion. The success of this technological transformation will depend not on any single policy, but on the sustained and collaborative execution of this multifaceted roadmap (see Figure 6).

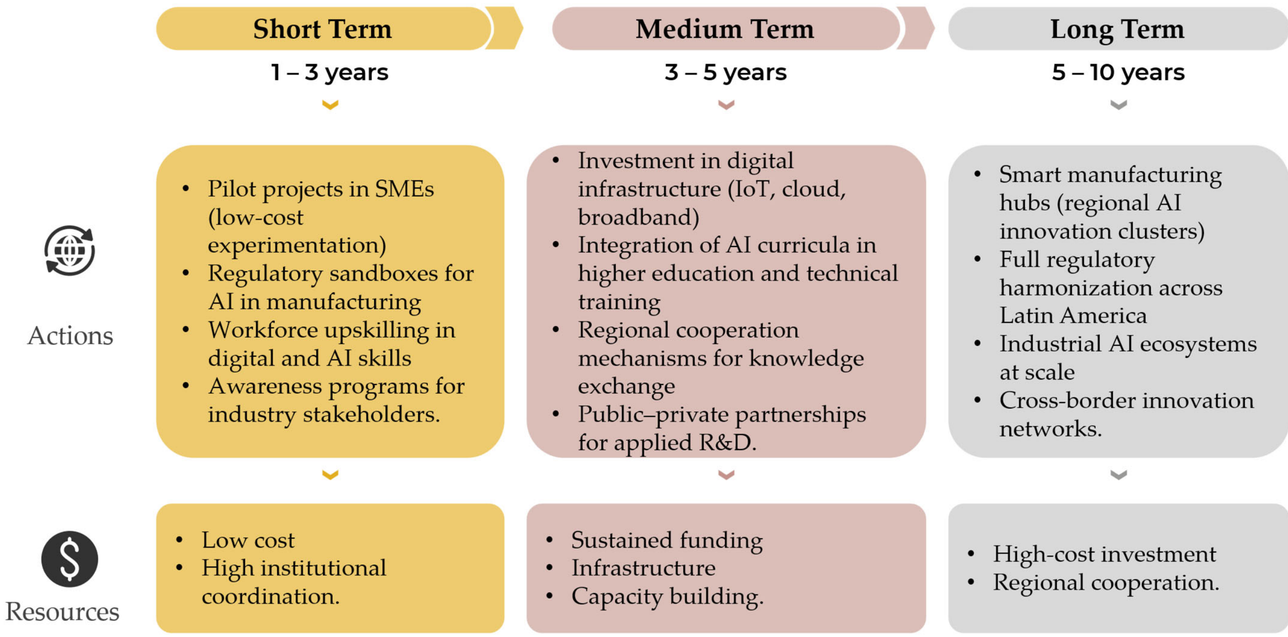

Figure 6. Phased roadmap for AI adoption in Latin American manufacturing: short-, medium-, and long-term actions with corresponding resource requirements.

6. Conclusions

This review was guided by a central research question: What structural conditions are required to enable the successful and sustainable integration of AI into Latin American manufacturing? To operationalize this inquiry, three sub-questions were derived from the Triadic Integration Framework, addressing policy and regulation, technical capabilities, and digital infrastructure.

Addressing these dimensions first required mapping the global landscape of AI applications across different manufacturing techniques. The evidence indicates that AI applications encompass a broad range of manufacturing processes, including additive, subtractive, and forming manufacturing techniques. In the context of AM, AI is increasingly used for topology optimization, process parameter prediction, and defect detection, among other applications, particularly through machine learning algorithms and convolutional neural networks. In subtractive manufacturing, AI enhances real-time monitoring and predictive maintenance by using technologies such as digital twins and sensor-based control. Forming processes benefit from AI-driven simulations and optimization models that reduce material waste and energy use. Across all techniques, the convergence of AI with Industry 4.0 and Industry 5.0 enablers, such as IoT, cloud computing, and edge AI, has accelerated innovation, but it also demands high levels of data integration, infrastructure, and skills that are unevenly distributed globally.

In relation to the Latin American context, the analysis reveals a fragmented and evolving policy landscape. While some countries, such as Brazil and Chile, have established national AI strategies, their alignment with industrial policy remains limited. Others, including Mexico and Panama, are still in the early stages of legislative development or participate in regional initiatives such as PARLATINO's model law. Regulatory initiatives in the region often emphasize ethical considerations and fundamental rights; however, they lack specific frameworks to guide the deployment of AI in industrial contexts, particularly in advanced manufacturing sectors.

Governance gaps are evident in key areas, including data protection, algorithmic transparency, and intellectual property. Algorithmic opacity in manufacturing applications may perpetuate biases and limit accountability in decision-making processes, while unresolved questions about intellectual property ownership in AI-generated design outputs pose legal uncertainties. From a socio-economic perspective, the risk of labor displacement due to automation remains high, particularly in low- and middle-income countries where reskilling policies and social protections are underdeveloped. Additionally, the digital divide continues to restrict equitable access to AI tools and benefits across typically marginalized communities.

Although AI holds significant potential to contribute to sustainable manufacturing, for instance, by reducing energy use and optimizing resource utilization, national strategies often lack robust mechanisms to integrate sustainability targets with digital transformation policies. Bridging this gap requires interdisciplinary approaches that align technical innovation with social inclusion and environmental responsibility.

Moreover, even if current coordination is limited, platforms such as MERCOSUR and the Latin American Parliament (Parlatino) offer institutional frameworks that could facilitate the regional alignment of AI adoption strategies in the manufacturing sector. Leveraging these institutions could help overcome fragmentation and foster collaborative governance.

In sum, the integration of AI into manufacturing in Latin America presents both opportunities and profound challenges. Regional efforts must prioritize regulatory harmonization, capacity-building, and inclusive governance. Strengthening public–private–academic partnerships and aligning national strategies with the Sustainable Development Goals (SDGs) will be essential for creating a future-ready, ethical, and equitable manufacturing ecosystem.

Furthermore, the review highlights that, despite increasing discourse on digital transformation, Latin America still lacks documented industrial-scale applications of AI in manufacturing. Most contributions remain at the level of strategies, surveys, and policy documents, which underline the early stage of development and the reliance on grey literature to capture the regional landscape. To address this gap, a Triadic Integration Framework was proposed, identifying three structural pillars: policy and regulation, technical capabilities, and digital infrastructure, which condition adoption. Building on this framework, a phased roadmap was outlined, detailing short-, medium-, and long-term actions and corresponding resource requirements, thereby transforming conceptual insights into actionable guidance. This integrated perspective ensures that the framework is not only analytical but also operational. Future research and policy initiatives should therefore prioritize generating empirical evidence of industrial implementations and strengthening monitoring systems, which remain critical to achieving sustained and inclusive AI adoption in the region's manufacturing sector.

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