

Article

Industry 4.0 Adoption in Large Manufacturing Companies: The Readiness–Adoption Gap in an Emerging Economy

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Abstract

Industry 4.0 is widely recognized as a strategic enabler of productivity, flexibility, and competitiveness in manufacturing systems. However, in emerging economies, declared preparedness for digital transformation often exceeds reported implementation. This study examines the readiness–adoption gap of Industry 4.0 in surveyed large manufacturing companies in Valle del Cauca, Colombia. An empirical cross-sectional study was conducted through a structured survey administered to large manufacturing companies in the region. The instrument was grounded in the Technology Acceptance Model and informed by a sociotechnical understanding of Industry 4.0 adoption. It captured perceptions of ICT infrastructure, workforce capabilities, expected benefits, implementation challenges, ease of use, and the reported implementation status of 20 Industry 4.0 technologies. Data from 59 valid responses were analyzed using descriptive statistical techniques, cross-technology comparisons, and an aggregate descriptive synthesis of readiness and adoption indicators. The findings suggest that adoption remains concentrated in foundational technologies such as cybersecurity, cloud computing, and data analytics, while advanced technologies, including artificial intelligence, cyber–physical systems, digital twins, and immersive technologies, show limited implementation despite favorable readiness perceptions. The aggregate synthesis points to a medium-to-high readiness proxy and a substantially lower average adoption level, suggesting the presence of a readiness–adoption gap. The study contributes empirical evidence from large manufacturing companies and derives two practical outputs: a readiness–adoption matrix and a staged roadmap for capability building and technology prioritization. These outputs are presented as context-specific exploratory tools rather than universally validated models.

Keywords: Industry 4.0; technology adoption; organizational readiness; readiness–adoption gap; large manufacturing companies; emerging economy



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1. Introduction

Technological change has historically shaped industrial development by transforming production systems, organizational structures, and competitive dynamics. Within this trajectory, Industry 4.0 (I4.0), originally promoted as part of the German strategic initiative for advanced manufacturing, has become a central reference for the digital transformation of industrial systems [1]. More broadly, Industry 4.0 is associated with the integration of cyber–physical systems, digital technologies, and intelligent automation across manufacturing value chains [2]. In this study, Industry 4.0 is understood not only as a technological paradigm but also as a sociotechnical transformation in which digital infrastructure, human capabilities, organizational routines, managerial decisions, and external constraints interact as part of a broader manufacturing system.

In manufacturing contexts, Industry 4.0 is closely associated with smart manufacturing and cyber–physical systems, where physical assets, computational systems, organizational processes, and human operators interact through real-time data exchange and decentralized decision-making [3]. Cyber–physical systems connect physical processes with computational and control architectures, enabling monitoring, coordination, and operational responsiveness [3,4]. Industry 4.0 is also supported by information and communication technologies that enable connectivity, data exchange, and digital integration [5]. Cloud computing and IoT technologies support scalable digital resources and real-time data capture from physical assets [6,7], while big data analytics strengthens data-driven decision-making in manufacturing environments [8]. Artificial intelligence and robotics expand the possibilities for intelligent control, automation, and adaptive production systems [9,10].

This technological base shows that Industry 4.0 adoption cannot be reduced to the isolated acquisition of digital tools. Successful implementation requires the coordinated integration of technologies, people, processes, and organizational capabilities. Design principles for Industry 4.0 emphasize interconnection, information transparency, decentralized decisions, and technical assistance [11]. Readiness-oriented approaches also indicate that firms require infrastructure, capabilities, managerial support, and organizational preparedness to exploit digital technologies effectively [12]. Thus, Industry 4.0 adoption should be analyzed as a sociotechnical process in which technological deployment and organizational readiness evolve together, but not necessarily at the same pace.

Despite its strategic relevance, Industry 4.0 adoption remains uneven across countries, sectors, and firm sizes. Firms face different drivers and barriers depending on their organizational scale, resources, and technological context [13,14]. In emerging economies, adoption is frequently constrained by implementation costs, readiness limitations, skills shortages, and difficulties in moving from intention to effective adoption [15]. Studies on readiness and maturity also indicate that favorable perceptions or maturity assessments do not necessarily imply deep implementation of Industry 4.0 technologies [16]. This distinction is central because perceived readiness and actual adoption are related but analytically different dimensions of digital transformation.

In Latin America, research has mainly examined adoption intention, readiness, maturity, and implementation challenges in small and medium-sized enterprises or multicountry organizational samples [17]. Cross-country evidence involving firms from Colombia and other Latin American economies suggests that adoption intention is relevant, but implementation remains conditioned by organizational, technological, and contextual factors [18]. Evidence from manufacturing firms in Argentina and Brazil also indicates that Industry 4.0 diffusion is uneven and influenced by firm size, capability development, and implementation conditions [19]. Studies focused on production and engineering capabilities in Brazil further highlight the importance of workforce preparation for digital transformation [20]. However, large manufacturing companies remain comparatively underexplored, despite

their relevance for industrial output, employment generation, technological diffusion, and regional competitiveness.

A key research gap therefore remains regarding the relationship between perceived organizational readiness and actual technology implementation in large manufacturing companies operating in emerging economy contexts. This gap is relevant because a company may report favorable perceptions regarding Industry 4.0, adequate ICT infrastructure, or positive expectations about digital transformation, while still showing limited implementation depth in advanced, systemic, or emerging technologies. In this study, this possible misalignment is conceptualized as the readiness–adoption gap.

Accordingly, the study addresses the following research questions:

- (RQ1) To what extent have the surveyed large manufacturing companies adopted Industry 4.0 technologies?
- (RQ2) Which Industry 4.0 technology categories exhibit the highest and lowest levels of current adoption, ongoing implementation, and future adoption intention among the surveyed companies?
- (RQ3) How do the surveyed large manufacturing companies perceive their organizational readiness for Industry 4.0 in terms of ICT infrastructure, employee capabilities, expected benefits, implementation challenges, and ease of use?
- (RQ4) To what extent does perceived organizational readiness align with reported adoption levels, and what readiness–adoption gap emerges from this relationship within the surveyed sample?

Based on these research questions, the main objective of this study is to examine the readiness–adoption gap of Industry 4.0 technologies in surveyed large manufacturing companies in Valle del Cauca, Colombia, by comparing perceived organizational readiness with reported implementation levels across 20 Industry 4.0 technologies.

The contribution of this study is fourfold. First, it provides empirical evidence from surveyed large manufacturing companies in Valle del Cauca. Second, it contrasts perceived organizational readiness with reported implementation levels across a broad set of Industry 4.0 technologies. Third, it offers an exploratory interpretation of the readiness–adoption gap. Fourth, it derives two practical outputs from the empirical findings: a readiness–adoption matrix and a staged roadmap to support capability building and technology prioritization. These outputs are presented as context-specific exploratory tools rather than universally validated models.

The remainder of this article is organized as follows. Section 2 presents the literature review on Industry 4.0 adoption, sociotechnical manufacturing transformation, and empirical evidence from Latin America and Colombia. Section 3 develops the conceptual framework that links technology acceptance, organizational readiness, implementation barriers, actual adoption, and the readiness–adoption gap. Section 4 presents the methodology and data collection process. Section 5 reports the empirical findings. Section 6 discusses the results in light of prior research and their practical implications. Finally, Section 7 concludes with the main findings, limitations, and directions for future research.

2. Literature Review

This section reviews the literature relevant to the analysis of Industry 4.0 adoption in large manufacturing companies. It focuses on two complementary dimensions. First, it examines Industry 4.0 adoption as a sociotechnical manufacturing process in which digital technologies, organizational capabilities, human resources, and operational routines interact. Second, it discusses empirical evidence on Industry 4.0 diffusion in Latin America and Colombia, with particular attention to adoption patterns, readiness conditions, implementation barriers, and the research gap addressed in this study.

2.1. Industry 4.0 Adoption as a Sociotechnical Manufacturing Process

Industry 4.0 adoption requires more than the incorporation of isolated digital technologies. In manufacturing contexts, it involves the transformation of production systems, information flows, decision-making routines, human–technology interaction, and organizational coordination. From this perspective, Industry 4.0 can be interpreted as a sociotechnical manufacturing process in which technological infrastructure and organizational capabilities must evolve together [21]. This systems-oriented interpretation is relevant because the effectiveness of digital transformation depends not only on what technologies are available, but also on how firms coordinate data, people, processes, and managerial decisions around those technologies.

Smart manufacturing studies emphasize that digital transformation depends on the integration of sensing, connectivity, analytics, automation, and feedback mechanisms across production environments [22]. These elements allow firms to move from isolated technological solutions toward more integrated manufacturing architectures. However, integration also increases organizational complexity because companies must align operational processes, information systems, workforce capabilities, and managerial priorities. Therefore, Industry 4.0 adoption should be analyzed as an organizational and operational transformation, not merely as a technological investment.

The implementation of Industry 4.0 also requires technological complementarities. Cloud-based services, cybersecurity solutions, and data analytics may operate as foundational enablers, while cyber–physical systems, digital twins, artificial intelligence, immersive technologies, and additive manufacturing usually require higher levels of interoperability, process standardization, specialized skills, and organizational coordination [23]. Digital transformation therefore advances through differentiated adoption trajectories, where some technologies are incorporated earlier as enabling infrastructure and others require more mature organizational and technical conditions [24]. This distinction helps explain why firms may report a favorable orientation toward Industry 4.0 while still lacking the internal conditions required to implement more complex technologies at scale.

Accordingly, readiness and adoption should not be treated as equivalent concepts. Readiness describes the organizational perception or condition of being prepared for digital transformation, whereas adoption refers to the reported implementation and use of specific technologies. The distance between these two dimensions constitutes the conceptual basis of the readiness–adoption gap examined in this study.

2.2. Industry 4.0 in Colombia and Latin America: Empirical Evidence and Research Gap

Empirical evidence from Latin America suggests that Industry 4.0 diffusion remains uneven and context-dependent. Studies focused on manufacturing firms in the region show that digital transformation is shaped by firm size, technological capabilities, organizational adaptation, and sectoral conditions [18,19]. This distinction matters because firms may recognize the importance of Industry 4.0 but still advance gradually, beginning with foundational technologies before moving toward more complex and integrated solutions.

Country-specific evidence also supports this interpretation. In Chile, the adoption and diffusion of Industry 4.0 technologies have been associated with firms' innovation trajectories and scale of operation [25]. In Peru, evidence from manufacturing MSMEs indicates that implementation is affected by technological, organizational, and contextual conditions [26]. Broader evidence also suggests that innovation research in Latin America remains unevenly developed and fragmented across countries and sectors [27]. These studies suggest that Industry 4.0 adoption in Latin America should not be interpreted as a homogeneous regional transition, but as a process mediated by local industrial structures, firm capabilities, and implementation constraints.

Brazilian evidence further highlights the importance of workforce competencies, organizational culture, and the alignment between professional capabilities and Industry 4.0 technologies [28,29]. Complementary literature also shows that Industry 4.0 adoption may require changes in business models and value creation mechanisms, not only the incorporation of isolated technologies [30]. These findings are relevant for large manufacturing firms because greater scale does not necessarily eliminate implementation complexity; instead, it may increase coordination demands across legacy systems, multiple operational areas, heterogeneous infrastructures, and different levels of decision-making.

Colombia represents a relevant empirical context for examining this process because the country combines growing interest in digital transformation with persistent challenges related to technological capabilities, skills development, and organizational adaptation. Previous research involving Colombian or comparable Latin American firms has mainly examined readiness, adoption intention, maturity, or implementation barriers, especially in SMEs and multicountry organizational samples [17,18]. Although these studies provide valuable evidence, there is still limited empirical understanding of how perceived readiness aligns with actual technology implementation among large manufacturing companies.

Regional studies on innovation and digital transformation suggest that firms' capacity to adopt advanced technologies depends on their ability to connect internal capabilities with external ecosystems, knowledge networks, open innovation mechanisms, and institutional support [31,32]. Therefore, the readiness–adoption gap may persist even in firms that appear better positioned to adopt Industry 4.0 technologies.

Another limitation in the regional literature is that several studies emphasize readiness, intention, or maturity, while providing less evidence on the reported implementation status of specific technologies and data-driven capabilities [16,18,33]. This reduces the ability to determine whether favorable perceptions toward Industry 4.0 are translated into concrete technological deployment. Addressing this limitation requires comparing readiness-related dimensions with reported implementation levels across a broad set of technologies.

Based on this literature, the present study adopts a readiness–adoption perspective to examine Industry 4.0 diffusion in surveyed large manufacturing companies in Valle del Cauca, Colombia. This perspective assumes that perceived organizational readiness and actual adoption are related but analytically distinct dimensions of digital transformation. The study does not treat readiness as a direct causal predictor of adoption; instead, it examines whether perceived readiness is aligned with reported implementation depth. This position supports the exploratory nature of the study and provides the conceptual basis for the readiness–adoption matrix and staged roadmap proposed later in the article.

3. Conceptual Framework

This section presents the conceptual framework used to analyze the readiness–adoption gap in Industry 4.0. It articulates technology acceptance, organizational readiness, implementation barriers, actual adoption, and the readiness–adoption gap as the main analytical elements guiding the comparison between perceived preparedness and reported implementation levels.

Technology Acceptance, Organizational Readiness, and Actual Adoption

The Technology Acceptance Model provides a useful starting point for understanding the perceptual component of digital transformation. TAM explains technology acceptance through constructs such as perceived usefulness, perceived ease of use, and attitudes toward technology [34]. In the context of Industry 4.0, these constructs help interpret why managers and technical personnel may perceive digital technologies as strategically valuable, operationally beneficial, or compatible with organizational expectations.

However, technology acceptance does not automatically imply organizational adoption. In manufacturing firms, the implementation of Industry 4.0 technologies depends on additional conditions, including infrastructure, investment capacity, digital skills, process maturity, interoperability, data governance, and managerial coordination [35]. Therefore, TAM is useful for explaining favorable perceptions toward technology, but it must be complemented with an organizational readiness perspective to understand whether those perceptions can be converted into reported implementation.

Organizational readiness studies highlight the importance of evaluating whether firms have the resources, capabilities, structures, and managerial conditions needed to adopt and use digital technologies effectively [12]. In Industry 4.0, readiness may involve ICT infrastructure, workforce capabilities, perceived benefits, expected productivity gains, ease of use, and perceived implementation challenges. These dimensions do not prove adoption by themselves; rather, they indicate whether firms perceive that they have favorable conditions for digital transformation.

Actual adoption, by contrast, refers to the implementation status of specific Industry 4.0 technologies. This distinction is important because a company may report high readiness in terms of expectations, infrastructure, or perceived benefits while still showing low implementation depth in advanced technologies. Consequently, comparing readiness dimensions with reported adoption levels provides a more precise analytical approach than evaluating readiness or adoption separately.

Implementation barriers further explain why readiness may not become adoption. Technological barriers are commonly related to interoperability problems, data integration limitations, cybersecurity requirements, and the complexity of connecting legacy systems with new digital platforms [23]. Economic barriers include high implementation costs, uncertainty about return on investment, and difficulties in scaling pilot projects into stable operational solutions [14,15]. Organizational barriers involve resistance to change, weak digital culture, limited managerial alignment, and shortages of specialized talent [13]. In addition, broader Industry 4.0 studies show that implementation is also influenced by innovation dynamics, operational practices, and capability alignment [31,36]. These barriers show that the transition from readiness to adoption is neither automatic nor linear.

In this study, the readiness–adoption gap is therefore interpreted as an exploratory construct that captures the misalignment between perceived organizational preparedness and reported implementation depth. This interpretation is consistent with the empirical scope of the article, which does not seek to test causal relationships, but rather to identify patterns, asymmetries, and gaps in Industry 4.0 adoption among surveyed large manufacturing companies.

Table 1 presents the conceptual framework adopted in this study by articulating the relationship between technology acceptance, organizational readiness, implementation barriers, actual adoption, and the readiness–adoption gap. The framework is presented as an author’s synthesis based on the cited literature, rather than as a direct reproduction of a previous model.

Table 1. Conceptual framework for the readiness–adoption gap in Industry 4.0.

Conceptual Element	Role in the Study	Interpretation for Industry 4.0 Adoption	Basis
Technology Acceptance Model	Perceptual foundation	Explains favorable perceptions toward technology, particularly perceived usefulness, perceived ease of use, and attitudes toward digital transformation.	[34]

Table 1. *Cont.*

Conceptual Element	Role in the Study	Interpretation for Industry 4.0 Adoption	Basis
Organizational readiness	Preparedness dimension	Captures whether firms perceive that they have ICT infrastructure, employee capabilities, expected benefits, and organizational conditions to support Industry 4.0.	[12,14]
Implementation barriers	Constraint dimension	Explains why favorable readiness may not become reported implementation, due to costs, skills shortages, integration problems, time requirements, or resistance to change.	[14,15]
Actual adoption	Implementation dimension	Refers to the reported operational use or implementation status of specific Industry 4.0 technologies.	[16,18]
Readiness–adoption gap	Analytical focus	Represents the misalignment between positive readiness perceptions and lower implementation depth, especially in advanced, systemic, or emerging technologies.	[12,16]

Note: The table was developed by the authors as a conceptual synthesis from the cited literature.

4. Methodology

This section describes the research design, bibliographic review strategy, sampling procedure, research instrument, Industry 4.0 technologies considered, and data analysis strategy. The study combined a structured bibliographic review with a quantitative, descriptive, and exploratory assessment of Industry 4.0 adoption among large manufacturing companies. The bibliographic review supported the literature review, the conceptual framework, the selection of Industry 4.0 technologies, and the design of the empirical instrument. The empirical component supported the analysis of the readiness–adoption gap based on cross-sectional and self-reported evidence.

4.1. Research Design and Approach

This study adopted a quantitative, descriptive, exploratory, and cross-sectional design to examine Industry 4.0 adoption among large manufacturing companies located in Valle del Cauca, Colombia. The descriptive component characterized current adoption levels, technology categories, implementation in progress, and future adoption intentions. The exploratory component examined perceived organizational readiness and its alignment with reported implementation levels.

Given the use of self-reported organizational data and one key informant per company, the study does not aim to establish causal relationships. Instead, it identifies empirical patterns, asymmetries, exploratory associations, and readiness–adoption gaps.

Figure 1 presents the methodological workflow of the study. It summarizes the sequence followed from the bibliographic review and instrument design to data collection, empirical analysis, and development of the readiness–adoption matrix and staged roadmap.

4.2. Bibliographic Review Strategy

A structured bibliographic review was conducted to support the conceptual framework, the identification of Industry 4.0 technologies, and the design of the empirical instrument. The review was not intended as a systematic review, meta-analysis, or formal bibliometric study, but as a focused analytical review of conceptual foundations, methodological approaches, readiness dimensions, adoption barriers, technology categories, and empirical gaps.

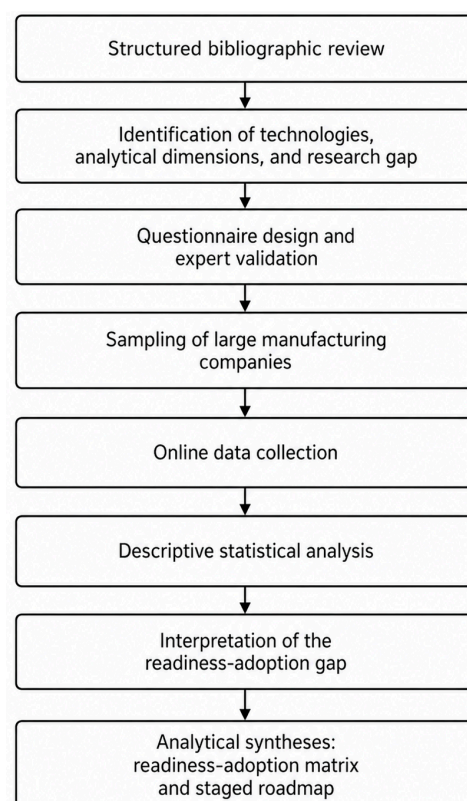


Figure 1. Methodological workflow of the study.

The search was conducted in Scopus because of its broad coverage of peer-reviewed literature in engineering, management, manufacturing, information systems, and technology-related fields. Web of Science was not included because the purpose was not to compare databases, but to construct a focused conceptual and empirical basis for the survey and research gap. This decision is treated as a methodological delimitation.

The primary search covered publications from 2014 to 2024. In addition, selected 2025–2026 references were incorporated during the revision stage when they provided directly relevant conceptual, empirical, or technological support for Industry 4.0 adoption, smart manufacturing, and immersive technologies. The review considered journal articles, review papers, conference papers, and book chapters when they were directly relevant to Industry 4.0 adoption, readiness, maturity, or implementation barriers.

The search used titles, abstracts, and keywords. The search terms combined Industry 4.0-related expressions with adoption, readiness, maturity, manufacturing, implementation barriers, and Latin American or country-specific terms. A representative Scopus query was:

TITLE-ABS-KEY ("Industry 4.0" OR "Fourth Industrial Revolution" OR "smart manufacturing" OR "digital transformation") AND TITLE-ABS-KEY ("adoption" OR "readiness" OR "maturity" OR "implementation" OR "barriers") AND TITLE-ABS-KEY ("manufacturing" OR "industrial firms") AND TITLE-ABS-KEY ("Latin America" OR "Colombia" OR "Brazil" OR "Argentina" OR "Chile" OR "Peru" OR "Ecuador" OR "Mexico").

The search strategy also included complementary country-specific queries to identify regional evidence. These queries combined Industry 4.0-related terms with country names and adoption-related concepts, including "Industry 4.0", "Fourth Industrial Revolution", "smart manufacturing", "digital transformation", "adoption", "readiness", "maturity", "implementation", "barriers", "manufacturing", "Latin America", "Colombia", "Brazil", "Argentina", "Chile", "Peru", "Ecuador", and "Mexico".

Although the review was not designed as a systematic review, the selection process was organized and reported using a PRISMA-informed logic [36], understood here

as a transparent organization of the identification, screening, eligibility assessment, exclusion, and final inclusion stages, without claiming full compliance with a systematic review protocol.

Documents were retained when they were directly relevant to Industry 4.0 adoption, readiness, maturity, implementation barriers, manufacturing firms, industrial digital transformation, or organizational technology adoption. They also had to contribute to at least one component of the study: the conceptual framework, the identification and classification of Industry 4.0 technologies, the questionnaire design, or the interpretation of the readiness–adoption gap. Documents were excluded when they were unrelated to the study topic, outside the industrial or organizational context, duplicated, insufficiently related to the research questions, or not useful for the conceptual, methodological, or empirical development of the article.

The retrieved documents were coded by country or regional scope, thematic focus, methodological relevance, duplicate status, and contribution to the article. The main coding categories were Industry 4.0 adoption, organizational readiness, maturity models, implementation barriers, manufacturing technologies, Latin American evidence, and technology-specific definitions. Bibliographic data were verified using title, authorship, year, source, abstract, keywords, and DOI when available. Full texts were used whenever accessible; when full texts were not available, records were retained only if the title, abstract, keywords, and bibliographic information were sufficient to assess relevance.

Table 2 was created by aggregating the identification and screening results by country. The “records identified” column reports the initial records retrieved through the Scopus search strategy and complementary country-specific searches. The exclusion columns distinguish between records removed because of irrelevance and records removed as duplicates. The “final records” column reports the documents retained to support the conceptual framework, technology selection, instrument design, and identification of the empirical research gap.

Table 2. Document selection process for Latin American countries.

Country	Records Identified	Excluded (Irrelevant)	Excluded (Duplicates)	Final Records
Chile	8	3	0	5
Colombia	19	4	0	15
Mexico	29	6	2	21
Argentina	6	1	2	3
Brazil	130	14	7	109
Ecuador	7	3	3	1
Peru	9	2	1	6
Venezuela	3	2	0	1
Other	3	0	0	3
Total	214	35	15	164

4.3. Sample and Data Collection

The empirical component was based on a population of 137 large manufacturing companies located in Valle del Cauca and identified through the EMIS database in 2024. Companies were classified as large according to the Colombian business-size classification in force, which defines firm size based on annual operating revenues by economic sector. For the manufacturing sector, large companies are those whose annual operating revenues exceed the upper threshold established for medium-sized firms [37].

The sampling frame was constructed from EMIS records by filtering companies located in Valle del Cauca, classified within manufacturing activities, and meeting the large-company criterion according to the Colombian business-size classification based on annual

operating revenues by economic sector. After applying these filters, the final sampling frame consisted of 137 eligible companies. Each company in this frame was assigned a unique identification code. A simple random sampling procedure was then applied using a computer-generated random sequence from the list of eligible firms, so that each company in the defined population had the same probability of selection.

The minimum sample size was calculated for a finite population of 137 companies, with a 95% confidence level, maximum variability assumption, and a maximum sampling error of 10%. Under these assumptions, the minimum required sample size was 57 companies. The 10% maximum sampling error was adopted because the study has a bounded regional, descriptive, and exploratory scope. The objective was not to produce national-level estimates or causal inference, but to identify adoption patterns, asymmetries, and readiness–adoption gaps within a defined regional population. This value is therefore interpreted as a maximum sampling error under finite-population assumptions and is acknowledged as a methodological limitation.

A total of 59 valid questionnaires were obtained, slightly exceeding the minimum threshold. The final dataset covered 43.1% of the defined population. This value is therefore reported as population coverage rather than as a conventional response rate because complete fieldwork traceability on the exact number of companies that effectively received the questionnaire was not available. This limitation is considered when interpreting the scope and generalizability of the findings.

The unit of analysis was the company, and data were provided by one key organizational informant per company. Respondents were personnel involved in ICT, digital transformation, production management, or Industry 4.0-related activities. To reduce uninformed responses, participants confirmed their organizational role and familiarity with these areas. Data-quality controls included completeness, duplicate response checking, consistency screening, and verification of the respondent profile.

The use of one key informant per company introduces a possible single-informant bias. This risk was mitigated by targeting knowledgeable respondents, providing operational definitions of each technology, and avoiding causal claims. Non-response bias was considered by comparing available characteristics of participating companies with the defined population whenever information was available in EMIS.

Table 3 presents the sample and data collection summary. It specifies the population, sampling frame, sampling parameters, valid responses, population coverage, respondent profile, and methodological precautions used to interpret the data.

Table 3. Sample and data collection summary.

Item	Value
Target population	137 large manufacturing companies
Sampling frame	EMIS database, Valle del Cauca, manufacturing sector, 2024
Firm-size criterion	Colombian business-size classification based on annual operating revenues by sector
Sampling technique	Simple random sampling
Confidence level	95%
Maximum sampling error	10% under finite population assumptions
Minimum required sample size	57 companies
Valid responses	59 questionnaires

Table 3. *Cont.*

Item	Value
Population coverage	43.1% of the defined population
Unit of analysis	Company
Source of information	One key informant per company
Data collection mode	Structured online questionnaire
Respondent profile	ICT/digital transformation/production management/Industry 4.0-related personnel
Data-quality controls	Completeness, duplicate responses, consistency, and informant-profile verification
Main methodological precautions	Single-informant bias, self-reported data, non-response bias, and cross-sectional design are considered in interpretation

4.4. Research Instrument

The research instrument was partially adapted from the Industry 4.0 adoption model proposed by Masood and Sonntag [14] and conceptually grounded in the Technology Acceptance Model [34]. The questionnaire captured two analytical planes: perceived organizational readiness and actual adoption of Industry 4.0 technologies.

The instrument included five analytical dimensions: contextual conditions, ICT use, attitudes toward Industry 4.0 technologies, perceived benefits and challenges, and perceptions of productivity and ease of use. Together, these dimensions comprised 30 variables, mainly measured through a five-point Likert scale. The questionnaire also included items on the implementation status of 20 Industry 4.0 technologies, allowing perceptual evidence to be contrasted with reported adoption.

Content validity was assessed through expert judgment involving 12 academic and industry specialists in ICT, Industry 4.0, manufacturing systems, digital transformation, or industrial management. Their feedback supported revisions to wording, clarity, relevance, technical precision, and usability. Operational definitions of the 20 technologies were also included to reduce ambiguity and improve response consistency.

The instrument was reviewed through expert judgment to assess content validity, clarity, relevance, and technical precision. Because the empirical analysis focused on aggregated descriptive indicators and combined perceptual Likert-scale items with categorical implementation-status items, reliability coefficients are not interpreted as the main validation criterion of the instrument.

Table 4 presents the structure of the instrument. It links each questionnaire component with its analytical role and the research questions it supports.

Table 4. Instrument structure and analytical use.

Instrument Component	Main Role in the Study	Related RQs
Contextual conditions	Organizational setting	RQ3, RQ4
ICT use	Infrastructure and digital base	RQ3, RQ4
Attitudes toward I4.0	Perceptions and disposition	RQ3, RQ4
Perceived benefits and challenges	Expected value and barriers	RQ3, RQ4
Productivity and ease of use	Perceived operational effect	RQ3, RQ4
Implementation status of 20 technologies	Actual adoption	RQ1, RQ2, RQ4

Table 5 summarizes the instrument validation and data-quality control procedures applied in the study.

Table 5. Instrument validation and data-quality control procedures.

Validation or Control Component	Procedure Applied	Purpose in the Study
Expert judgment	Review by 12 academic and industry specialists in ICT, Industry 4.0, manufacturing systems, digital transformation, or industrial management	Assess content validity, clarity, relevance, technical precision, and usability
Operational definitions	Concise definitions of the 20 Industry 4.0 technologies were provided to respondents	Reduce ambiguity and improve response consistency
Respondent-profile verification	Respondents confirmed their organizational role and familiarity with ICT, digital transformation, production management, or Industry 4.0-related activities	Reduce uninformed responses
Completeness control	Questionnaires were reviewed for completeness before inclusion in the final dataset	Exclude incomplete or unusable responses
Duplicate-response checking	Responses were screened to identify possible duplicate submissions	Preserve one valid response per company
Consistency screening	Responses were reviewed for internal coherence across adoption and readiness items	Improve data quality and reduce inconsistent records
Interpretation precaution	The analysis was based on aggregated descriptive indicators rather than individual-level inferential modeling	Avoid causal overinterpretation of self-reported and cross-sectional data

4.5. Industry 4.0 Technologies Considered

Based on the bibliographic review, the survey incorporated 20 representative Industry 4.0 technologies relevant to manufacturing contexts. These technologies covered foundational digital infrastructure, connectivity, data-driven systems, automation, advanced integration technologies, systemic technologies, and emerging digital infrastructures.

The technologies were categorized according to their function and degree of sophistication within the digital transformation process. This classification supports the analysis of adoption depth across technology groups and provides the empirical basis for the readiness–adoption matrix and staged roadmap.

Table 6 presents the 20 technologies included in the survey. For each technology, it reports the analytical category, purpose in the study, operational definition provided to respondents, and supporting literature. To avoid excessive citation clustering, one or two directly relevant sources were retained for most technologies.

Table 6. Industry 4.0 technologies included in the survey.

Technology	Category	Analytical Purpose in the Study	Operational Definition Provided to Respondents	Source(s)
Cybersecurity	Foundational digital infrastructure	Baseline adoption indicator	Measures, practices, and technologies used to protect information systems from cyber threats and unauthorized access.	[38]
Cloud Computing	Foundational digital infrastructure	Baseline adoption indicator	On-demand access to computing resources such as storage, data processing, and software without local infrastructure.	[7]

Table 6. Cont.

Technology	Category	Analytical Purpose in the Study	Operational Definition Provided to Respondents	Source(s)
ERP/CRM/SCM Systems	Enterprise digital systems	Operational digital maturity indicator	Integrated systems used to manage organizational resources, customer relations, and supply chain processes.	[39]
Internet of Things and RFID	Connectivity technologies	Intermediate adoption indicator	Network of physical objects equipped with sensors and connectivity to collect and exchange data in real time.	[6]
Industrial Internet of Things	Industrial connectivity technologies	Intermediate adoption indicator	Networked industrial assets and cyber-physical components enabling real-time monitoring and control of industrial processes.	[40]
Big Data and Data Analytics	Data-driven technologies	Intermediate adoption indicator	Techniques and tools for analyzing large and complex datasets to identify patterns, trends, and relationships for decision-making.	[8,33]
Automation and Robotics	Automation technologies	Intermediate adoption indicator	Technologies enabling automated and autonomous execution of manufacturing tasks through robotic systems.	[10]
Embedded Systems	Control systems	Intermediate adoption indicator	Dedicated computer systems embedded within machines to perform specific real-time control functions.	[41]
Artificial Intelligence	Advanced digital intelligence	Advanced adoption indicator	Systems capable of simulating human intelligence to learn, reason, and perform tasks autonomously.	[9]
Machine Learning	Advanced digital intelligence	Advanced adoption indicator	Algorithms that allow systems to learn from data and improve performance without explicit programming.	[42]
Cyber-Physical Systems	Advanced integration technologies	Advanced adoption indicator	Integrated systems combining physical processes and computational elements to monitor, control, and optimize operations in real time.	[3,4]
Digital Twins	Advanced simulation technologies	Advanced adoption indicator	Virtual replicas of physical systems or processes used for simulation, monitoring, and optimization.	[43]
Modeling and Simulation	Simulation technologies	Advanced adoption indicator	Techniques that replicate the behavior of systems under specific conditions to support analysis and decision-making.	[44]
Additive Manufacturing	Advanced manufacturing technologies	Advanced adoption indicator	Production of three-dimensional objects by adding material layer by layer based on digital models.	[45]

Table 6. *Cont.*

Technology	Category	Analytical Purpose in the Study	Operational Definition Provided to Respondents	Source(s)
Augmented Reality	Visualization technologies	Advanced adoption indicator	Technology that overlays digital elements onto the real world in real time through visual devices.	[46]
Virtual Reality	Visualization technologies	Advanced adoption indicator	Immersive digital environments that simulate interactive three-dimensional experiences.	[47,48]
Smart Manufacturing	System-level integration	Systemic adoption indicator	Integration of digital and intelligent technologies across manufacturing processes to enhance efficiency and flexibility.	[22]
Smart Product	Product-level digitalization	Systemic adoption indicator	Products embedded with digital technologies that enable connectivity, data exchange, and advanced functionalities.	[49]
Blockchain	Data governance technologies	Emerging adoption indicator	Distributed ledger technology enabling secure and transparent recording of transactions without intermediaries.	[50]
5G Communication Systems	Enabling communication infrastructure	Emerging adoption indicator	Fifth-generation cellular networks providing high-speed, low-latency connectivity for industrial applications.	[51]

4.6. Data Analysis Strategy

The empirical analysis followed a descriptive, comparative, and exploratory strategy. Frequencies, percentages, comparative distributions, cross-technology comparisons, and exploratory association measures were used to characterize adoption patterns and examine the readiness–adoption gap.

The analysis was organized in five stages. First, company and respondent profiles were summarized. Second, the implementation status of the 20 technologies was analyzed by distinguishing between adopted technologies, technologies under implementation, technologies planned for future adoption, and technologies with no adoption plans. Third, perceived organizational readiness was assessed through Likert-scale responses grouped into agreement, neutral, and disagreement categories.

Fourth, a simple readiness score and a simple adoption score were calculated. The readiness score was based on the proportion of agreement responses in readiness-related dimensions, including ICT infrastructure, employee capabilities, expected benefits, productivity expectations, and ease of use. Implementation challenges were treated as a constraint dimension. The adoption score was based on the proportion of Industry 4.0 technologies reported as already implemented by each company or technology group.

Fifth, the relationship between perceived readiness and adoption depth was examined through an aggregate descriptive synthesis. This synthesis contrasted readiness-related agreement indicators with adoption-depth indicators by technology group. Because the available analysis was based on aggregated survey results, the study does not report individual-level inferential statistics such as Spearman correlations or regression models.

Table 7 presents the operationalization criteria used to derive the readiness–adoption matrix and staged roadmap. It specifies the analytical components, operational definitions, empirical indicators, and classification criteria used to transform the descriptive survey results into interpretive outputs.

Table 7. Operationalization criteria for the readiness–adoption matrix and staged roadmap.

Analytical Component	Operational Definition	Empirical Indicator	Classification Criterion
Perceived readiness	Organizational perception of preparedness for Industry 4.0 adoption	Agreement responses related to ICT infrastructure, employee capabilities, expected benefits, productivity expectations, and ease of use	Low: <33.3%; Medium: 33.3–66.6%; High: >66.6%
Adoption depth	Reported implementation of Industry 4.0 technologies	Percentage of companies reporting that each technology is already implemented	Low: <33.3%; Medium: 33.3–66.6%; High: >66.6%
Readiness–adoption gap	Misalignment between readiness and implementation	Difference between readiness level and adoption-depth level	Gap identified when readiness is medium/high and adoption remains low
Implementation momentum	Technologies currently being introduced but not yet fully adopted	Percentage of companies reporting implementation in progress	Used to identify short-term transition priorities
Adoption resistance	Technologies with no reported adoption plans	Percentage of companies reporting no plans for adoption	Used to identify low-priority or high-barrier technologies
Implementation constraints	Barriers affecting the transition from readiness to adoption	Agreement responses related to costs, skills requirements, implementation time, and resistance to change	Used to interpret the readiness–adoption gap
Roadmap stage	Suggested sequence of adoption priorities	Combined interpretation of maturity category, adoption depth, implementation momentum, and constraints	Foundational consolidation; intermediate integration; advanced scaling; systemic transformation

For interpretive purposes, readiness and adoption depth were classified into three descriptive levels: low (<33.3%), medium (33.3–66.6%), and high (>66.6%). These thresholds were used as tercile-based descriptive criteria, not as inferential cut-off points. The interpretation was contrasted against alternative threshold scenarios during the analytical review of the matrix to verify that the main classification pattern did not depend exclusively on a single cut-off scheme.

A readiness–adoption gap was identified when perceived readiness was medium or high while actual adoption depth remained low, particularly for advanced, systemic, or emerging technologies. The matrix and roadmap were developed as structured analytical syntheses of the empirical findings and are presented as interpretive tools grounded in the survey results, rather than as predictive models or universally validated frameworks.

5. Results

This section presents the empirical findings obtained from the 59 valid questionnaires. The results are organized according to the research questions and the analytical logic of the study. First, the profile of respondents is described. Second, the overall adoption of Industry 4.0 technologies is examined. Third, adoption is analyzed by technology category. Fourth, perceived organizational readiness, expected benefits, implementation challenges, ease of use, and perceived usefulness are reported. Finally, the readiness–adoption gap is synthesized through the readiness–adoption matrix and the staged roadmap.

All results reported in this section refer exclusively to the 59 surveyed companies. Therefore, the findings should be interpreted as evidence from the analyzed sample and should not be extrapolated to all large manufacturing companies in Colombia, Latin America, or other emerging economy contexts.

5.1. Characteristics of the Sample

A total of 59 large manufacturing companies located in Valle del Cauca, Colombia, participated in the study. All organizations met the inclusion criteria defined in the method-

ology and were classified as large according to the Colombian business-size classification based on annual operating revenues by economic sector. This sample provides an empirical basis for examining Industry 4.0 adoption in companies with established organizational structures and potential capacity for technological implementation.

Figure 2 presents the distribution of respondents according to their organizational role. This information is relevant because the study relies on one key informant per company; therefore, the respondent profile helps assess the quality and relevance of the information collected.

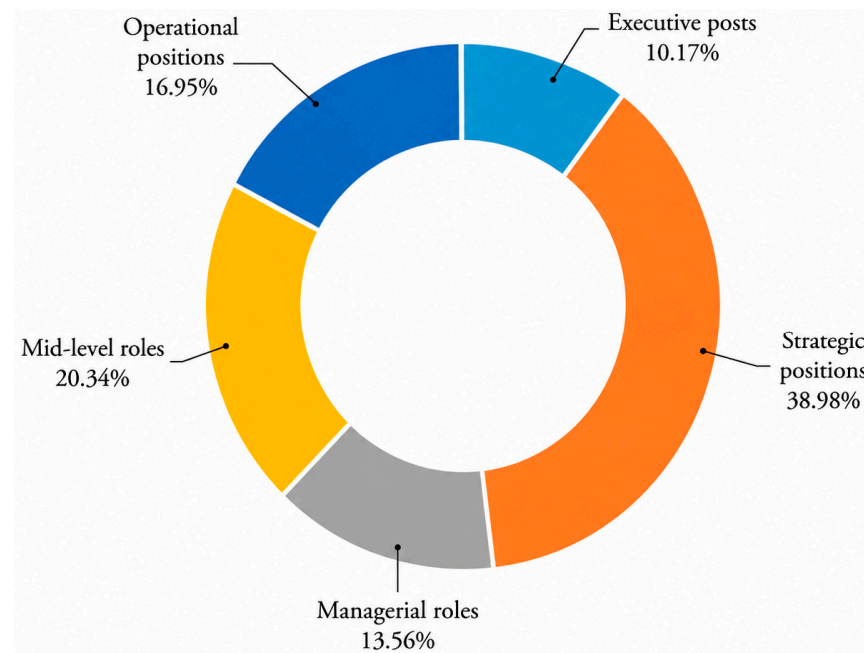


Figure 2. Distribution of survey respondents according to their organizational role.

Regarding the profile of the respondents, the largest proportion corresponded to strategic-level positions (38.98%), followed by middle management (20.34%) and operational staff (16.95%). Smaller shares were represented by managerial positions (13.56%) and executive-level roles (10.17%). This distribution indicates that most responses were provided by personnel with decision-making, coordination, or implementation responsibilities. Therefore, although the study relies on one key informant per company, the respondent profile supports the analytical relevance of the dataset for examining organizational priorities, technology-related decisions, and implementation dynamics.

5.2. Overall Adoption of Industry 4.0 Technologies

Overall, the adoption of Industry 4.0 technologies among the surveyed large manufacturing companies shows meaningful but uneven progress. Approximately 66.10% of the companies reported having incorporated Industry 4.0 initiatives into their organizational strategy, indicating that most firms recognize the strategic relevance of digital transformation. At the same time, 23.73% reported that they had not yet started implementing Industry 4.0 technologies, which shows that a relevant share of companies remains outside the current adoption trend.

Figure 3 presents the number of years since the beginning of Industry 4.0 adoption among the surveyed companies. This figure helps distinguish between firms in early adoption stages and those with more consolidated trajectories.

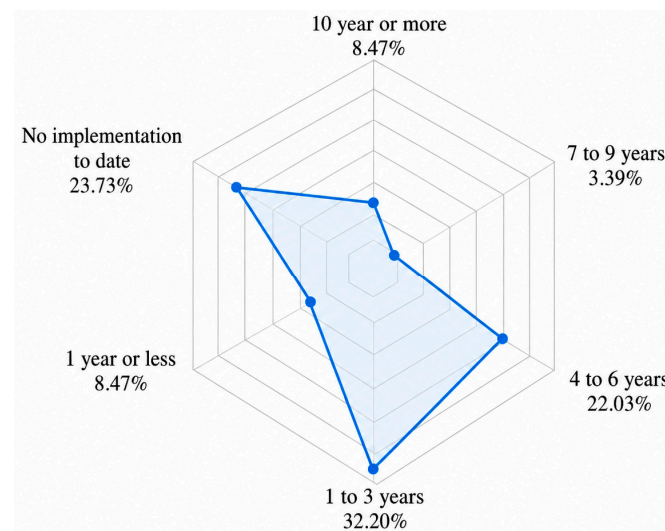


Figure 3. Years since the beginning of Industry 4.0 adoption in surveyed companies.

The temporal distribution of adoption reflects an early and gradual transition. Among the surveyed companies, 32.20% reported that their Industry 4.0 adoption process had begun within the last one to three years, while 22.03% indicated an implementation trajectory of four to six years. Only a smaller proportion reported more consolidated trajectories, with 3.39% adopting these technologies for seven to nine years and 8.47% for ten years or more. These results suggest that most companies are not yet in a mature Industry 4.0 stage, but rather in initial or intermediate phases of digital transformation.

In addition to implementation status, the results reveal high levels of awareness and future expectation. A total of 88.14% of respondents stated that they were familiar with the concepts of Industry 4.0 and smart manufacturing, while 67.80% expected greater implementation of these technologies in their companies within the next five years. This combination of high awareness and positive expectations is relevant because it anticipates the readiness–adoption gap examined later: firms recognize the strategic value of Industry 4.0, but this recognition does not necessarily translate into advanced implementation depth.

Figure 4 presents the ten Industry 4.0 technologies with the highest implementation levels. It provides an initial overview of technology penetration before the category-based analysis.

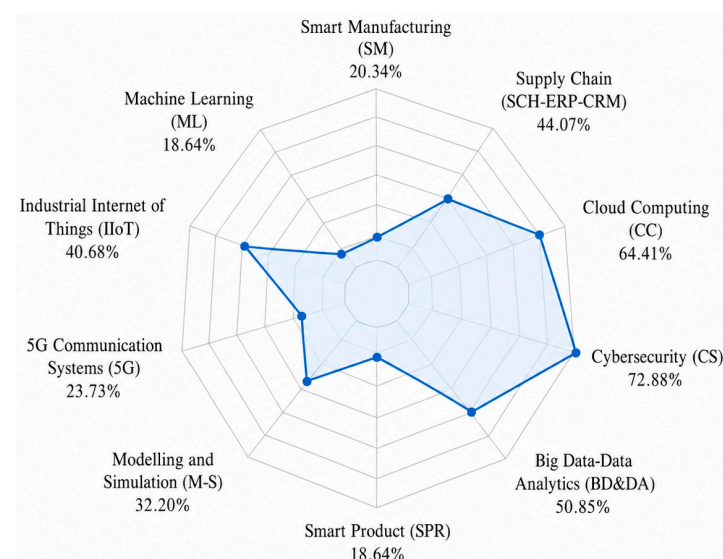


Figure 4. Highly implemented Industry 4.0 technologies among surveyed companies.

A first overview of technology penetration shows marked differences across tools. Foundational or enabling technologies exhibit the highest implementation levels, whereas more advanced or specialized solutions remain less widespread. Cybersecurity and cloud computing appear as the most widely implemented technologies, followed by big data and data analytics. This pattern indicates a selective adoption process in which companies first consolidate basic digital capabilities before moving toward more complex and integrated Industry 4.0 technologies.

5.3. Adoption by Technology Category

When Industry 4.0 technologies are examined by analytical category, significant asymmetries in adoption become evident. The highest implementation levels are concentrated in foundational digital infrastructure and data-oriented technologies. Cybersecurity (72.88%) and Cloud Computing (64.41%) are the most widely adopted technologies, followed by Big Data and Data Analytics (50.85%) and enterprise systems such as ERP–CRM–SCM (44.07%). These results indicate that the most widespread advances are associated with information protection, cloud-based resource access, data management, and operational digitalization.

Connectivity, industrial integration, and system-level technologies show intermediate but still uneven implementation levels. Industrial Internet of Things (IIoT) reached an adoption rate of 40.68%, while Modeling and Simulation showed an adoption rate of 32.20%. In contrast, IoT–RFID (22.03%), Smart Manufacturing (20.34%), Embedded Systems (15.25%), and Automation and Robotics (10.17%) remain less consolidated. This pattern suggests that the surveyed companies have made progress in selected connectivity and analytical capabilities, but broader operational integration across physical assets, automated systems, and real-time decision-support environments remains limited.

By contrast, several advanced, emerging, visualization, and product-level technologies exhibit lower adoption levels. Artificial Intelligence (11.86%), Cyber–Physical Systems (16.95%), Machine Learning (18.64%), and Digital Twins (6.78%) remain in early or selective stages of adoption. Similarly, Augmented Reality (8.47%), Virtual Reality (10.17%), Smart Product (18.64%), Blockchain (6.78%), and Additive Manufacturing (6.78%) show limited penetration. These low implementation levels should be interpreted together with the perceived barriers reported later, particularly cost, specialized skills, integration complexity, implementation time, and resistance to change.

Table 8 presents the implementation status of the 20 Industry 4.0 technologies included in the survey. Technologies are organized according to the analytical categories defined in the methodology. To avoid ambiguity, the table reports four implementation conditions: already adopted, currently in progress, planned adoption, and no reported adoption plans. The planned adoption column captures the proportion of companies that had not yet implemented each technology but reported some level of future adoption intention.

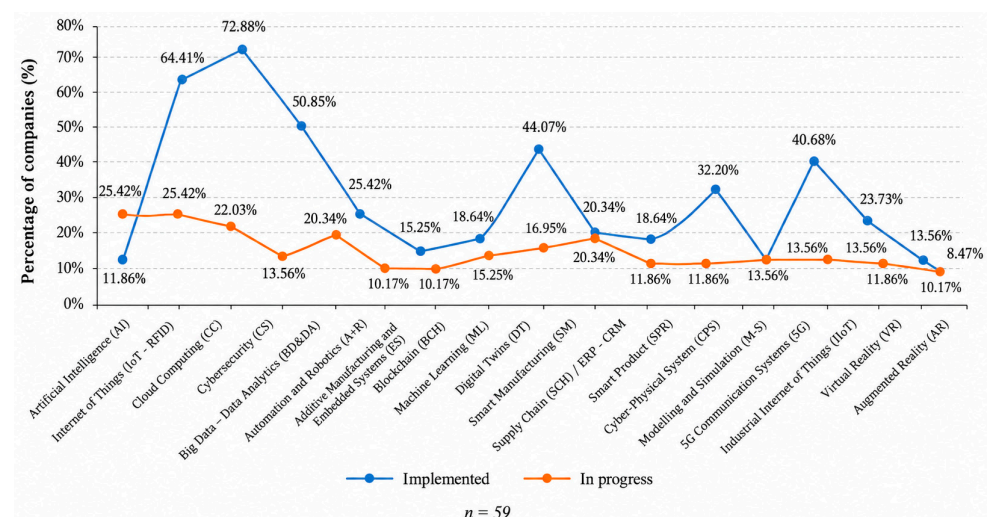
Table 8 shows that the adoption landscape is not binary. Several technologies with low current adoption show considerable levels of planned adoption or implementation in progress. This is particularly visible in Artificial Intelligence, IoT–RFID, Automation and Robotics, Machine Learning, Smart Product, Blockchain, and 5G. Therefore, the results should not be interpreted only as low adoption of advanced technologies, but as evidence of an incomplete and gradual transition.

Figure 5 compares adoption and implementation-in-progress rates across Industry 4.0 technologies. This figure highlights both consolidated technologies and those currently moving through the implementation process.

Table 8. Adoption of Industry 4.0 Technologies by Analytical Category.

Analytical Category	Technology	Adoption (%)	In Progress (%)	Planned Adoption (%)	No Plans (%)
Foundational digital infrastructure	Cybersecurity (CS)	72.88	8.47	16.95	1.69
	Cloud Computing (CC)	64.41	13.56	15.25	6.78
Enterprise digital systems	ERP–CRM–SCM	44.07	16.95	25.42	13.56
Data-driven technologies	Big Data and Data Analytics (BD&DA)	50.85	20.34	23.73	5.08
Connectivity technologies	Internet of Things and RFID (IoT–RFID)	22.03	25.42	30.51	22.03
Industrial connectivity technologies	Industrial Internet of Things (IIoT)	40.68	13.56	22.03	23.73
Automation and control technologies	Automation and Robotics (ARo)	10.17	25.42	37.29	27.12
	Embedded Systems (ES)	15.25	10.17	32.20	42.37
Advanced digital intelligence	Artificial Intelligence (AI)	11.86	25.42	37.29	25.42
	Machine Learning (ML)	18.64	15.25	38.99	27.12
Advanced integration technologies	Cyber–Physical Systems (CPS)	16.95	11.86	28.81	42.37
Advanced integration technologies	Digital Twins (DT)	6.78	6.78	42.37	44.07
Advanced simulation technologies	Modeling and Simulation (MS)	32.20	11.86	28.81	27.12
Advanced manufacturing technologies	Additive Manufacturing (3D Printing)	6.78	5.08	30.51	57.63
Visualization technologies	Augmented Reality (AR)	8.47	13.56	27.12	50.85
	Virtual Reality (VR)	10.17	11.86	28.81	49.15
System-level integration	Smart Manufacturing (SM)	20.34	20.34	35.59	23.73
Product-level digitalization	Smart Product (SPR)	18.64	6.78	35.59	38.98
Data governance technologies	Blockchain (BCH)	6.78	8.47	40.68	44.07
Enabling communication infrastructure	5G Communication Systems (5G)	23.73	13.56	33.90	28.81

Note. Values are reported as percentages of surveyed companies. Adoption refers to technologies already implemented; In progress refers to technologies currently under implementation; Planned adoption refers to technologies expected or intended for future implementation; No plans refers to technologies for which companies reported no adoption plans. Small differences may occur due to rounding.

**Figure 5.** Adoption and implementation rates of Industry 4.0 technologies among surveyed companies.

The comparison confirms the dominance of foundational technologies, with cybersecurity and cloud computing standing above the rest in terms of completed adoption. At the same time, several advanced technologies appear more prominently in the implementation stage than in full adoption, suggesting that companies are beginning to allocate resources to technologies that have not yet been fully integrated into operations.

Figure 6 focuses on the technologies with the highest rates of ongoing implementation. This figure is useful for identifying short-term technological momentum among companies that are still transitioning toward more advanced Industry 4.0 configurations.

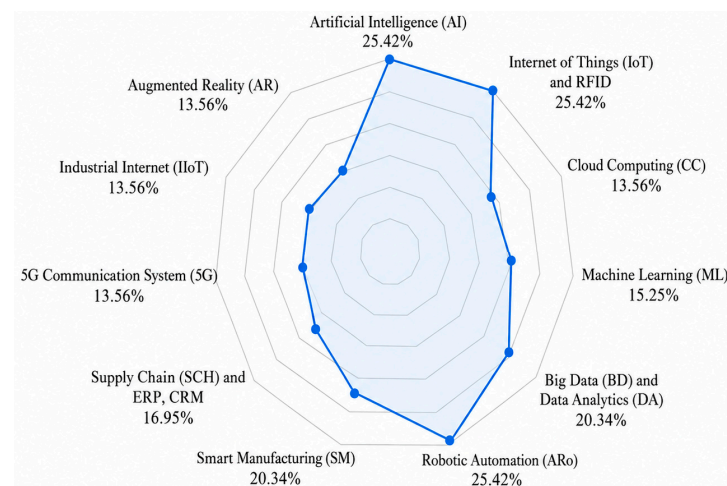


Figure 6. Leading Industry 4.0 technologies currently under implementation among surveyed companies.

Artificial Intelligence, Automation and Robotics, and IoT-RFID each show implementation-in-progress levels of 25.42%, while Big Data and Data Analytics and Smart Manufacturing also display relevant ongoing deployment activity. These results suggest that some advanced technologies are not absent from companies' agendas; rather, they remain in transition between intention, pilot implementation, and operational consolidation.

Figure 7 contrasts current adoption levels with the proportion of companies reporting no adoption plans. This figure identifies technologies facing greater resistance, lower perceived priority, or higher implementation barriers.

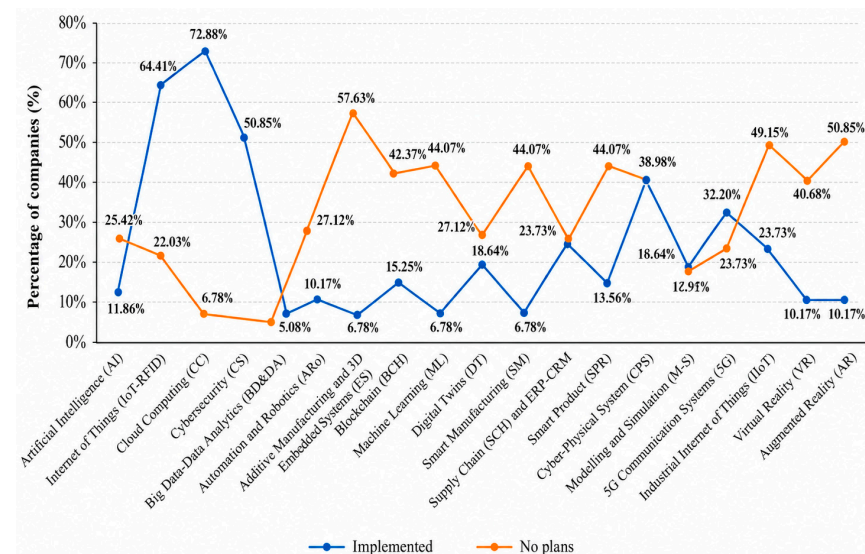


Figure 7. Comparison between implemented Industry 4.0 technologies and technologies for which companies report no adoption plans.

More than half of the surveyed companies reported no intention to adopt 3D printing (57.63%), while similarly high levels of non-intention were observed for augmented reality (50.85%), virtual reality (49.15%), blockchain (44.07%), and digital twins (44.07%). This pattern indicates that some technologies remain outside the short-term priorities of many companies, possibly because of their technical complexity, uncertain applicability, investment requirements, or insufficient organizational readiness.

5.4. Perceived Technological Readiness and Attitudes

Survey responses indicate that the participating companies perceive themselves as having a moderately favorable organizational base for Industry 4.0 adoption, although important internal gaps remain. Regarding ICT-related readiness, 83.05% of respondents considered their organization's ICT infrastructure robust enough to support new digital initiatives, while 62.71% agreed that the current infrastructure could support Industry 4.0 projects without major difficulties. Perceptions of workforce capabilities were also generally positive, although less strongly so: 61.02% reported that employees had sufficient specific ICT knowledge and skills, 55.93% considered general ICT competencies adequate, and 59.32% indicated that their companies provided ongoing ICT training. In addition, 76.27% expected their organizations to invest further in ICT to improve productivity.

Figure 8 presents perceived organizational readiness for Industry 4.0 adoption. It compares infrastructure-related, skills-related, training-related, and investment-related dimensions.

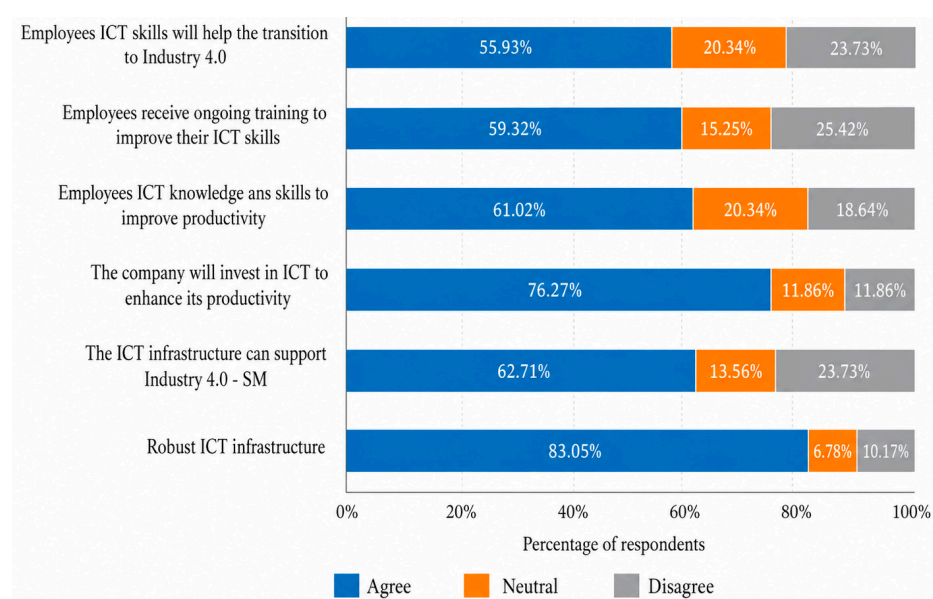


Figure 8. Perceived organizational readiness for Industry 4.0 adoption. Note: The blue bars represent agreement responses, while the orange and gray bars represent neutral and disagreement responses, respectively.

Figure 8 shows that infrastructure-related items received stronger levels of agreement than skills development and training. This result is relevant because it suggests that readiness is stronger in technological infrastructure than in human capability development, which may help explain why advanced technologies remain limited in implementation.

Respondents also reported strongly positive attitudes toward the expected benefits of Industry 4.0 while recognizing substantial implementation challenges. On the benefits side, more than 90% agreed that these technologies improve productivity (93.22%) and create competitive advantages (91.53%), while 89.83% associated them with greater flexibility and employee skill development. Additional expected gains were reported in manufacturing

quality (84.75%), cost reduction (83.05%), and innovation (76.27%). At the same time, respondents acknowledged major barriers to adoption: 98.31% agreed that Industry 4.0 requires new knowledge and skills, 86.44% identified high implementation costs, and 79.66% pointed to long deployment periods and cultural resistance to change.

Figure 9 presents the perceived benefits and challenges associated with Industry 4.0 adoption. Panel (a) summarizes expected organizational benefits, while panel (b) shows perceived implementation constraints.

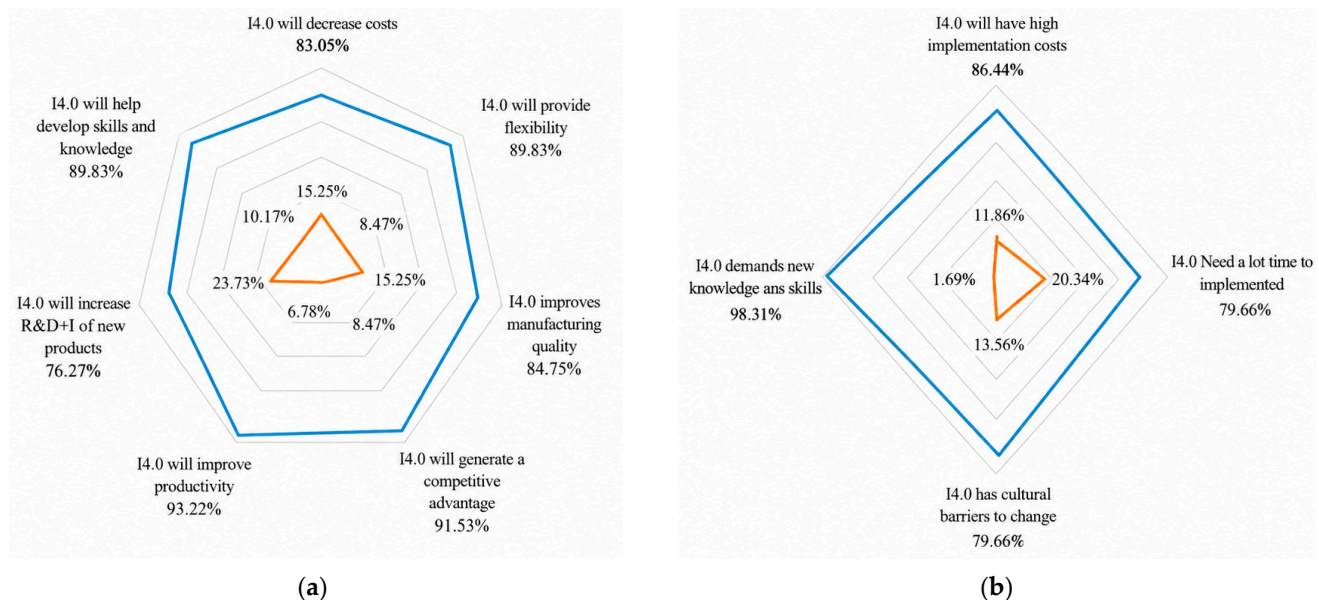


Figure 9. Perceived benefits and challenges associated with Industry 4.0 adoption: (a) perceived benefits; (b) perceived challenges. Note: In both ring charts, the outer blue ring represents the percentage of “agree” and “strongly agree” responses, whereas the inner orange ring represents neutral responses.

The results in Figure 9 show that companies recognize both the strategic value and the organizational difficulty of Industry 4.0 adoption. This dual perception is central to the readiness–adoption gap: firms expect productivity, quality, flexibility, and competitiveness gains, but they also perceive high requirements in skills, cost, time, and cultural change.

A more nuanced picture emerges when respondents assess ease of use and perceived usefulness. In relation to usability, responses were notably more ambiguous than those observed for benefits and barriers. Around 71% of respondents selected neutral responses regarding whether interacting with Industry 4.0 technologies is easy, suggesting uncertainty or limited direct experience. Likewise, opinions were divided regarding whether these technologies are frustrating to use, with 33.90% agreeing and 35.59% disagreeing. By contrast, perceptions of usefulness were clearly positive. More than 90% agreed that Industry 4.0 technologies improve task quality, provide greater control over work activities, support critical aspects of work, and enhance productivity and performance.

Figure 10 presents employee perceptions of Industry 4.0 ease of use and perceived usefulness. Panel (a) reports ease-of-use perceptions, while panel (b) summarizes perceived usefulness.

Figure 10 shows a contrast between perceived usefulness and perceived ease of use. Companies tend to believe that Industry 4.0 technologies are valuable for work performance, but they show greater uncertainty regarding usability. This suggests that positive expectations alone may not be sufficient to accelerate adoption if users lack direct experience, training, or confidence in operating these technologies.

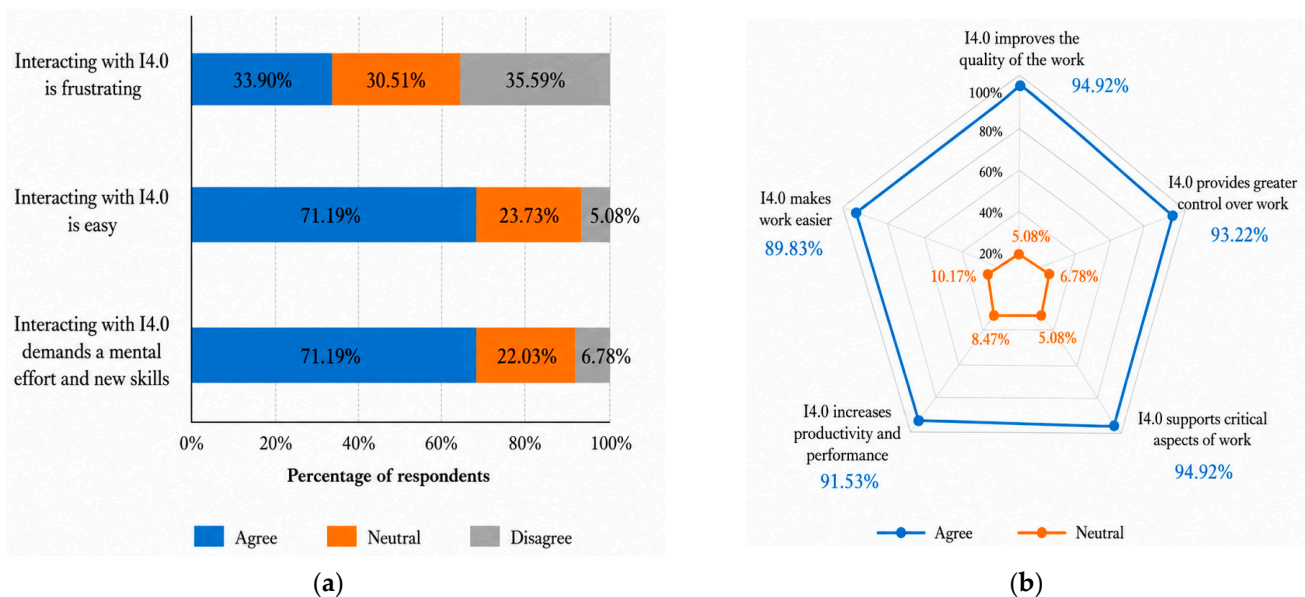


Figure 10. Employee perceptions of Industry 4.0 ease of use and perceived usefulness: (a) ease of use; (b) perceived usefulness. Note: In the bar chart, the blue bar represents the sum of “agree” and “strongly agree” responses, the orange bar represents neutral responses, and the gray bar corresponds to “disagree” and “strongly disagree”. In the ring chart, the outer blue ring represents the percentage of “agree” and “strongly agree” responses, whereas the inner orange ring represents neutral responses.

Overall, the results show that respondents perceive Industry 4.0 positively in terms of organizational relevance, expected benefits, and strategic value, while simultaneously recognizing important barriers related to capabilities, cost, implementation time, resistance to change, and usability. This combination informs the readiness–adoption gap examined in the following subsection.

5.5. Readiness–Adoption Gap

In this study, the readiness–adoption gap is understood as the coexistence of relatively positive perceptions of organizational readiness and limited implementation depth, particularly in advanced Industry 4.0 technologies. The gap does not imply the absence of digital progress; rather, it reflects an incomplete transition in which favorable expectations, perceived preparedness, and strategic interest are only partially translated into effective technological deployment. This subsection addresses RQ4 by integrating the evidence on adoption levels, category-based asymmetries, and perceived organizational readiness.

The results show that companies do not adopt Industry 4.0 technologies indiscriminately. Instead, their choices reflect a selective response to perceived feasibility and internal preparedness. Firms tend to prioritize foundational and intermediate technologies that are more compatible with their existing infrastructure and organizational routines, while more demanding solutions are postponed, piloted, or excluded. This indicates a partial alignment between readiness and adoption: companies appear to recognize their implementation limits and sequence their adoption efforts accordingly.

At the same time, the findings reveal a mismatch between favorable perceptions and implementation depth. Respondents reported strong agreement regarding expected benefits, especially in relation to productivity, quality, competitiveness, and operational value. They also expressed relatively favorable views of ICT infrastructure and future investment intentions. However, these positive perceptions have not translated into broad adoption of advanced technologies. Artificial intelligence, cyber–physical systems, digital twins, augmented reality, virtual reality, blockchain, and additive manufacturing remain

weakly adopted despite the generally positive orientation toward digital transformation. This mismatch constitutes the core empirical expression of the readiness–adoption gap identified in the study.

The observed gap is consistent with the barriers identified in the previous subsection. High implementation costs, the need for specialized knowledge and skills, long implementation periods, and resistance to change act as constraints that slow the translation of readiness into adoption. As a result, the surveyed companies appear to be located in an incomplete transition stage: they recognize the relevance of Industry 4.0 and have adopted foundational technologies, but they have not yet reached consolidated or systemic implementation.

Figure 11 presents the planned implementation timelines for Industry 4.0 technologies. It complements the adoption analysis by showing whether technologies with low current implementation are being considered for future deployment.

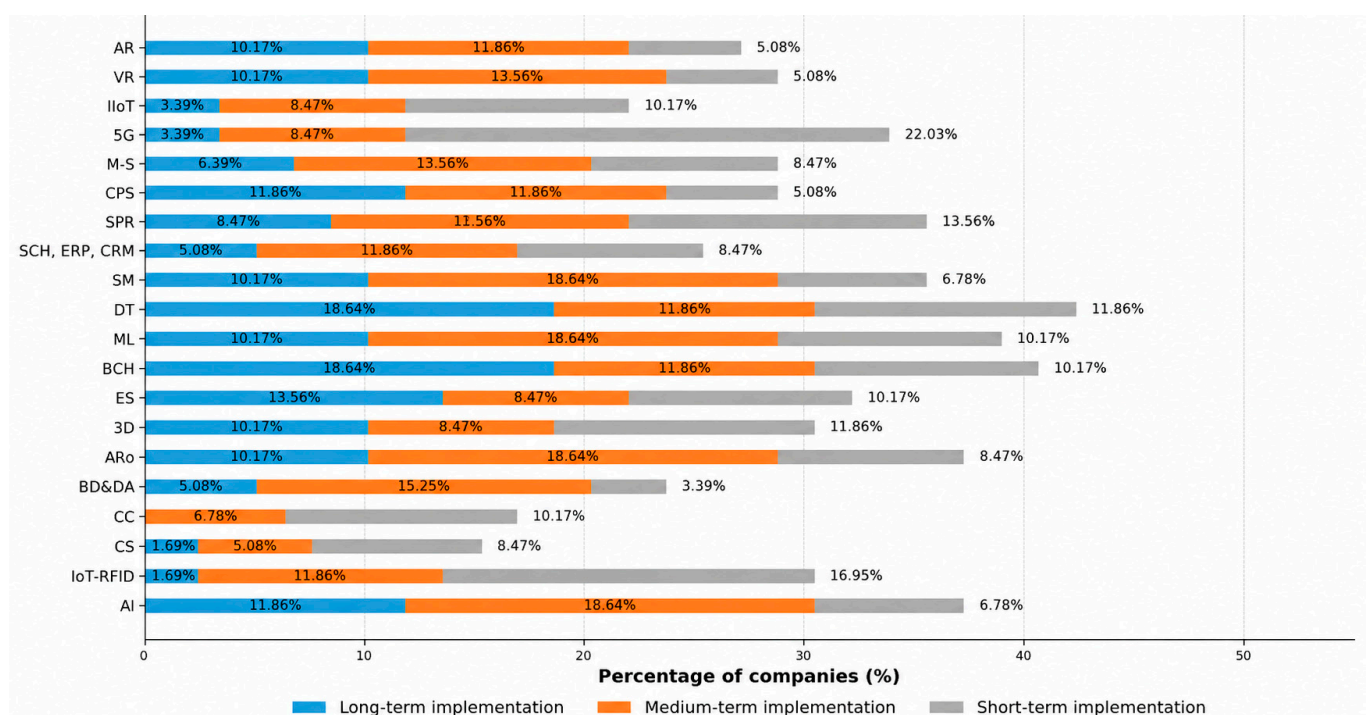


Figure 11. Planned implementation timelines for Industry 4.0 technologies.

Figure 11 shows that some technologies with low current adoption, such as 5G, IoT-RFID, and smart production systems, appear more prominently in short-term adoption plans. This suggests that some companies are not rejecting these technologies permanently, but postponing them until internal conditions become more favorable. Other technologies, including augmented reality and virtual reality, tend to be deferred to medium- or long-term horizons, indicating lower short-term priority.

Overall, the evidence indicates that positive perceptions of organizational readiness do not automatically lead to advanced Industry 4.0 adoption. Rather, the transition from readiness to implementation remains conditioned by organizational capabilities, workforce preparedness, implementation constraints, and the perceived feasibility of each technology.

5.6. Exploratory Synthesis of the Readiness–Adoption Gap

To strengthen the empirical interpretation of the readiness–adoption gap, an aggregate synthesis was developed using the descriptive indicators reported in the previous subsections. This synthesis does not replace individual-level statistical testing, but it provides a

clearer analytical bridge between perceived organizational readiness, technology adoption depth, implementation momentum, and the staged roadmap.

First, perceived readiness was summarized using the agreement percentages reported for ICT infrastructure, infrastructure support for Industry 4.0 projects, specific ICT knowledge, general ICT competencies, ongoing ICT training, and expected future ICT investment. These indicators capture the organizational conditions that firms perceive as enabling Industry 4.0 adoption. In parallel, the main implementation constraints were summarized through the agreement percentages associated with knowledge and skills requirements, implementation costs, implementation time, and resistance to change.

Table 9 presents the aggregate readiness and implementation-constraint indicators used to support the interpretation of the readiness–adoption gap.

Table 9. Aggregate readiness and implementation-constraint indicators.

Analytical Dimension	Indicator	Agreement/Reported Value (%)	Interpretation
ICT infrastructure	Robust ICT infrastructure to support new digital initiatives	83.05	Strong perceived technological base
ICT infrastructure	Infrastructure able to support Industry 4.0 projects without major difficulties	62.71	Moderate-to-favorable perceived support
Workforce capabilities	Employees have sufficient specific ICT knowledge and skills	61.02	Moderate workforce readiness
Workforce capabilities	Employees have sufficient general ICT competencies	55.93	Moderate but less consolidated capability base
Training	Company provides ongoing ICT training	59.32	Moderate training support
Future investment	Expected future ICT investment to improve productivity	76.27	Strong strategic investment orientation
Aggregate readiness proxy	Arithmetic mean of the six readiness indicators above	66.38	Medium-to-high perceived readiness
Knowledge and skill requirements	Industry 4.0 requires new knowledge and skills	98.31	Very high perceived capability requirement
Implementation cost	High implementation costs	86.44	High economic constraint
Implementation time	Long deployment periods	79.66	High temporal constraint
Resistance to change	Cultural resistance to change	79.66	High organizational constraint
Aggregate constraint proxy	Arithmetic mean of the four constraint indicators above	86.02	High perceived implementation pressure

Note. The aggregate readiness and constraint proxies are descriptive arithmetic means based on the percentages already reported in the survey results. They are not psychometric scale scores and should not be interpreted as causal indicators.

Second, adoption depth was summarized by grouping the 20 Industry 4.0 technologies according to their function in the digital transformation process. The grouping follows the analytical logic used in the methodology and in the staged roadmap: foundational digital base, operational and connectivity integration, advanced digital and integration technologies, and emerging systemic/data-governance technologies.

Table 10 presents the average adoption status by technology group.

Third, the readiness–adoption gap was examined by contrasting the aggregate readiness proxy with the average adoption depth of each technology group. This comparison shows that the gap is not uniform. It is smaller for foundational technologies, where adoption is more consolidated, and larger for operational, advanced, systemic, and emerging technologies, where positive organizational perceptions have not yet translated into broad implementation.

Table 10. Aggregate adoption status by Industry 4.0 technology group.

Technology Group	Technologies Included	Adoption (%)	In Progress (%)	Planned Adoption (%)	No Plans (%)	Empirical Interpretation
Foundational digital base	Cybersecurity; Cloud Computing; ERP–CRM–SCM; Big Data and Data Analytics	58.05	14.83	20.34	6.78	Most consolidated group; low adoption resistance
Operational and connectivity integration	IoT–RFID; IIoT; Smart Manufacturing; Embedded Systems; Automation and Robotics	21.69	18.98	31.52	27.80	Low current adoption but visible transition momentum
Advanced digital and integration technologies	Artificial Intelligence; Machine Learning; Cyber–Physical Systems; Digital Twins; Modeling and Simulation; Additive Manufacturing; Augmented Reality; Virtual Reality	13.98	12.71	32.84	40.47	Low adoption depth and high postponement or resistance
Emerging systemic/data-governance technologies	Smart Product; Blockchain; 5G Communication Systems	16.38	9.06	36.72	37.29	Low current adoption, but relevant future intention
Overall average	20 Industry 4.0 technologies	27.52	13.89	30.35	28.08	Uneven and incomplete Industry 4.0 transition

Note. Values are arithmetic means calculated from the technology-level percentages reported in the adoption table. Adoption refers to technologies already implemented; In progress refers to technologies currently under implementation; Planned adoption refers to technologies expected or intended for future implementation; No plans refers to technologies for which companies reported no adoption plans.

Table 11 presents the descriptive readiness–adoption gap by technology group.

Table 11. Descriptive readiness–adoption gap by technology group.

Technology Group	Aggregate Readiness Proxy (%)	Adoption Depth (%)	Descriptive Gap (Percentage Points)	Gap Interpretation	Roadmap Implication
Foundational digital base	66.38	58.05	8.33	Limited gap; adoption is relatively aligned with perceived readiness	Consolidate and standardize the digital base
Operational and connectivity integration	66.38	21.69	44.69	High gap; readiness is not yet translated into operational integration	Prioritize interoperability, process integration, and operational data use
Advanced digital and integration technologies	66.38	13.98	52.40	Very high gap; advanced technologies remain limited in implementation	Promote pilots, specialized skills, experimentation, and change management
Emerging systemic/data-governance technologies	66.38	16.38	50.00	Very high gap; adoption is mostly postponed or planned	Evaluate feasibility, governance, and strategic prioritization before scaling

Note. The descriptive gap was calculated as the difference between the aggregate readiness proxy and the average adoption depth of each technology group. Because readiness was measured as an organizational perception and not as a technology-specific score, this table should be interpreted as an aggregate descriptive synthesis, not as an inferential test.

The aggregate synthesis provides descriptive support for the central pattern identified in the study. Although the surveyed companies report a medium-to-high readiness proxy of 66.38%, the average adoption across the 20 technologies is only 25.08%. This difference indicates that favorable organizational perceptions coexist with limited implementation depth. The gap is especially marked in advanced digital and integration technologies, where average adoption reaches only 13.98%, and in emerging systemic/data-governance technologies, where average adoption reaches 16.38%.

At the same time, the data show that low current adoption should not be interpreted as complete rejection of Industry 4.0 technologies. Planned adoption is relatively high in operational and connectivity integration technologies (31.52%), advanced digital and integration technologies (32.84%), and emerging systemic/data-governance technologies

(36.72%). This suggests that many companies are not excluding advanced technologies permanently, but are postponing them until organizational, technical, financial, or human capabilities become more favorable.

Therefore, the readiness–adoption gap observed in this study is better interpreted as an incomplete and capability-constrained transition. Foundational technologies form the current digital base, while operational integration, advanced piloting, and systemic transformation remain pending stages. This empirical pattern supports the readiness–adoption matrix and informs the staged roadmap presented in the following subsection.

5.7. Empirical Synthesis of the Readiness–Adoption Gap

The evidence presented in the previous subsections allows a more integrated interpretation of the transition pattern observed among the surveyed companies. Beyond describing adoption levels, perceived organizational readiness, implementation barriers, and future adoption intentions, the results reveal the central empirical configuration of the study: large manufacturing companies show favorable readiness perceptions, but their adoption depth remains uneven and limited, particularly in advanced Industry 4.0 technologies.

The previous aggregate indicators provide the empirical basis for the readiness–adoption matrix. The matrix is not intended to replace the descriptive evidence reported above; rather, it synthesizes the observed transition pattern by contrasting perceived organizational readiness with adoption depth across technology groups. In this sense, Figure 12 should be interpreted as an exploratory visual synthesis of the readiness–adoption gap, not as a predictive model or as a validated positioning tool for individual companies.

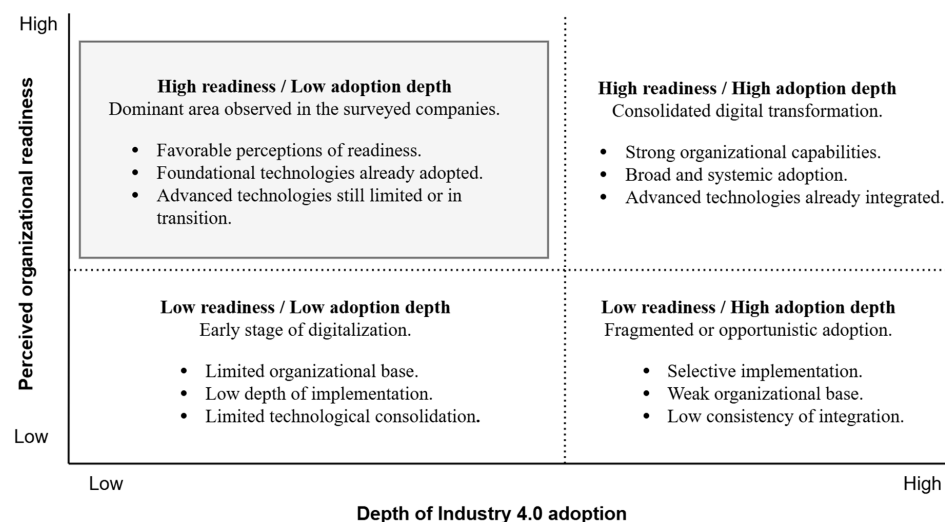


Figure 12. Readiness–adoption matrix for Industry 4.0 in large manufacturing companies.

The dominant pattern does not correspond either to low readiness or to fully consolidated transformation. Instead, the evidence points to an intermediate transition zone characterized by relatively favorable readiness perceptions and limited implementation depth, especially in advanced and emerging technologies. This pattern suggests that the surveyed companies have moved beyond the earliest stage of digitalization through the adoption of foundational technologies such as cybersecurity, cloud computing, ERP–CRM–SCM systems, and data analytics. However, they have not yet reached advanced and systemic Industry 4.0 adoption, since technologies such as artificial intelligence, cyber-physical systems, digital twins, augmented reality, virtual reality, blockchain, and additive manufacturing remain limited in implementation or deferred to later stages.

Technologies or categories with medium-to-high perceived readiness but low adoption were interpreted as evidence of a readiness–adoption gap. In this sense, the matrix condenses the main empirical finding of the study: readiness is present as a favorable organizational perception, but implementation remains selective, gradual, and constrained by capability, cost, integration, and change-management barriers.

Table 12 presents the staged roadmap for capability building and technology prioritization. This roadmap organizes the observed transition pattern into sequential stages based on current adoption levels, implementation momentum, technological complexity, and capability-building needs.

Table 12. Staged roadmap for capability building and technology prioritization in Industry 4.0 adoption.

Stage	Empirical Focus	Priority Technologies	Capability-Building Priorities	Transition Logic
Stage 1. Foundational digital consolidation	Highest current adoption and lowest adoption resistance	Cybersecurity; Cloud Computing; ERP–CRM–SCM; Big Data and Data Analytics	ICT infrastructure; data management; digital security; basic staff training; standardization of digital practices	Build and stabilize the digital base
Stage 2. Operational and connectivity integration	Moderate adoption, visible implementation momentum, and relevant planned adoption	IIoT; IoT–RFID; Smart Manufacturing; Embedded Systems; Automation and Robotics	Interoperability; process integration; operational data use; cross-functional coordination; connection between assets, processes, and information systems	Connect assets, processes, and information flows
Stage 3. Advanced technology piloting	Low adoption depth, high readiness–adoption gap, and high technological complexity	Artificial Intelligence; Machine Learning; Cyber–Physical Systems; Digital Twins; Augmented Reality; Virtual Reality; Additive Manufacturing	Specialized skills; pilot testing; experimentation; technical integration; change management; evaluation of operational feasibility	Test complex technologies before scaling
Stage 4. Systemic transformation and scaling	Low current adoption but relevant future intention in systemic and emerging technologies	Smart Product; Blockchain; 5G Communication Systems; integrated portfolio of foundational, intermediate, and advanced technologies	Strategic alignment; governance; data interoperability; organizational learning; scaling capability; digital culture; external ecosystem collaboration	Move from selective adoption to broader transformation

The roadmap in Table 12 should be interpreted as a context-specific analytical synthesis derived from the empirical findings, rather than as an external prescriptive model. The surveyed companies appear to be concentrated mainly between the first and second stages, with stronger consolidation in foundational technologies and more limited progress in advanced and systemic solutions. Consequently, the roadmap complements the readiness–adoption matrix by clarifying how capability-building needs and technology priorities may evolve over time in large manufacturing companies.

Overall, the empirical synthesis reinforces the main argument of the study: Industry 4.0 adoption among the surveyed companies is not absent, but it remains incomplete, staged, and capability-constrained. The readiness–adoption gap is therefore not simply a lack of technological interest; it reflects the difficulty of converting favorable organizational perceptions into reported implementation, especially when technologies demand higher levels of interoperability, specialized knowledge, investment, experimentation, and organizational change.

6. Discussion

The results show that Industry 4.0 adoption among large manufacturing companies in Valle del Cauca remains uneven and only partially consolidated. Adoption is stronger in foundational technologies, such as cybersecurity, cloud computing, ERP–CRM–SCM systems, and data analytics, while advanced, systemic, and emerging technologies remain limited in implementation. This pattern suggests that the surveyed companies have built an initial digital base, but have not yet reached a mature or systemic Industry 4.0 transformation stage.

This result is consistent with the view of Industry 4.0 adoption as a sociotechnical and capability-dependent process. Firms do not move directly from awareness to full implementation; instead, they usually consolidate technologies that are compatible with their existing infrastructure, routines, and capabilities before adopting more complex systems [21,24]. Therefore, Industry 4.0 adoption should be understood not only as technological acquisition, but as a gradual process requiring data integration, workforce preparation, organizational coordination, and managerial alignment [35].

The main contribution of this study is the identification of a readiness–adoption gap. Although respondents reported favorable perceptions regarding ICT infrastructure, expected benefits, productivity gains, usefulness, and the strategic relevance of Industry 4.0, these perceptions were not matched by broad implementation of advanced technologies. This finding extends readiness- and maturity-oriented studies by showing that positive organizational perceptions do not necessarily translate into deeper technological adoption [12,16]. It also contributes to Latin American literature by providing evidence from large manufacturing companies, a segment less frequently examined than SMEs in regional Industry 4.0 studies [17–19].

From a sociotechnical perspective, the gap appears to be shaped by the interaction of infrastructure, human capabilities, implementation barriers, and technological complexity. The surveyed firms show relatively favorable ICT conditions, but still face limitations related to specialized skills, implementation costs, deployment time, resistance to change, interoperability, and operational integration. These factors help explain why foundational technologies are more consolidated, while advanced technologies remain postponed, piloted, or excluded from short-term priorities.

The readiness–adoption matrix and staged roadmap should be interpreted with caution. The matrix does not position individual companies through a predictive index, nor does it validate a universal maturity model. Its value lies in synthesizing the aggregate pattern observed in the surveyed companies. Similarly, the roadmap is a context-specific analytical synthesis of the findings, not a prescriptive framework. It organizes the observed transition into stages of foundational consolidation, operational integration, advanced piloting, and systemic scaling.

From a managerial and policy perspective, the findings suggest that Industry 4.0 adoption should be approached as a staged capability-building process. Firms need to align technological priorities with data infrastructure, workforce skills, integration capacity, governance, and organizational culture. At the regional level, innovation ecosystems, technology transfer mechanisms, training programs, and experimentation spaces can support firms in moving from isolated digital initiatives toward more integrated Industry 4.0 trajectories [32].

Several limitations must be acknowledged. The study is restricted to Valle del Cauca and relies on self-reported data from one key informant per company, which may introduce perception bias, social desirability effects, single-informant bias, and common method bias. Its cross-sectional design prevents observing adoption trajectories over time, and the 10% maximum sampling error limits the precision of estimates. In addition, sectoral

heterogeneity within manufacturing may influence adoption patterns, and implementation was not objectively verified through audits, technical inspections, or operational records. Finally, longitudinal evidence is still required to validate whether the proposed roadmap reflects firms' actual transition over time.

Overall, the surveyed companies are not at the beginning of digitalization, but neither have they reached a consolidated Industry 4.0 transformation. Their trajectory is cautious, incremental, and capability-constrained. The central challenge is converting readiness, expectations, and strategic recognition into effective and sustained technological implementation.

7. Conclusions

This study examined Industry 4.0 adoption among large manufacturing companies in Valle del Cauca, Colombia, with particular attention to the relationship between perceived organizational readiness and reported implementation levels. The findings show that digital transformation is underway in the surveyed companies, but remains uneven and only partially consolidated. Adoption is stronger in foundational technologies such as cybersecurity, cloud computing, ERP–CRM–SCM systems, and data analytics, whereas advanced, systemic, and emerging technologies show more limited implementation.

The main contribution of the study is the identification of a readiness–adoption gap based on the aggregate descriptive synthesis of the survey results. Although the surveyed companies reported favorable perceptions regarding ICT infrastructure, expected benefits, productivity, usefulness, and the strategic relevance of Industry 4.0, these perceptions were not matched by broad implementation of advanced technologies. This indicates that positive organizational readiness does not automatically result in deep technological adoption, especially when implementation requires specialized skills, investment capacity, interoperability, operational integration, and organizational change.

The readiness–adoption matrix and staged roadmap synthesize this transition. The matrix shows that perceived readiness and adoption depth are not fully aligned, while the roadmap organizes the observed pattern into stages of foundational digital consolidation, operational and connectivity integration, advanced technology piloting, and systemic transformation. Both outputs should be interpreted as context-specific analytical tools grounded in the survey results, not as universal maturity models, predictive frameworks, or externally validated roadmaps.

From a practical perspective, Industry 4.0 adoption should be approached as a staged and capability-dependent process. Firms need to consolidate data infrastructure, strengthen workforce skills, improve interoperability, promote organizational learning, and develop mechanisms for experimentation and scaling. From a policy perspective, the findings highlight the importance of regional ecosystems that support training, technology transfer, pilot projects, and collaboration between firms, universities, technology providers, and public institutions.

Future research should expand this line of inquiry through longitudinal designs, interregional comparisons, and mixed-method approaches. Longitudinal studies would make it possible to observe how readiness and adoption evolve over time and to validate whether the staged roadmap reflects actual transition trajectories. Future studies could also compare large companies with SMEs, incorporate objective indicators of technological implementation, and examine differences among manufacturing subsectors.

Overall, the study shows that the key challenge for large manufacturing companies in emerging economies is not only to recognize the value of Industry 4.0, but to convert that recognition into effective, coordinated, and sustained technological deployment. In this

sense, the readiness–adoption gap offers a useful analytical lens for understanding why digital transformation may be strategically accepted but operationally incomplete.

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