

A Comprehensive and Structured Maturity Model for Measuring AI Adoption Levels in Industry 4.0

Leonildo Carnevalli Junior

Universidade Presbiteriana Mackenzie,
São Paulo SP 01239-001, Brazil
leonildo.carnevalli@hotmail.com

and

Maria Amelia Eliseo

Universidade Presbiteriana Mackenzie,
São Paulo SP 01239-001, Brazil
mariaamelia.eliseo@mackenzie.br

and

Ismar Frango Silveira

Universidade Presbiteriana Mackenzie,
São Paulo SP 01239-001, Brazil
ismar.silveira@mackenzie.br

Abstract

Industry 4.0 (I4.0) represents a transformative approach to industrial processes, fostering global competitiveness through cost reduction, process agility, and improved product quality. At the same time, Artificial Intelligence (AI) is reshaping organizational management, optimizing operations, and enhancing society's interaction with technology. As industries grow increasingly complex and innovation accelerates, AI emerges as a pivotal tool for driving efficiency and competitiveness across various domains. This study proposes a structured maturity model tailored to evaluate the levels of AI adoption within I4.0 contexts. By leveraging insights from established maturity frameworks, the model aims to assess companies' readiness and proficiency in integrating AI into daily operations and strategic initiatives. The resulting index provides a benchmark for organizations to identify strengths, address gaps, and monitor progress as they advance their digital transformation journeys.

Keywords: Industry 4.0, Maturity Level, Artificial Intelligence.

1 Introduction

Since its introduction at the Hannover Fair in 2011, Industry 4.0 (I4.0) has become a focal point in academic and industrial circles, driven by the need for innovative strategies to enhance efficiency and personalize products and services. Technologies such as the Internet of Things (IoT), Big Data, and Artificial Intelligence (AI) are propelling innovation, making companies more competitive. Consequently, the adoption of Industry 4.0 necessitates a reevaluation of conventional business models. A digital maturity model for companies is a key tool in this context, providing a benchmark to evaluate and improve processes, optimize resources, and mitigate risks. This study addresses a critical challenge: assessing how companies adopt Artificial Intelligence (AI) as they progress toward the digital transformation envisioned by I4.0. Despite AI's transformative potential, limited practical knowledge and awareness hinder its effective implementation, increasing the risks of missed opportunities or poor decisions.

To address these gaps, this research presents the development of a structured maturity model tailored to measure AI adoption in industrial contexts. The model evaluates key domains and criteria, providing companies with a practical framework to assess their readiness, identify areas for improvement, and guide their digital transformation efforts. By standardizing the measurement of AI maturity, this study aims to support organizations in leveraging the full potential of AI within Industry 4.0 frameworks.

To complement the theoretical framework and ensure practical applicability, this study also includes the development of a dedicated application for AI maturity assessment. This tool supports the structured implementation of the model and provides actionable feedback, enabling companies to optimize their strategies and continuously improve their AI adoption levels.

2 Theoretical framework

Digital Transformation is a concept that extends beyond the industrial sector, influencing all areas of society. It involves the application of digital technologies to improve processes, develop new business models, and enhance customer experiences. Within the industry, Digital Transformation is closely tied to I4.0, as both aim to leverage technologies like IoT (Internet of Things), Artificial Intelligence, Big Data, and cloud computing to optimize operations and foster innovation [4].

The adoption of technologies such as the Internet of Things (IoT) in enterprise environments has been widely studied for its potential to drive efficiency and innovation. However, challenges persist in understanding their technological maturity and integration processes. Recent bibliometric analyses, such as those by Solis Pino [26], highlight the need for standardized maturity assessment frameworks that can provide actionable insights into the readiness and progression of IoT adoption in businesses. These frameworks play a crucial role in identifying gaps and enabling targeted improvements, ensuring alignment with broader Industry 4.0 goals.

According to [5], I4.0 can be viewed as an ecosystem built upon a diverse array of technological systems and interconnected multidisciplinary innovations, capable of transmitting and receiving information rapidly, thereby facilitating the automation of decision-making processes. The shift towards adopting new technologies has the potential to drive significant organizational change, compelling companies to introduce new approaches and techniques for value creation, business remodeling, and enhancing customer relationships.

The human element is of paramount importance in I4.0. Recognizing that no system can be entirely automated and reliable at the same time, the integration of human and technological capabilities leads to superior outcomes. This digital transformation requires companies to adapt to the expectations of customers, partners, employees, and competitors who already utilize and demand the adoption of new digital technologies [6]. Therefore, the digital transformation in the context of I4.0 is not merely a final destination but an ongoing journey towards achieving digital maturity,

2.1 AI in the context of I4.0

The field of Artificial Intelligence (AI) is fundamentally centered on creating systems capable of executing tasks that typically require human intelligence [7]. These systems, which exhibit intelligence through machines, are grounded in mathematical algorithms and the statistical analysis of data [8]. A subset of AI is Machine Learning (ML), which focuses on developing methods that can autonomously identify patterns in data and utilize these patterns to predict future events of interest [9]. Machines are trained using historical data to recognize patterns, enabling them to make autonomous, data-driven decisions. Deep Learning (DL), a specialized area within ML, has led to significant advancements, particularly over the past decade, with notable applications such as autonomous vehicles and gaming systems that outperform human players [10] and [11].

Cyber-physical systems facilitate a seamless integration between humans and machines. Intelligent Industrial Automation Systems (IIAS) are a prominent example of this, making automated decisions based on AI and ML. These systems often incorporate ML processes alongside domain knowledge that is not directly extracted from the data. A crucial aspect to consider is the quality of the data, as these IIAS systems depend heavily on high-quality input data. In this context, AI and its branches, including ML and DL, are at the heart of I4.0, enabling the development of "intelligent" systems that can learn from data, make predictions, and autonomously make decisions. These advancements are driving a transformation across various sectors of the economy, reshaping how organizations operate and make decisions.

Within I4.0, there is an increasing trend towards integrating AI into a wide range of processes and operations, enabling software and machines to acquire the capabilities to perceive, understand, act, and learn from human activities. This approach has the potential to significantly enhance the efficiency of industrial systems, which carries important implications for the manufacturing sector—a sector experiencing robust growth, partly due to AI advancements integrated into the I4.0 framework.

2.2 Digital Maturity Models

Maturity Models (MMs) are critical tools designed to assess and compile specific competencies necessary for organizations to achieve a desired state, as illustrated by [12]. Structured as logical pathways divided into maturity levels, MMs guide organizations through acquiring the necessary skills to meet their objectives. These models evaluate an organization's current state, identify gaps, and enable progression along the maturation journey defined by each stage.

In dynamic and competitive markets, MMs are pivotal for driving organizational transformation. As emphasized by [13], they help identify a company's current position, establish a corporate vision and process excellence goals, and facilitate comparisons across companies and business units. MMs often aim to standardize practices across various areas and dimensions, frequently employing scoring systems for maturity assessment. This scoring system frequently aims to pinpoint critical areas, and highlight improvement opportunities during digital transformation, enabling companies to understand their maturity level and digital readiness [14].

Assessing maturity in the context of Industry 4.0 (I4.0) is essential to understanding the integration of technological innovations within organizations. Reference [15] conducted a study on MMs and I4.0, identifying 62 dimensions critical for evaluating maturity and readiness. Consolidating these into 10 main dimensions, they highlighted organizational strategy, products, technology, processes, people/staff, services, manufacturing and operations, customers, culture, and information technology as essential areas for assessment.

2.3 Comparative Analysis of Existing Maturity Models

Various maturity models have been proposed, each with unique focuses and methodologies. Below is a critical analysis of prominent models, highlighting their limitations and how the proposed model addresses them.

The Digital Readiness Evaluation Maturity Model (DREAMY) evaluates digital readiness across five levels—Initial (ML1) to Digital-Oriented (ML5)—and four dimensions: Process, Monitoring and Control, Technology, and Organization [24]. DREAMY provides a structured framework for assessing digitization but lacks customization for AI-specific challenges, such as algorithmic readiness or ethical considerations.

SIMMI 4.0 focuses on IT system readiness for I4.0 through four dimensions—Vertical Integration, Horizontal Integration, Digital Product Development, and Cross-Technology Criteria—and five maturity stages [21]. While effective for IT landscapes, SIMMI 4.0 insufficiently addresses broader organizational and cultural readiness for AI adoption.

The ACATECH model outlines six stages—Computerization to Adaptability—analyzing resources, information systems, culture, and organizational structure [22]. While comprehensive, it overlooks actionable feedback mechanisms and tailored recommendations for AI integration, limiting its usability for industries prioritizing AI.

IMPULS categorizes companies into Novices, Apprentices, and Leaders across six dimensions [23]. This model is effective for initial assessments but lacks the depth needed for advanced AI maturity evaluation or continuous improvement tracking.

CMMI's five levels—Initial to Optimizing—focus on process improvement [25]. However, its static approach and high implementation complexity hinder its applicability in dynamic I4.0 contexts. The model's lack of focus on technological integration makes it less effective for AI-centric industries.

2.4 Limitations of Existing Models

Insufficient AI Focus: Most models lack dimensions explicitly addressing AI readiness, ethical considerations, and algorithmic integration.

Static Structures: Many models are designed for linear progression and do not accommodate the iterative nature of AI development and deployment.

Limited Feedback Mechanisms: Few models provide actionable recommendations or dynamic progress tracking.

High Complexity: Models like CMMI require significant resources, limiting their accessibility to SMEs.

2.5 The Proposed AI Maturity Model

The maturity model introduced in this study distinguishes itself by focusing on the integration of AI within industries. Drawing from DREAMY and CMMI, as well as insights from [15], this model evaluates AI usage maturity in I4.0 contexts through:

- **AI-Centric Dimensions:** Incorporates dimensions like algorithmic readiness, data governance, and ethical AI practices.
- **Dynamic Feedback:** Offers real-time insights and action plans for continuous improvement.
- **Customizability:** Adapts to sector-specific needs, enabling diverse industry applications.

- Proactive Recommendations: Bridges the gap between evaluation and actionable strategies, fostering sustainable AI integration.

3 The Maturity Model in the Use of Artificial Intelligence

Maturity models are generally organized into progressive stages that describe the organization's evolution concerning a specific process or set of processes. The development strategy of a maturity model involves identifying and defining these stages, as well as determining the key process areas associated with each stage. In this context, the Maturity Model for AI utilization within I4.0 was developed based on the DREAMY model, as proposed by [24], due to its flexible structure, which can encompass multiple dimensions and sub-dimensions. The model also draws on the domains identified by [15] and the maturity levels of CMMI.

3.1 Dimensions Selection

The proposed maturity model leverages dimensions carefully selected through a rigorous review of the literature, as well as adaptations from established frameworks. This process aimed to ensure relevance, comprehensiveness, and alignment with the specific challenges and opportunities associated with AI adoption in Industry 4.0 (I4.0).

The selection of dimensions was based on the study by Hajoary [16], which consolidated 62 dimensions from academic and industrial maturity models into ten key categories. These categories include Organizational Strategy, Technology, Processes, People, and Culture, among others. By combining these categories with insights from models like DREAMY and CMMI, the proposed framework refines and integrates these elements into a context-specific structure. For example, the dimension "Products and Services" was combined due to the increasingly blurred boundaries between the two in the era of smart technologies.

3.2 Differentiation from Existing Models

While many existing maturity models focus on general technological readiness or broader Industry 4.0 capabilities, the proposed model distinctly emphasizes AI's role within these domains. Unlike Schumacher's framework, which prioritizes strategic and cultural readiness, or SIMMI 4.0, which focuses on IT system integration, the proposed model introduces AI-specific criteria such as AI Strategic Alignment and AI Governance, enabling a more nuanced evaluation of companies' maturity.

Moreover, the model extends DREAMY's flexibility by integrating a refined Likert scale (0-5), allowing for granular assessment across nine dimensions and 32 sub-dimensions. This adaptation not only facilitates a multidimensional view of AI maturity but also ensures practical applicability through clear metrics and actionable insights.

3.3 Practical Implications

In comparing existing models, Table 1 outlines the key dimensions and their relevance to AI maturity. This structured approach allows for a clearer understanding of how the proposed model advances the field, bridging the gaps identified in prior research. For instance, while the ACATECH model emphasizes resources and information systems, it lacks focus on AI-specific strategies and governance, which are critical for fostering innovation and ensuring ethical practices in AI deployment.

Table 1: Measurement of I4.0 maturity level of the proposed model

Dimensions	Level 0	Level 1	Level 2	Level 3	Level 4	Level 5
<i>Organizational Strategy</i>	<i>N.A</i>	<i>Initial</i>	<i>Alert</i>	<i>Acceptable</i>	<i>Ideal</i>	<i>Optimal</i>
<i>People/Employees</i>	<i>N.A</i>	<i>Initial</i>	<i>Alert</i>	<i>Acceptable</i>	<i>Ideal</i>	<i>Optimal</i>
<i>Process</i>	<i>N.A</i>	<i>Initial</i>	<i>Alert</i>	<i>Acceptable</i>	<i>Ideal</i>	<i>Optimal</i>
<i>Technology</i>	<i>N.A</i>	<i>Initial</i>	<i>Alert</i>	<i>Acceptable</i>	<i>Ideal</i>	<i>Optimal</i>
<i>Customers</i>	<i>N.A</i>	<i>Initial</i>	<i>Alert</i>	<i>Acceptable</i>	<i>Ideal</i>	<i>Optimal</i>
<i>Manufacturing and Operations</i>	<i>N.A</i>	<i>Initial</i>	<i>Alert</i>	<i>Acceptable</i>	<i>Ideal</i>	<i>Optimal</i>

Dimensions	Level 0	Level 1	Level 2	Level 3	Level 4	Level 5
<i>Products e Services</i>	<i>N.A</i>	<i>Initial</i>	<i>Alert</i>	<i>Acceptable</i>	<i>Ideal</i>	<i>Optimal</i>
<i>Operational Technology</i>	<i>N.A</i>	<i>Initial</i>	<i>Alert</i>	<i>Acceptable</i>	<i>Ideal</i>	<i>Optimal</i>
<i>Culture</i>	<i>N.A</i>	<i>Initial</i>	<i>Alert</i>	<i>Acceptable</i>	<i>Ideal</i>	<i>Optimal</i>

3.4 Identifying maturity's value by dimension and total value

Each sub-level within a specific dimension is evaluated using a score ranging from 0 to 5. This score is determined based on responses to questions corresponding to each sub-level, reflecting the degree of maturity or readiness in that particular aspect of the dimension. For each dimension, the scores of all its sub-levels are totaled. For example, if a dimension consists of 5 sub-levels and each sub-level can achieve a maximum score of 5, the highest possible total for that dimension would be 25 points (5 sub-levels × 5 points each).

The total score for a dimension is then normalized to a scale from 0 to 1. This normalization is accomplished by dividing the total sum of the dimension's points by the maximum possible score for that dimension. This step converts the aggregate score into a proportional value that represents the relative maturity level within the established scale.

The normalized value, now on a scale from 0 to 1, is then multiplied by 5 to readjust it to a maturity scale ranging from 0 to 5. This transformation facilitates a more intuitive interpretation of the results while ensuring consistency with the original scoring scale. Eq. 1 illustrates this process:

$$MD = \left(\frac{\sum_{i=1}^n MSD}{n} \right) * 5$$

Where: MD = Dimension Maturity; MSD = Maturity of the sub-dimension as answered in the questionnaire; N = Total number of sub-dimensions for the analyzed Dimension.

Finally, to obtain the overall maturity score, all the adjusted scores of the dimensions are summed and then divided by the total number of dimensions. This calculation yields an average that represents the organization's overall maturity level concerning Industry 4.0 and is expressed by Eq. 2:

$$MMT = \left(\frac{\sum_{i=1}^9 MD}{9} \right)$$

Where: MMT = Total Maturity Mean; MD = Mean per dimension.

This mathematical approach ensures a quantitative assessment of maturity, enabling a detailed analysis of progress across various areas and offering an overview of readiness for Industry 4.0. The normalization and averaging techniques ensure that scores are proportionally representative and comparable across different dimensions

Example

#	Dimension	Sub-dimensions Scores	Maturity of Dimension (MD)
1	Organizational Strategy	[5, 4, 3, 4, 5]	4.2
2	People/Employees	[4, 3, 5]	4.0
3	Process	[5, 5, 5, 4]	4.75
4	Technology	[4, 3, 4, 5]	4.0
5	Customers	[3, 3, 3]	3.0
6	Manufacturing & Operations	[5, 4, 4]	4.33
7	Products & Services	[4, 4]	4.0
8	Operational Technology	[5, 5, 4]	4.67
9	Culture	[4, 4, 3]	3.67
Overall Maturity Mean (MMT)			4.07

3.2 Motivation for Implementing a Specific Application

While various tools for assessing maturity levels are available, the development of a dedicated application in this study was driven by the need to validate the proposed maturity model and enhance its practical application. This custom software not only evaluates maturity levels but also provides tailored feedback and actionable recommendations based on the responses.

By integrating a system for personalized action planning and recommendation, the application serves as a dynamic tool for continuous improvement. In its initial phase, it validates the constructs of the maturity model, ensuring alignment with theoretical principles. Over time, it enables deeper insights and improvements by evolving into a recommendation system that guides companies toward achieving higher levels of maturity.

The application optimizes the assessment process by offering immediate feedback and a structured action plan, thus addressing gaps identified during evaluation. This capability distinguishes it from generic tools, making it a vital resource for companies navigating the complexities of AI adoption in the context of Industry 4.0.

4 System Development

To implement the proposed rules and questionnaires outlined in this article, a comprehensive system was developed. This system serves to operationalize the methodologies and guidelines suggested, allowing companies to effectively assess their Industry 4.0 maturity levels. By providing a structured platform for evaluation and improvement, the system facilitates the practical application of the concepts discussed, ensuring that the assessment process is both interactive and actionable.

4.1 System Objective

The objective of the system is to develop an interactive and secure web application that assesses the Industry 4.0 maturity level of companies. This application will enable companies to identify their strengths and weaknesses, receive personalized recommendations, and create tasks to address areas needing improvement. Additionally, the system allows for anonymous benchmarking by segment, market, and company type, and includes task management functionalities for assigning tasks to team members.

4.2 Application Overview

The application implements the proposed domains and levels by presenting a questionnaire to determine a company's AI maturity level. Within the application, companies can view their maturity level and, if they authorize participation in comparison, benchmark their position against the average for their segment, market, and company type. The platform also provides recommendations to help improve their maturity level.

4.3 Development Platform

Frontend: The frontend is developed using standard web technologies—HTML, CSS, and JavaScript—ensuring a rich and interactive user experience across different devices:

- **HTML:** Structures the content and layout of the user interface;
- **CSS:** Styles the user interface, ensuring consistency with design standards;
- **JavaScript:** Adds interactivity and asynchronous communication with the backend, enhancing user experience.

Backend: The backend is built using .NET Core APIs running on a Linux environment, offering high performance and cross-platform capabilities:

- **C#:** Used for business logic and data manipulation, providing a robust and secure backend foundation;
- **.NET Core:** Supports the development of scalable and efficient web applications, with cross-platform execution;
- **SQL Server:** Selected for database management due to its reliability, SQL compliance, and support for complex data operations, making it ideal for enterprise-level applications.

4.4 System Functionality Overview

This section provides an overview of the system's functionality, detailing the steps users take to interact with the platform and how the system processes and utilizes the data to assess Industry 4.0 maturity.

Users begin by choosing to either log in to the solution or create a new account if they do not already have one. This initial step is crucial as it enables the user to access the system and ensures that the necessary basic information is collected. This data is essential for identifying the company within the system and for grouping companies by similar size and annual revenue, allowing for accurate benchmarking and comparison. As illustrated in Fig. 1 below, this step captures fundamental company details, which are subsequently used to tailor the evaluation and recommendations.

The system interface is currently in Portuguese, so the figures presented reflect this language. However, the process and functionalities described are universally applicable, regardless of language.

Figure 1: Company and Respondent Registration

After the company and employee registration is complete, users can proceed to answer the questionnaires designed to identify the company's maturity level. These questionnaires are based on the domains and subdomains outlined in the proposed model and assess the maturity level with responses ranging from 0 to 5. Each response reflects the company's current standing in the respective areas, helping to pinpoint strengths and areas for improvement. Fig 2 shows an example of a questionnaire screen (in Portuguese), where users can input their responses.

Figure 2: Questionnaire Screen

Once the responses are submitted, the system applies the formulas proposed in the article to calculate the average maturity level for each domain and subdomain. The system then generates a graph that visually represents the maturity levels across the nine evaluated domains, as well as an overall average maturity level. This graphical representation provides a clear overview of the company's standing in each area, allowing for easy identification of strengths and areas that require attention. Fig. 3 illustrates this graph, showcasing the maturity levels in each domain.

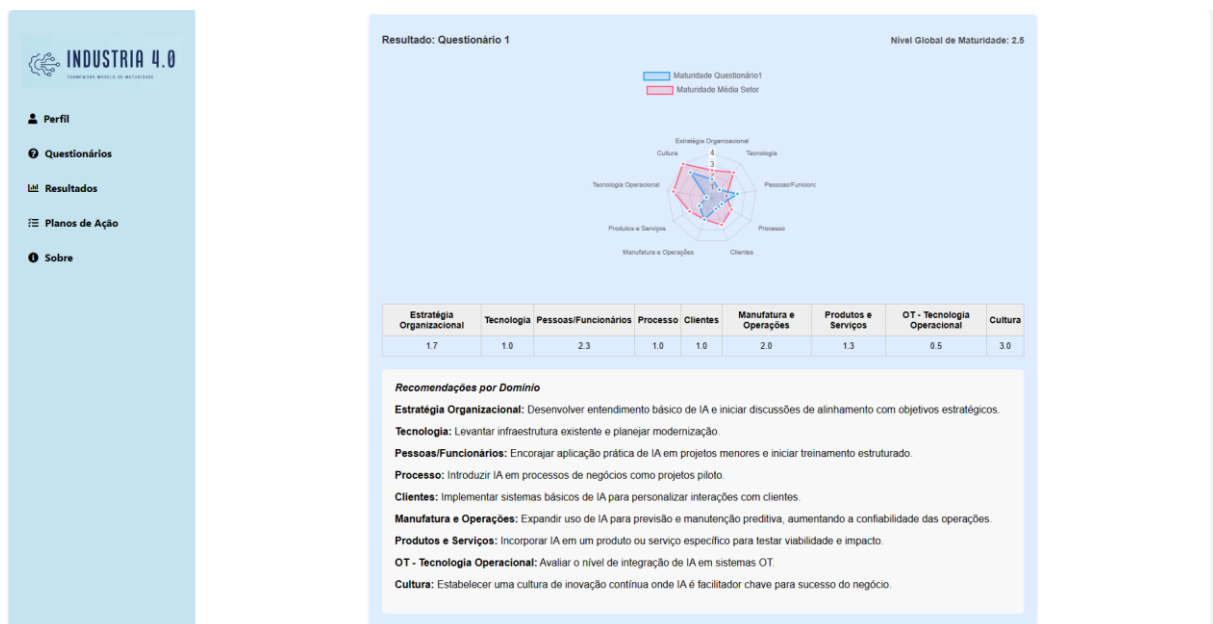


Figure 3: Results Screen

Finally, and no less importantly, the system presents the action planning screen. On this screen, each question and its corresponding maturity level are displayed, allowing the company or employee to create an action plan for each item. This feature is designed to assist the company in improving its maturity index by addressing specific areas identified in the questionnaire. Fig. 4 shows a section of these action plans created for one of the questions asked, illustrating how users can strategize and implement steps to enhance their overall maturity level.



Figure 4: Action Plan Screen

5 Results and Discussion

The emergence of AI stands out as one of the most significant topics of our time, driving a profound revolution in organizational management and operations, redefining daily professional routines, and transforming society's interaction with technology. The growing complexity of the business landscape, particularly the inherent challenges within industrial sectors, combined with ongoing technological advancements, establishes AI as a crucial tool for driving innovation, optimizing efficiency, and enhancing competitiveness across all organizational domains.

The proposed model enables an integrated assessment, providing a comprehensive overview for analyzing and potentially enhancing organizational capabilities within an increasingly integrated and data-driven industrial environment. The following sections outline the dimensions and sub-dimensions proposed in the model, as well as their application:

- **Organizational Strategy:** The team's leadership capacity to make long and short-term strategic decisions regarding the I4.0 roadmap;
 - **AI Strategic Alignment:** Focuses on the company's vision regarding AI and its strategic objectives;
 - **AI Governance:** Involves defining policies, procedures, and responsibilities to ensure ethical, safe, and effective AI use;
 - **AI Skills and Culture:** Refers to developing AI-related skills and competencies within the organization and promoting a culture supporting innovation and AI adoption;
- **People/Employees:** The team's leadership capacity to make long and short-term strategic decisions regarding the I4.0 roadmap. Employees are a crucial asset for the organization. It's essential for organizations to understand their current skills, roles, and qualifications and re-skill them with the latest skills as per I4.0 needs. Another aspect relates to the ability to change employees' mindset and willingness to change;
 - **AI Competency:** Refers to the level of skill and knowledge employees have regarding AI;
 - **AI Talent Recruitment:** Recruiting specialized AI talents is essential to drive innovation and maintain a competitive advantage;
 - **AI Innovation Culture:** Where AI is not only implemented but is also an integral part of the organizational mindset;
- **Process:** I4.0 has brought a drastic change in the manufacturing process, transforming it into a more agile and automated manufacturing process;

- **AI Integration in Processes:** Refers to the incorporation of AI systems into existing operational processes;
- **Decision Automation:** Involves using AI to automate operational or strategic decisions;
- **Process Optimization:** Using AI algorithms and machine learning techniques to continually improve manufacturing process efficiency;
- **Operational Technology:** The team's leadership capacity to make long and short-term strategic decisions regarding the I4.0 roadmap. Manufacturing production technology has evolved over the years, from artisanal to the shop floor, assembly line, just-in-time, to flexible manufacturing systems;
 - **OT-IA Integration:** Combining AI with these operational systems to improve process efficiency, productivity, and flexibility;
 - **OT Security with AI:** Using AI algorithms to detect, predict, and respond to security threats automatically;
- **Customers:** A large amount of customer data is generated daily from sales and services;
 - **Personalization with AI:** The ability to personalize experiences, products, and services for individual customer;
 - **AI Customer Support:** Involves using chatbots, virtual assistants, and intelligent response systems to provide quick and effective customer service;
 - **Feedback and Continuous Improvement:** Represents a virtuous cycle where customer feedback is used to continuously refine and improve products and services;
- **Manufacturing and Operations:** Manufacturing and operations form the foundation and are considered the heart of the I4.0 vision by producing products autonomously in a self-optimized environment;
 - **Operational Efficiency with AI:** AI can be applied to improve operational efficiency, optimize processes, reduce waste, and increase production without compromising quality;
 - **Quality Monitoring and Control with AI:** AI application in monitoring and quality control allows for continuous and real-time assessment of manufacturing processes;
 - **Supply Chain Management with AI:** AI provides valuable insights for supply chain management, from demand forecasting to inventory optimization and logistics improvement;
- **Products and Services:** Products and services go hand in hand as products are equipped with intelligent sensors, RFID, GPS, embedded systems, etc., to track status, quality, and location;
 - **Product Development with AI:** AI can be used to enhance the product development process, from design to prototyping and testing;
 - **AI as a Service (AIaaS):** Refers to the business model where AI capabilities are offered as a service through the cloud;
 - **AI-enhanced Customer Experience:** Involves using technology to improve consumer interaction with products and services;
- **Information Technology:** Technologies such as Enterprise Resource Planning (ERP), Manufacturing Execution Systems (MES), Flexible Manufacturing Systems (FMS), Computer-Aided Manufacturing (CAM), Numerical Control (NC), etc., are enhancing productivity, operational efficiency, and increasing visibility in the manufacturing process;
 - **Technological Infrastructure:** Refers to the hardware and software base supporting all IT operations;
 - **AI Tools and Platforms:** Software and environments that enable the development and operation of AI systems;
 - **Technology Integration:** The ability to unite different technological systems and processes, allowing AI systems to work seamlessly with other technologies;
 - **Security and Privacy:** Ensures that information is protected against unauthorized access and that data is handled in accordance with privacy laws and regulations;

- **Technological Adaptability:** The ease with which an organization can adopt new technologies and adapt existing ones to changes in demands and the business environment;
- **Training and Updating:** Involves educating the workforce about new technologies and keeping IT systems up to date;
- **Automation and Efficiency:** Refers to the use of technology to automate tasks and make business processes more efficient;
- **Maintenance and Support:** Ensures that IT systems, including those using AI, are always available and functioning correctly;
- **Technology Investment:** Reflects a company's financial commitment to upgrading and improving its technological capabilities, including AI;
- **Interoperability:** The ability of IT systems, including those with AI, to operate together and exchange data efficiently. Interoperability is critical for collaboration and process optimization throughout the organization;
- **Culture:** I4.0 has significant implications for how the organization functions and organizes its work culture;
 - **AI Adoption in Organizational Culture:** Refers to how AI is perceived and integrated into the company's values, behaviors, and everyday practices;
 - **AI Empowerment and Development:** Addresses education and training in AI for employees at all levels of the organization.

In summary, the maturity model for AI utilization within the context of Industry 4.0 encompasses nine dimensions: Organizational Strategy, People, Processes, Technology, Customers, Manufacturing and Operations, Products and Services, Information Technology, and Culture. This model can be employed by industrial managers to evaluate the maturity level of AI usage within their sector. The model operates on a six-level scale (0 to 5), specifically: Level 0 (Not Applicable), Level 1 (Initial), Level 2 (Alert), Level 3 (Acceptable), Level 4 (Ideal), and Level 5 (Optimal), as previously illustrated in Table 1. (Fig. 5). synthesizes the core concepts of this maturity model for I4.0.

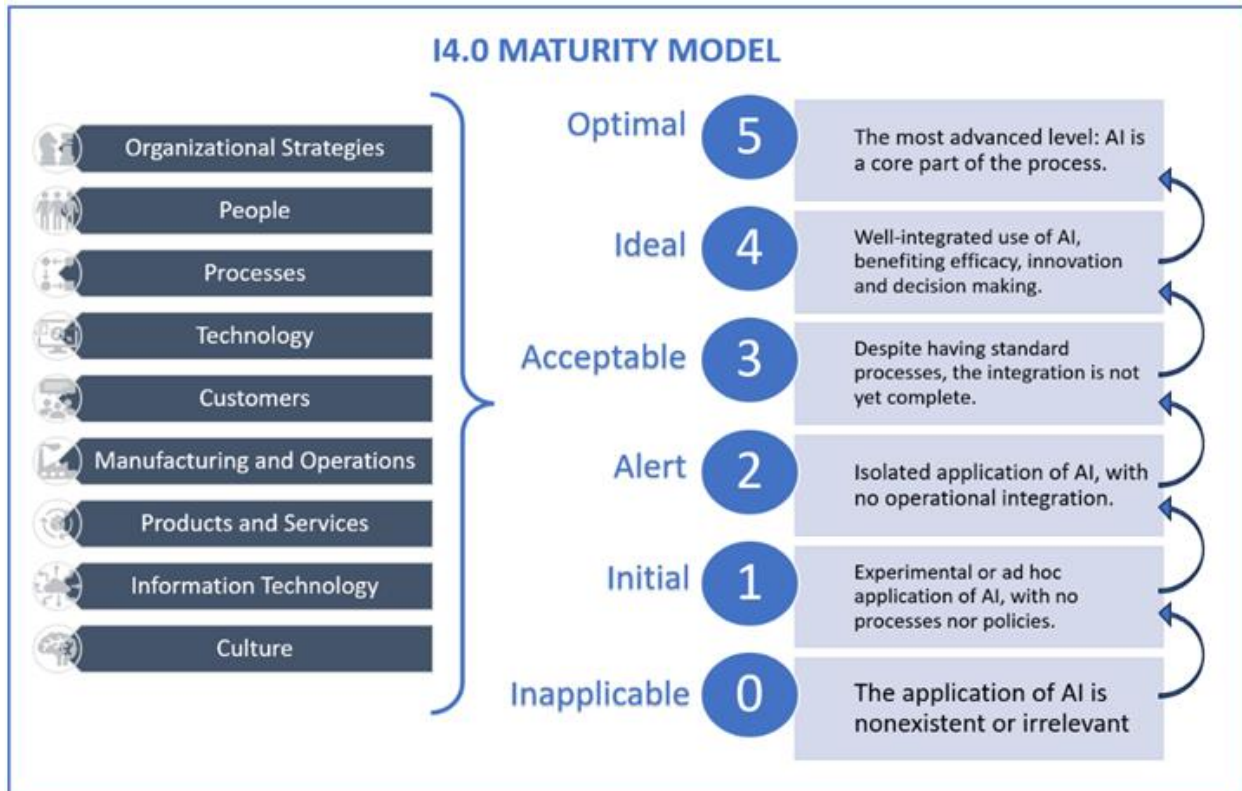


Figure 5: I4.0 maturity model

Industries Analyzed

- Metalworking: Represents 43% of the companies analyzed.
- Construction: Includes one company focusing on architectural and urban planning projects.
- Professional Services: Consultancies including law, accounting, and others.
- Agriculture: One company active in agricultural production.
- IT Services: One company specializing in technology services (Business-to-Business)**: Dominates with 71% of the companies serving other businesses.

Revenue Ranges:

- An range from below R\$1 million to above R\$50 million. This variation highlights a mix of small, medium, and large enterprises .

Regional Distribution:

- Most colocated in the Southeast region of Brazil, with only two operating nationally .

5.1 Limitations

This study has some inherent limitations that may affect the generalizability and applicability of its findings. The developed tool focuses on the maturity assessment of AI adoption within Industry 4.0 contexts, which may restrict its utility in non-industrial sectors or specific use cases. Additionally, the data used to validate the tool are derived from a limited sample, potentially underrepresenting diverse industrial scenarios. The initial stage of validation might also overlook nuanced industry-specific variables.

While the tool provides feedback and action plans, its recommendations may lack the granularity needed for highly specialized scenarios. Furthermore, the fast-paced evolution of AI technologies demands continuous updates to ensure the tool remains relevant and effective. Addressing these limitations in future iterations of the tool will enhance its robustness and applicability.

6 Final remarks and further works

Throughout the research, specific qualifiers were identified to guide the evaluation of Artificial Intelligence (AI) maturity within organizations, addressing the core question of how to assess the extent of AI adoption as companies advance towards the digital transformation envisioned by Industry 4.0. A digital tool implementing the proposed model was developed to facilitate the assessment of AI usage within organizations. The methodological approach involved an examination of theoretical concepts from the literature, with a focus on Industry 4.0 frameworks and existing digital maturity models. A comprehensive literature review initially facilitated the analysis of existing maturity models within the industrial context, emphasizing the digital environment. This review highlighted various applications of maturity models in organizational settings, including their role in supporting strategic decision-making and monitoring progress toward technological maturity.

This investigation not only enhanced the understanding of the current state of AI maturity but also informed the development of the proposed model within this research. Building upon the studied concepts, a maturity model specifically tailored to the integration of AI in industrial contexts was developed. This phase entailed synthesizing best practices and concepts derived from the literature review, resulting in the creation of a novel model designed to assess the degree of AI maturity. The developed model offers a practical and measurable approach for evaluating AI maturity, facilitating the effective implementation of AI-driven technologies, particularly within the framework of Industry 4.0.

To automate the proposed model, a system was developed to operationalize the methodologies and guidelines suggested, enabling companies to effectively assess their Industry 4.0 maturity levels. The tool assists in analyzing action plans implemented across companies, identifying effective and commonly used tasks in specific situations. Consequently, when facing similar challenges, a company could receive task suggestions that have been proven effective, thereby aiding in the development of more precise action plans aligned with industry best practices.

As a future work suggestion, the solution would greatly benefit from the capability to create customized questionnaires tailored to specific industry segments, rather than relying on a general assessment. This customization would provide more accurate and relevant insights for each sector, fostering more precise benchmarking and targeted recommendations that align with the distinct needs of various industries.

Additionally, integrating multi-language support into the system would broaden its applicability, allowing it to serve companies across different countries and regions. This enhancement would make the framework more accessible and useful, ensuring that diverse organizations can effectively utilize the tool to advance their AI maturity within the Industry 4.0 context.

References

- [1] Culot, G. et al.: Behind the definition of industry 4.0: Analysis and open questions. *International Journal of Production Economics*, Elsevier, v. 226, p. 107617, (2020). <https://doi.org/10.1016/j.ijpe.2020.107617>
- [2] Yu, Y., Huo, B.: Supply Chain Quality Integration: Relational Antecedents and Operational Consequences. *Supply Chain Management: An International Journal*, Emerald Publishing Limited, Vol. 23 No. 3, pp. 188-206 (2018). <https://doi.org/10.1108/SCM-08-2017-02802018>.
- [3] Wendler, R.: The maturity of maturity model research: A systematic mapping study. *Information and Software Technology*, Elsevier, v. 54, n. 12, p. 1317–1339 (2012).
- [4] Matt, C. et al.: Digital Transformation Strategies. *Business & Information Systems Engineering*, v. 57, n. 5, p. 339-343 (2015).
- [5] Palmeira J., Coelho G., Carvalho, A., Carvalhal P. and Cardoso, P.: Migrating legacy production lines into an Industry 4.0 ecosystem. In: 20th International Conference on Industrial Informatics, pp. 429-434. INDIN, Perth (2022). <https://doi.org/10.1109/INDIN51773.2022.9976084>.
- [6] Tadeu, H. F. B., duarte, A., chede, C.: Transformação digital: perspectiva brasileira e busca da maturidade digital. *Revista DOM. Fundação Dom Cabral. Nova Lima, DOM*, v. 11, n. 35, p. 32–37 (2018).
- [7] Saygin, A. P., Cicekli, I., Akman, V.: Turing test: 50 years later. *Minds and Machines*, Springer, v. 10, n. 4, p. 463–518 (2000).
- [8] Warwick, K.: Artificial intelligence: the basics. [S.l.]: Routledge (2013).
- [9] Murphy, K. P.: Machine learning: a probabilistic perspective. [S.l.]: MIT press (2012).
- [10] Silver, D. et al.: Mastering chess and shogi by self-play with a general reinforcement learning algorithm. *arXiv preprint arXiv:1712.01815* (2017).
- [11] Martínez-díaz, M., Soriguera, F.: Autonomous vehicles: theoretical and practical challenges. *Transportation Research Procedia*, v. 33, p. 275–282, 2018. ISSN 2352-1465. XIII Conference on Transport Engineering (2018). <https://doi.org/10.1016/j.trpro.2018.10.103>
- [12] Schumacher, A., Erol, S., Sihn, W.: A maturity model for assessing industry 4.0 readiness and maturity of manufacturing enterprises. *Procedia CIRP*, Elsevier, v. 52, p. 161–166 (2016). <https://doi.org/10.1016/j.procir.2016.07.040>
- [13] Felch, V., Asdecker, B., Sucky, E.: Maturity models in the age of industry 4.0 – do the available models correspond to the needs of business practice? *Proceedings of the 52nd Hawaii International Conference on System Sciences*, v. 6, p. 5165–5174 (2019). https://aisel.aisnet.org/hicss-52/in/digital_supply_chain/3/
- [14] Velho, S. R. K., Barbalho, S. C. M.: Um observatório latino-americano da indústria 4.0. Blucher (2019). <http://repositorio2.unb.br/jspui/handle/10482/37899>
- [15] Hajoary, P. K.: Industry 4.0 maturity and readiness models: A systematic literature review and future framework. *International Journal of Innovation and Technology Management*, World Scientific, v. 17, n. 07, p. 2030005 (2020). <https://doi.org/10.1142/S0219877020300050>
- [16] Weber, C. et al.: M2DDM—a maturity model for data-driven manufacturing. *Procedia Cirp*, v. 63, p. 173-178 (2017). <https://doi.org/10.1016/j.procir.2017.03.309>
- [17] Enke, J., Glass, R., Metternich, J.: Introducing a maturity model for learning factories. *Procedia Manufacturing*, v. 9, p. 1-8 (2017). <https://doi.org/10.1016/j.promfg.2017.04.010>
- [18] Tonelli, Flavio et al. A novel methodology for manufacturing firms value modeling and mapping to improve operational performance in the industry 4.0 era. *Procedia CIRP*, v. 57, p. 122-127 (2016). <https://doi.org/10.1016/j.procir.2016.11.022>

- [19] Gökalp, E., Şener, U., Eren, P. E.: Development of an assessment model for industry 4.0: industry 4.0-MM. In: Software Process Improvement and Capability Determination: 17th International Conference, SPICE 2017, Palma de Mallorca, Spain, October 4–5, 2017, Pro-ceedings. Springer International Publishing, p. 128-142 (2017). https://doi.org/10.1007/978-3-319-67383-7_10
- [20] Ganzarain, J., Errasti, N.: Three stage maturity model in SME's towards Industry 4.0 (2016). <http://dx.doi.org/10.3926/jiem.2073>
- [21] Leyh, C. et al.: SIMMI 4.0 – A Maturity Model for Classifying the Enterprise-wide IT and Software Landscape Focusing on Industry 4.0. ACSIS, v. 8, p. 1297–1302 (2017).
- [22] Schuh, G. et al.: acatech STUDY: Industrie 4.0 Maturity Index Managing the Digital Trans-formation of Companies (2017).
- [23] Lichtblau, K. et al.: Industrie 4.0 Readiness. Aachen, Cologne (2015).
- [24] De Carolis, A. et al.: A Maturity Model for Assessing the Digital Readiness of Manufactur-ing Companies. IFIP Advances in Information and Communication Technology, 2017, p. 13–20. doi:10.1007/978-3-319-66923-6_2
- [25] Magno, A. et al.: Modelos de Maduridade. [S.l.]: UNEB (2011).
- [26] Solis Pino, A. F., Ruiz, P. H., Mon, A., & Collazos, C. A. (2024). A bibliometric analysis of the landscape of measuring technology maturity in the enterprise internet of things. International Journal of Electrical and Computer Engineering, 14(4), 4697-4713. DOI: 10.11591/ijece.v14i4.pp4697-4713