

DEVELOPMENT OF AN INTEGRATED INTELLIGENT MANUFACTURING SYSTEM UTILIZING IOT AND DATA MINING FOR THE DIGITAL TRANSFORMATION OF INDUSTRY 4.0

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ABSTRACT

The advancement of Industry 4.0 has driven digital transformation in manufacturing environments, promoting greater integration between machines, processes, and teams through smart technologies. In this context, this paper proposes the development and implementation of an integrated smart manufacturing platform based on Artificial Intelligence (AI), the Internet of Things (IoT), and Data Mining, aiming to optimize production processes and enhance the digital maturity of the company that manufactures bumper strips: Guillotine, Crease Cutting, Rewinder, and Reflective Film (Slitter). The main objective is to integrate systems, automate data collection, and enable real-time monitoring, predictive maintenance, and support for autonomous decision-making on the factory floor. The materials and methods involve detailed mapping of production processes, identification of bottlenecks, and definition of strategic points for installing IoT sensors on 11 cutting machines (side strip). The system architecture consisted of sensors, microcontrollers, gateways, a database, APIs, and interactive dashboards, integrated with existing corporate systems such as ERP and R&D Core. Data mining and machine learning techniques were applied for pattern analysis, anomaly detection, and prediction of operational failures. In addition, the system was validated in a real manufacturing environment, followed by training for the teams involved. As the results were effective in practice, they demonstrated greater operational efficiency, reduced waste, improved quality, increased traceability, and faster decision-making. It can be concluded that the implementation of the platform will contribute significantly to the consolidation of smart manufacturing, providing cyber-physical integration, greater industrial competitiveness, and a solid foundation for continuous innovation and future expansion of the solution in light of the maturity level of Industry 4.0.



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I. INTRODUCTION

Digital transformation has driven significant changes in industrial processes, spurring the adoption of technologies capable of making production more efficient, connected, and intelligent. In this context, Industry 4.0 represents a new manufacturing model based on the integration of physical and digital systems, utilizing technologies such as Artificial Intelligence (AI), the Internet of Things (IoT), Big Data, and Data Mining. These tools enable real-time monitoring, process automation, and data-driven decision-making, contributing to increased productivity, cost reduction, and improved industrial competitiveness, as was the case in the research application [1-4]. Despite technological advances, many industries still operate with limited digital integration across departments, machines, and processes.

In many cases, production controls rely on manual records or isolated systems, hindering the continuous flow of information and reducing the ability to identify failures, bottlenecks, and operational losses. This limitation compromises production efficiency, process predictability, and the speed of decision-making. Given this scenario, this paper proposes the development and implementation of an integrated smart manufacturing system, based on the combined use of Artificial Intelligence, the Internet of Things, and Data Mining. The initiative aims to expand the company's existing smart manufacturing platform (GateMove), incorporating Industry 4.0 principles onto the factory floor. The objective was to integrate machines, processes, and teams into a single digital platform, enabling continuous monitoring, greater operational predictability, and automated responses to production deviations in the manufacture of tapes using machines for bumpers: Guillotine, Crease Cutter, Rewinder, and Reflective Film (Slitter) [5]. The proposal involved the use of IoT sensors installed at strategic points along the production line to automatically collect data related to operational performance, cycle times, production volume, and machine downtime.

This information was transmitted in real time to central processing systems, enabling greater traceability and control of industrial operations. In addition, the collected data was integrated into the company's corporate systems, promoting a continuous flow of information between the shop floor and management levels. Another important aspect of the research is the application of Data Mining and Machine Learning techniques. Through the analysis of historical and operational data, intelligent algorithms enabled the identification of patterns, the detection of anomalies, and the prediction of failures before they occur. This approach enabled the implementation of predictive maintenance strategies, reducing unplanned downtime and increasing production efficiency [6-8]. In addition to the operational benefits, the implementation of the platform helped strengthen the company's culture of technological innovation, promoting greater team training in the process and encouraging data-driven decisions, given that the company has achieved Maturity Levels 1 (Computerization) and 2 (Connectivity) of Industry 4.0 according to the Acatech Manual. Thus, the research represented an important initiative to consolidate the digitization of the manufacturing environment and enhance industrial competitiveness by raising the Maturity Level to Level 3 (Visibility). Consequently, the developed solution delivered significant gains in productivity, quality, waste reduction, and operational agility. The integration of AI, IoT, and Data Mining enabled the creation of a smarter manufacturing environment that is more connected, efficient, and prepared for the challenges of Industry 4.0.

II. BIBLIOGRAPHY REVIEW

II.1 NATURE OF THE TECHNOLOGICAL CHALLENGE

This paper presents a highly complex technological challenge, characterized by the need to integrate different fields of knowledge, such as industrial automation, data science, process engineering, and embedded systems development. The objective is to develop a novel solution aimed at creating an intelligent system capable of monitoring, interpreting, and reacting in real time to critical events in production processes, which requires the conduct of applied research and experimental development activities. The proposal involves building novel solutions for industrial environments, which require the generation of technical and scientific knowledge aimed at solving practical problems and innovating in production processes. The nature of the challenge is rooted in the need to integrate physical devices, control systems, artificial intelligence algorithms, and digital interfaces into an ecosystem capable of operating intelligently, autonomously, and in real time. Such integration requires overcoming technical uncertainties related to communication between devices, the processing of time-sensitive data, precise control of industrial operations, and ensuring the reliability of information for decision-making. Among the main technological challenges to be addressed, the following stand out:

- a. The definition and control of the operating frequency, latency, and memory capacity of the devices responsible for collecting and tracking manufacturing data, ensuring stability in the transmission and reception of critical information [9], [10];
- b. The development of analytical models capable of identifying complex patterns in productivity and quality metrics, in order to generate alerts, key performance indicators (KPIs), and automated decision recommendations for operators and managers [11], [12].
- c. The implementation of integration mechanisms between hardware and software layers, with a focus on minimizing data loss and maximizing event synchronization, ensuring consistency in the data feed to Business Intelligence systems [13], [14];
- d. The creation of intelligent strategies for dynamic production replanning based on predictive analysis of failures, non-conformities, and adjustments to manufacturing schedules, using graphical visualizations and dashboards to support decision-making [15-17].

Among the key technical aspects of the paper, the following challenges stand out: controlling the frequency and memory capacity of traceability devices; efficient processing of data from production and inspections; integration between hardware and software with minimal loss of information; and the generation of dynamic reports and graphs to aid in fault mitigation, non-conformity management, and the continuous improvement of key performance indicators (KPIs). Thus, the technical aspects of this project are in accordance with the levels of technological challenge defined in the legislation:

- a. Level 3 – Conducting experimental development: involving systematic work based on pre-existing knowledge, aimed at developing new systems, improving industrial processes, and integrating technological solutions into a real manufacturing environment;
- b. Level 4 – Conducting applied research: characterized by original investigation aimed at acquiring technical and scientific knowledge focused on specific practical problems, such as the intelligent analysis of production data and the generation of automated decisions.

II.2 APPLICATIONS OF INDUSTRY 4.0 IN INDUSTRIAL PROCESSES.

Industry 4.0 represents the fourth industrial revolution and is associated with the integration of advanced digital technologies into production processes. This concept emerged in Germany with the goal of promoting smart factories that are highly connected and capable of operating autonomously, flexibly, and efficiently. Industry 4.0 combines technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), Big Data, cloud computing, advanced robotics, cyber-physical systems, and real-time data analysis.

These technologies enable communication between machines, equipment, systems, and people, providing greater integration and automation in industrial environments [18]. In practice, Industry 4.0 is applied across various industrial sectors, such as automotive, electronics, chemicals, food, and energy. In smart factories, sensors installed on machines continuously collect data, enabling real-time monitoring of production. This data is analyzed by intelligent systems capable of identifying faults, predicting maintenance needs, and optimizing production performance. In addition, the use of collaborative robots and automated systems reduces operational errors, increases productivity, and improves product quality. Another important aspect is the integration of the supply chain, allowing suppliers, manufacturers, and customers to share information quickly and efficiently [18]. Manufacturing processes have also undergone profound transformations with Industry 4.0. Traditional manufacturing, based on rigid and inflexible production, is being replaced by intelligent and adaptive processes. In this context, smart manufacturing stands out, in which machines and systems are able to make decisions autonomously based on collected data.

Key advancements include predictive maintenance, automated quality control, product traceability, large-scale customized production, and the integration of the physical and virtual environments through digital twins. These capabilities help reduce waste, lower operating costs, and increase energy and production efficiency. In addition, the digitization of processes promotes greater agility in decision-making and a better ability to respond to market demands [20]. To assess companies' level of digital development, Acatech developed the "Industrie 4.0 Maturity Index," a maturity model consisting of six evolutionary levels. The first level is Computerization, characterized by the basic computerization of industrial processes. The second level is Connectivity, in which systems and equipment begin to communicate via a network. The third level is Visibility, in which process data can be monitored in real time. The fourth level is Transparency, which allows for understanding the causes of production events through data analysis. The fifth level is Predictive Capability, in which algorithms can predict failures and future behaviors. Finally, the sixth level is Adaptability, considered the most advanced stage, in which industrial systems become autonomous and capable of automatically adapting to changes in the production environment. This model helps companies build strategic roadmaps for the gradual implementation of digital transformation [18].

II.3 THE CHALLENGES OF THESE TECHNIQUES

II.3.1 Intelligent Systems

Intelligent systems represent one of the main pillars of digital transformation and Industry 4.0, characterized by their ability to collect, process, interpret, and use information to support decision-making autonomously or semi-autonomously. These systems combine technologies such as Artificial Intelligence, machine learning, the Internet of Things, cloud computing, neural networks, and Big Data analytics to perform complex tasks with a high level of efficiency and precision [21]. Currently, intelligent systems are widely used in industrial, logistics, medical, energy, and urban environments, providing advanced automation, increased productivity, and improved process quality [22]. One of the key characteristics of intelligent systems is their learning capability. Through machine learning algorithms, these systems can analyze large volumes of data, identify patterns, and continuously improve their performance without the need for explicit programming for each situation. This characteristic enables applications such as predictive maintenance, automatic fault detection, pattern recognition, and optimization of production processes.

In addition, intelligent systems are adaptable, allowing them to adjust their operation in response to changes in the operating environment and working conditions [23], [24]. Another key feature is connectivity. Smart systems operate in an integrated manner, sharing information among sensors, machines, devices, and digital platforms. This communication occurs primarily through the Internet of Things (IoT), enabling real-time monitoring, remote control, and decision-making based on continuously updated data. In industrial settings, for example, sensors installed on equipment can detect variations in temperature, vibration, or energy consumption, sending this information to central systems capable of identifying potential problems before critical failures occur [25], [26]. Despite the numerous benefits, smart systems face various technical, economic, and operational challenges.

One of the main challenges relates to cybersecurity. Since these systems depend on the constant exchange of information over digital networks, they become vulnerable to cyberattacks, intrusions, and data breaches. The protection of industrial information and the security of critical infrastructure require the development of advanced security protocols, encryption, and user authentication. Another significant challenge relates to technological integration. Many companies still use outdated equipment and legacy systems that have difficulty communicating with new digital platforms. Integrating different technologies, protocols, and automation architectures requires substantial financial investment and specialized technical expertise. Furthermore, implementing smart systems demands robust data storage and processing infrastructure, particularly in applications that utilize Big Data and Artificial Intelligence in real time [27]. Data quality and reliability also pose significant challenges. Intelligent systems rely directly on accurate and consistent data to perform precise analyses.

Incomplete, inconsistent, or improperly collected information can compromise algorithm performance and lead to incorrect decisions. In this context, the development of efficient strategies for data collection, processing, and management becomes essential. Another key aspect is the need for professional training. Digital transformation requires professionals skilled in areas such as data science, programming, automation, artificial intelligence, and information security. However, many organizations still struggle to find skilled workers capable of developing, operating, and maintaining intelligent systems. Therefore, the challenge related to implementation costs stands out. The adoption of intelligent systems involves investments in sensors, software, communication infrastructure, cloud storage, and technical training. Despite this, the benefits associated with operational efficiency, cost reduction, increased productivity, and improved decision-making make these technologies essential for industrial competitiveness and for advancing digital transformation within organizations.

II.3.2 Internet of Things (IoT)

The Internet of Things (IoT) is a technology based on connecting physical devices to the internet, enabling the collection, exchange, and analysis of data in real time. These devices may include sensors, machines, industrial equipment, measuring instruments, and automated systems capable of communicating with one another without direct human intervention.

The IoT has become one of the main pillars of Industry 4.0, promoting greater integration between the physical and digital environments and contributing to the development of smarter, more efficient, and automated industrial processes [28], [29]. In process engineering, the Internet of Things has wide-ranging applications in sectors such as oil and gas, the chemical industry, food, mining, energy, and manufacturing. Smart sensors installed on industrial equipment are capable of monitoring key variables such as temperature, pressure, flow rate, vibration, humidity, and energy consumption. This information is continuously transmitted to digital platforms and supervisory systems, enabling real-time monitoring of production operations. One of the main applications of IoT in process engineering is the remote monitoring of industrial systems. Through this technology, engineers and operators can monitor the performance of equipment and processes remotely, reducing response times in the event of failures and increasing operational efficiency. In addition, the IoT contributes significantly to predictive maintenance, allowing for the identification of anomalies and the prediction of failures before unexpected production shutdowns occur.

This reduces maintenance costs, extends equipment lifespan, and improves the reliability of industrial processes. Another important application relates to energy optimization and resource management. Connected sensors enable real-time monitoring of energy, water, and raw material consumption, helping to reduce waste and improve industrial sustainability. In chemical and petrochemical processes, for example, the IoT aids in the precise control of reactions and operating conditions, ensuring higher quality and safety in production processes [30]. Despite the benefits, the implementation of IoT faces challenges related to cybersecurity, systems integration, and the storage of large volumes of data. Connectivity between devices increases vulnerability to digital attacks, requiring robust information protection protocols. Furthermore, many companies still use legacy systems that hinder integration with modern technologies [31]. Thus, the Internet of Things is transforming process engineering by enabling smarter, more connected, and more efficient operations, contributing to increased productivity, cost reduction, and the advancement of industrial digital transformation.

II.3.3 Data Mining

Data mining is the process of extracting useful information, patterns, and insights from large volumes of data. This technique combines methods from statistics, machine learning, artificial intelligence, and databases to identify hidden relationships and relevant trends that aid in decision-making. The rapid growth of data generation in industrial, commercial, scientific, and digital environments has made data mining an essential tool for organizations seeking to transform raw data into strategic knowledge [32], [33]. The data mining process involves several stages, including data collection, cleaning, integration, selection, transformation, and analysis. After the information is processed, specific algorithms are applied to identify patterns, classify data, detect anomalies, and make predictions. Among the most commonly used techniques are artificial neural networks, decision trees, classification algorithms, clustering, and association analysis. Data mining applications are wide-ranging and span various industries. In manufacturing, data mining is used to optimize production processes, monitor equipment, and predict failures through predictive maintenance. Sensors installed on machines continuously generate data, allowing for the identification of behavioral patterns and the anticipation of operational problems.

This reduces maintenance costs, increases productivity, and improves the efficiency of industrial systems [34], [35]. In the financial sector, data mining is applied to fraud detection, credit analysis, and risk forecasting. Banks and financial institutions use intelligent algorithms to analyze suspicious transactions and identify unusual behavior in real time. In e-commerce and digital marketing, data mining enables a better understanding of consumer behavior, the personalization of product recommendations, and the development of more efficient sales strategies. In the healthcare sector, data mining aids in the diagnosis of diseases, the analysis of medical tests, and the identification of epidemiological patterns. Furthermore, in smart cities and transportation systems, data mining helps improve urban mobility and optimize public resources. Despite these benefits, the use of data mining faces challenges related to privacy, security, and data quality. Inconsistent or incomplete information can compromise the accuracy of analyses. Thus, data mining has become a fundamental tool for supporting strategic decisions and promoting innovation in various fields of knowledge and industry [32], [34], [35].

II.3.4 Artificial Intelligence

Artificial Intelligence (AI) is a branch of computer science dedicated to the development of systems capable of simulating human intelligence. These systems can learn, reason, make decisions, recognize patterns, and solve problems autonomously or semi-autonomously. AI uses techniques such as machine learning, artificial neural networks, natural language processing, and computer vision to analyze large volumes of data and perform complex tasks with high efficiency [36]. Currently, Artificial Intelligence has applications in various industrial, scientific, and commercial sectors. In industry, AI is widely used in automation systems, predictive maintenance, quality control, and production process optimization. Sensors and intelligent algorithms monitor machines in real time, identifying failures before they occur and reducing operational costs. In smart manufacturing environments, AI helps increase productivity, improve energy efficiency, and reduce waste [37]. In the healthcare sector, Artificial Intelligence assists in diagnosing diseases, interpreting medical tests, and developing personalized treatments. AI-based systems can analyze medical images with high precision, helping doctors identify diseases at an early stage. In the financial sector, AI is used for fraud detection, risk analysis, and the automation of banking services. Another important application is in transportation systems and smart cities, where intelligent algorithms help manage traffic, optimize routes, and improve urban mobility. In addition, virtual assistants, chatbots, and recommendation platforms in digital services use Artificial Intelligence to offer more personalized experiences to users [37], [38]. Despite these benefits, AI faces challenges related to data privacy, cybersecurity, ethics, and the need for qualified professionals. Even so, Artificial Intelligence continues to evolve rapidly and plays a fundamental role in the digital transformation and technological advancement of modern society.

II.3.5 Digital Transformation

Digital transformation refers to the integration of digital technologies into organizations' processes, products, and business models. In industry, this transformation is directly linked to the concepts of Industry 4.0, promoting greater connectivity, automation, intelligence, and operational efficiency.

Technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), Big Data, cloud computing, and cyber-physical systems enable machines, sensors, and systems to exchange information in real time, making industrial processes smarter and more integrated [39], [40]. The applications of digital transformation in industry are wide-ranging. One of the main ones is advanced industrial automation, which uses robots and intelligent systems to perform tasks with greater precision, productivity, and safety. Another important application is predictive maintenance, in which sensors continuously monitor machine performance to predict failures before they occur, reducing costs and unexpected downtime. Digital transformation also contributes to quality control, product traceability, and energy consumption optimization. In addition, the use of real-time data analysis assists managers in making strategic decisions and increasing industrial competitiveness [39], [40]. Despite the benefits, the implementation of digital transformation faces challenges related to cybersecurity, high investment costs, and the need for professional training. Even so, digital transformation has become essential for the modernization of industries and for the development of more efficient, sustainable, and intelligent production processes.

III. MATERIALS AND METHODS

The study was conducted as applied research, utilizing existing secondary data and direct information collection within the manufacturing environment. Data collection and observations will be conducted with managers, administrators, and operational technicians to ensure that the project's development is fully aligned with the company's actual needs and the specific characteristics of its production process. Project execution will be the responsibility of a multidisciplinary team composed of developers, engineers, and technicians. Each team member will be assigned well-defined responsibilities, in accordance with the competencies required at each project phase, ensuring efficiency, clear communication, and adherence to established deadlines and goals. For the planning, execution, and management of the project, a methodology based on the principles of the PMBOK (Project Management Body of Knowledge), an international reference for best practices in project management, will be adopted. As illustrated in Figure 1, the five process groups that structure the conduct of the research will be followed.

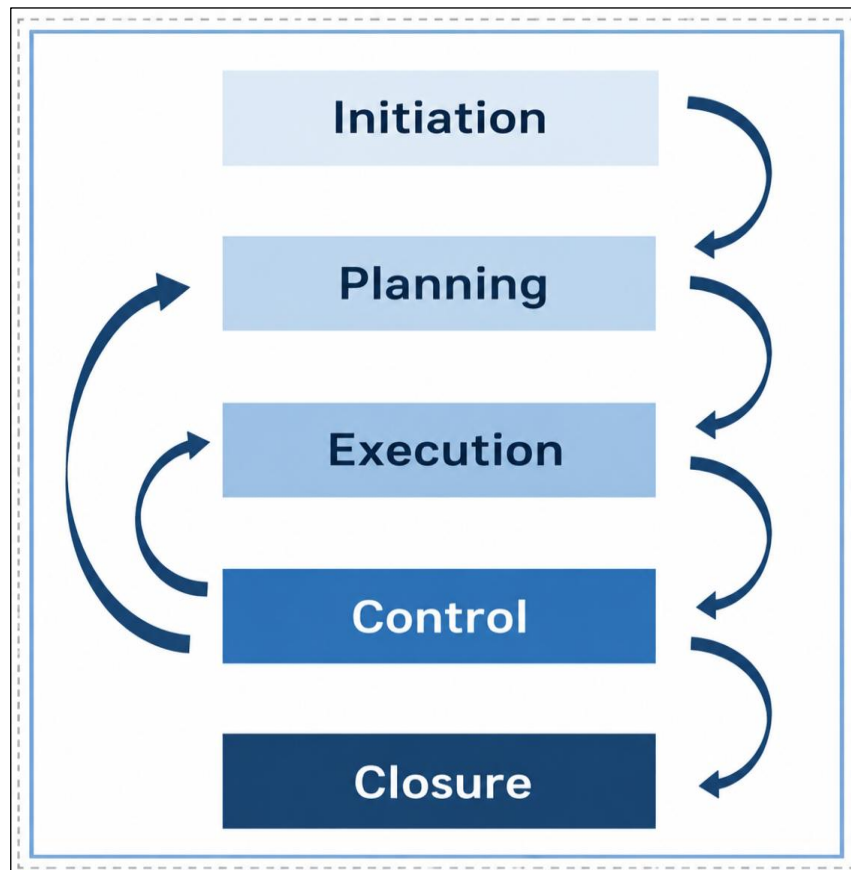


Figure 1: PMBOK Project Management Model.

Source: Authors, (2026).

Each process group will be broken down into practical activities tailored to the company's context, using tools such as detailed schedules (Gantt charts), RACI matrices, risk analysis, cost controls, and performance indicators. Management will be conducted in an iterative and delivery-oriented manner, ensuring the traceability of results and the effective implementation of the proposed solution. In addition, the incremental methodology will be adopted as the approach for software development. In this model, the system will be built progressively through iterative cycles, in which functional and integrated parts of the system will be implemented in each iteration. This method allows critical components to be delivered and validated in advance, providing greater control over the product's quality and evolution. The adoption of the incremental approach enables clear measurement of the process phases, such as: requirements gathering and analysis, functional modeling, modular development, partial testing, continuous integration, and validation with end users. This aims to reduce risks, improve alignment with the company's needs, and facilitate adjustments throughout development, as shown in Figure 2.

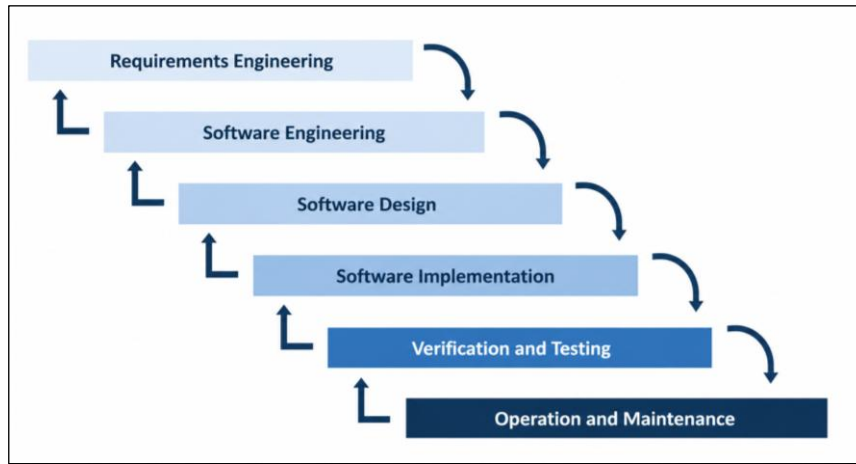


Figure 2: The software development lifecycle.

Source: Authors, (2026).

- **Requirements Engineering:** In this phase, the software requirements will be defined, specifically for the module to be developed, so that the solution meets the company's needs while taking into account visual and behavioral elements, actions, criteria, and constraints.
- **Software Engineering:** In this phase, diagrams and documentation regarding the module and implemented features will be developed. This document should address the software design by describing the limitations, use cases, features, technologies, and technical definitions of the functional and non-functional requirements.
- **Software Design:** In this phase, the software design will be developed based on user interaction interfaces, visual identity definitions, element layout, actions, behaviors, and company standards, taking into account operational limitations.
- **Software Implementation:** In this stage, the process of developing, defining, and executing the coding of the functionalities specified in the requirements document and strategies to achieve the module to be delivered will be carried out.
- **Validation and Testing:** This stage involves activities to validate and test the developed application and module. To this end, functionality, integrity, security, unit, and installation tests will be performed to assess product quality, identify and fix bugs, and carry out code refactoring.
- **Operation and Maintenance:** This phase will involve code refactoring and adjustments; depending on new requirements or technological updates, maintenance may be required, which will involve coding work during this phase.

Research Development Tools

To carry out this project, it will be necessary to use support tools that enable the creation of scenario projections and technical drawings, as well as the coding of the items described in Table 1.

Table 1: Creation of scenario projections, technical drawings, and coding of items.

Tool	Concept	Application in the project
Proteus VSM	Software that allows users to design circuits, simulate, and create layouts for analog and digital applications, including microcontrollers.	It will be used for the development of electronic boards and connections.
Solid Works	Software designed for creating three-dimensional virtual mechanical prototypes. It also allows users to simulate the operation of parts, assemblies, and movements, among other things.	In this project, the software will be used to model mechanical parts and devices. Based on 3D prototypes, 2D drawings will be generated and sent to the machining process..
PMBOK Guide	It is a set of project management practices established by the PMI and is considered the foundation of project management knowledge by professionals in the field.	It will be used to manage the project, from the initial stage through to completion.
Visual Studio Code	A source code editor developed by Microsoft for Windows, Linux, and macOS. It includes support for debugging, built-in Git version control, syntax highlighting, and intelligent code completion.	Development environment
Draw io	An online graphic editor that allows you to create drawings, graphics, and other designs without the need for expensive, resource-intensive software. It offers tools for creating any type of design and includes a section dedicated to information architecture.	Architecture design and flowchart diagrammer.
Trello	A collaboration tool that organizes projects into boards. At a glance, Trello shows what's being worked on, who's working on what, and where something is in the process.	Activity Manager
GIT	Version control and development history tool for code and artifacts	Code Versioning

Source: Authors, (2026).

Technologies for Research Development

The technologies to be used and applied in the project were selected based on their alignment with the technical requirements defined in the scope, which includes the application of the Internet of Things (IoT) and Intelligent Systems, with the aim of efficiently meeting the demands of the proposed solution as presented in Table 2.

Table 2: Application of the Internet of Things (IoT) and Intelligent Systems.

Technology	Concept	Application in the project
NodeJS	A server-side JavaScript runtime environment based on asynchronous, event-driven architecture, enabling the development of scalable web applications, APIs, and real-time processing services.	Used as the foundation for developing the system's backend, enabling the creation of APIs, the processing of data received from IoT devices, and the execution of business rules.
Express	A Node.js framework for developing modern, scalable web applications	Used to structure API routes, receive requests from IoT devices and the frontend, organize controllers, and make processed data available to the platform's consumer modules.
Swagger	A tool and specification used for documenting, standardizing, and testing REST APIs, allowing users to view endpoints, parameters, HTTP methods, request structures, and expected responses.	Used to document and test backend endpoints, facilitating integration between IoT devices, frontends, dashboards, and other systems that consume the API.
Redis	An in-memory database used for caching, queues, temporary state management, and performance optimization in applications that require low latency.	Used to support real-time event processing and updates, reducing the load on the main database.
Docker	A containerization platform that allows you to package applications and their dependencies into isolated, standardized, and portable environments.	Used to streamline the deployment of backend services, databases, and other infrastructure components, ensuring greater standardization across development, testing, and production environments.
TypeScript	A JavaScript superset that adds static typing to the code, improving the application's security, readability, and maintainability.	Used in the backend to improve code organization, reduce typos, standardize entities, services, and controllers, and facilitate the maintenance of business rules.
Websockets	WebSocket is a technology that enables bidirectional communication over full-duplex channels using a single Transmission Control Protocol (TCP) socket. It is designed to run on browsers and web servers that support HTML5, but can be used by any client or application server.	Used to enable real-time communication between the backend and dashboards, allowing for the automatic transmission of updates regarding machines, production orders, operational events, and metrics.
Postgres	Relational database	Used to store data from machines, production orders, IoT readings, operational events, historical data, logs, and information needed to calculate industrial metrics.

Source: Authors, (2026).

IV. RESULTS

IV.1 SOLUTION WORKFLOW

With the advancement of Industry 4.0 enabling technologies, integration between the shop floor and digital systems has become essential for achieving greater operational efficiency, real-time traceability, and data-driven decision-making. In this context, the project proposes a technological architecture that connects sensors installed on machines and equipment in the Bumper Tape, Reflective Film, and Side Strip processes of the production line to a central platform for processing, storing, and visualizing information, enabling continuous monitoring of industrial processes. Figure 3 illustrates the functional flow of this solution, showing how data will be collected directly from the operation, sent to a secure processing environment, and made available to different user profiles through user-friendly interfaces updated in real time. This structure aims to ensure complete production visibility, early detection of failures, improved decision-making, and integration among the company's technical, operational, and managerial areas.

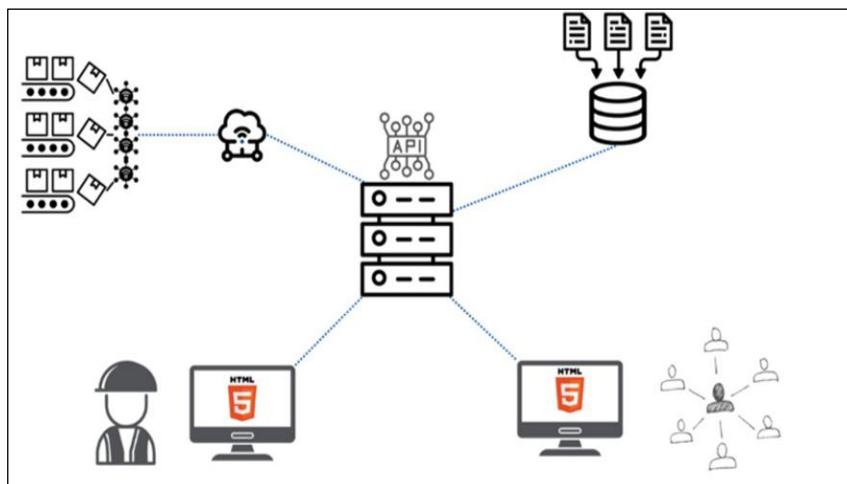


Figure 3: Operational flowchart of the intelligent production monitoring and control system.

Source: Authors, (2026).

Figure 3 illustrates the operational workflow of the intelligent production monitoring and control system, based on Industry 4.0 technologies. On the left is a production line equipped with connected sensors that monitor variables such as the presence of parts, quantity produced, cycle time, and machine downtime. These sensors send the collected data in real time to the cloud using wireless or wired connections. At the center of the architecture is the main server, responsible for processing this information. This server has an API that enables communication between the data collection devices, the database, and the visualization systems. The API also allows integration with other company systems, such as ERPs and production management platforms. At the top right, the database stores all received information, organizing the records so they can be used for both immediate visualization and historical analysis and management reports. At the bottom of the image are the system users. On the left, the plant operator uses a simple, visual interface—developed in HTML5—to monitor production data in real time, identify faults, and validate process steps.

In the center, managers and analysts have access to more comprehensive dashboards, featuring key performance indicators (KPIs), productivity metrics, and machine status. On the right, other users—such as engineers, maintenance teams, and even external partners—can also access the system with different permission levels, facilitating decision-making and promoting more transparent and connected management. In short, the flowchart illustrates how data flows directly from the shop floor, passes through a secure processing infrastructure, and is made available in real time to different levels of the operation, contributing to greater efficiency, traceability, and control of the production process. Implementing the proposed solution requires a robust hardware and connectivity infrastructure capable of supporting everything from field data collection to advanced data processing, with high availability and reliability. Each item to be procured will play a strategic role in enabling this architecture, forming an integrated ecosystem that supports the project's objectives. At the bottom of the image are the system users.

On the left, the plant operator uses a simple, visual interface—developed in HTML5—to monitor production data in real time, identify faults, and validate process steps. In the center, managers and analysts have access to more comprehensive dashboards, featuring key performance indicators (KPIs), productivity metrics, and machine status. On the right, other users—such as engineers, maintenance teams, and even external partners—can also access the system with different permission levels, facilitating decision-making and promoting more transparent and connected management. In short, the flowchart illustrates how data flows directly from the shop floor, passes through a secure processing infrastructure, and is made available in real time to different levels of the operation, contributing to greater efficiency, traceability, and control of the production process. Implementing the proposed solution requires a robust hardware and connectivity infrastructure capable of supporting everything from field data collection to advanced data processing, with high availability and reliability.

Each item to be procured will play a strategic role in enabling this architecture, forming an integrated ecosystem that supports the project's objectives. At the heart of this acquisition, the ESP32 WiFi and Bluetooth 38-pin CP2102 module serves as the foundation for developing smart IoT nodes. This microcontroller, with wireless connectivity and multiple communication interfaces, will enable the creation of embedded devices capable of collecting, processing, and transmitting data directly to the cloud or local servers without the need for physical cabling, ensuring scalability and flexibility in deployment. A stable power supply for these modules is ensured by the 5V 3A Micro USB Switching DC Power Supply, whose ability to provide continuous current with surge and short-circuit protection will be crucial for preventing operational failures and data loss. The development and adaptation of interface circuits will require essential components such as the 500 Resistor Kit, indispensable for current adjustments, voltage division, and sensor biasing, and the PC817 Integrated Circuit (optocoupler), which protects microcontrollers against surges and noise from industrial environments, ensuring safe electrical isolation between different voltage levels.

Physical control interfaces are provided by the 22mm Industrial Pushbuttons, which will enable manual actuation, event simulation, and enhanced safety on test benches. For local display and debugging, the 20x4 LCD display with I2C will provide a visual representation of data and messages from the embedded system, while the DS3231 RTC clock module will ensure temporal accuracy in logs, which is essential for event correlation and traceability. The communication and network infrastructure is supported by the Ubiquiti UniFi Indoor 122m Access Point, which will ensure high-availability Wi-Fi connectivity in industrial environments, supporting multiple devices simultaneously. For high-performance wired connections, the Furukawa SohoPlus Cat6 Network Cable and Shielded Cat6 RJ45 Connectors will ensure stable data transmission, reducing interference and signal loss, and meeting industrial technical standards. Complementing the physical integration, the NPN 24V to 5V 8-Channel Signal Converter Module is designed to ensure electrical compatibility between industrial sensors and low-power controllers.

For real-time visualization and immediate decision-making on the factory floor, the Samsung 55" UHD 4K Smart TV will be installed at a strategic location, displaying dynamic dashboards with operational and quality indicators. The prototyping and adaptation of specific supports and parts will be enabled through 3D Printer Filaments, allowing for rapid additive manufacturing of functional and structural elements. The 4-Way Shielded Cable protects sensitive signals from electromagnetic interference, ensuring data integrity between sensors and controllers, while the 4-Way Wago-Style Connectors facilitate quick and secure connections during prototype assembly. Visual status indicators will be provided by the 5mm High-Brightness LED Kit, which will provide immediate feedback during testing and operations. At the heart of the processing and storage infrastructure, the Dell PowerEdge R260 Rack Server will be responsible for continuously receiving and processing sensor data, running data mining and failure prediction algorithms, hosting interactive dashboards, and managing the historical database. Its high processing capacity, redundancy, and scalability ensure stable operation even under high-demand conditions.

To protect and organize this infrastructure, the Dell APC NetShelter SX 24U Rack will provide secure installation, adequate ventilation, and ease of maintenance, meeting the robustness and physical protection requirements demanded by industrial environments. Working together, each acquisition will contribute to forming a complete chain of data capture, processing, communication, and visualization. From data collection on the factory floor to the display of strategic information, all components have been pre-selected to ensure electrical compatibility, operational reliability, resilience against adverse conditions, and the capacity for future expansion. This combination of equipment and materials will not only enable the technical operation of the system but also ensure that the final solution meets the performance, safety, and scalability requirements established for the project, supporting its operation in critical industrial environments.

However, during the refinement process, technical detailing of requirements, and development, it is possible to determine that some initially planned components may be replaced or adjusted to better meet the actual demands for performance, compatibility, and reliability. This review will ensure that the final selection of equipment is aligned not only with the proposed solution architecture but also with the operating conditions and strategic objectives of the research.

IV.2 DEVELOPMENT OF THE INTELLIGENT SYSTEM'S BACKEND LAYER

The development of the intelligent system focused on building a backend layer capable of integrating data from the manufacturing environment, processing it in a structured manner, and making it available to the other modules of the platform. This layer was designed to act as the computational core of the solution, connecting data collection devices, databases, business rules, and real-time visualization interfaces. Figure 4 presents the backend architecture of the integrated smart system, illustrating the data flow from the IoT devices installed on the machines to the provision of information for dashboards and client systems. The structure demonstrates the central role of the backend in receiving data, validating it, applying business rules, storing it in the database, generating indicators, and triggering events in real time.

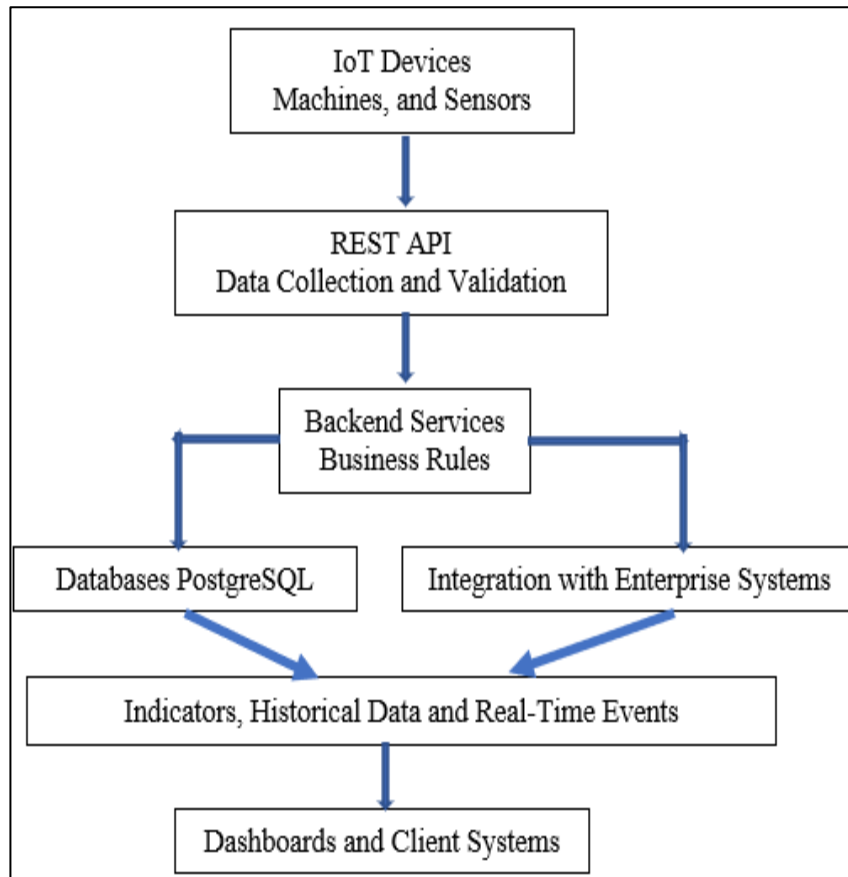


Figure 4: Backend Architecture of the Intelligent System.

Source: Authors, (2026).

The backend architecture was designed around services responsible for receiving, processing, storing, and distributing industrial data. Information collected on the factory floor—such as production volume, machine operational status, production order progress, cycle times, and downtime events—is sent to the server via defined communication channels. Upon receipt, the data undergoes validation and standardization processes to ensure greater reliability before being stored or used in the calculation of indicators. The API layer was developed to enable communication between IoT devices, the database, and the applications that consume the information. Through these routes, the system receives operational records, queries historical data, returns consolidated information on machines and production orders, and provides indicators used by the dashboards.

This architecture enables different modules of the platform to access data in a standardized manner, reducing dependencies and facilitating the system's evolutionary maintenance. The backend architecture was designed around services responsible for receiving, processing, storing, and distributing industrial data. Information collected on the factory floor—such as production volume, machine operational status, production order progress, cycle times, and downtime events—is sent to the server via defined communication channels. Upon receipt, the data undergoes validation and standardization processes to ensure greater reliability before being stored or used in the calculation of indicators. The API layer was developed to enable communication between IoT devices, the database, and the applications that consume the information.

Through these routes, the system receives operational records, queries historical data, returns consolidated information on machines and production orders, and provides indicators used by the dashboards. This organization enables different platform modules to access data in a standardized manner, reducing coupling and facilitating the system's evolutionary maintenance. Figure 5 shows the backend API documentation interface via Swagger, highlighting the organization of the endpoints used for integration between IoT devices, the database, and the platform's consumer modules. This documentation helps standardize requests, facilitates route testing, and supports the system's ongoing maintenance.

Machines

- GET `/Machines/Dashboard` — Retrieves machine dashboard metrics
- GET `/Machines/{id}/Productivity` — Calculates the productivity rate of a machine
- GET `/Machines/{id}/Inactivity` — Calculates the unplanned inactivity index
- GET `/Machines/{id}/FPY` — Calculates the FPY index (First Pass Yield)
- GET `/Machines/Availability` — Calculates the real-time availability index
- POST `/collection` — Registers IoT sensor data collection
- GET `/Machines/{id}/CriticalityLevels` — Retrieves the criticality levels of a machine
- POST `/Machines/{id}/CriticalityLevels` — Saves/Updates the criticality levels of a machine
- DELETE `/Machines/{id}/CriticalityLevels` — Deletes all criticality levels of a machine

Figure 5: Documentation of the backend API endpoints in Swagger.

Source: Authors, (2026).

As noted, the available endpoints cover both query operations—such as productivity, downtime, FPY, and real-time visibility—and data recording and updating operations, such as collection routes and machine criticality levels. This architecture reinforces the API's role as an intermediary layer between IoT devices, the database, and the modules that consume the information. One of the central focuses of the backend was the modeling and persistence of industrial data. The database was organized to store information related to machines, production orders, completed collections, operational events, equipment status, and productivity histories. This structure enables the traceability of operations and allows for queries by period, machine, and development; aspects of data reliability and integrity were also considered. Since industrial data can be generated at high frequency and from different sources, it became necessary to implement validations, handle inconsistent values, control duplicate records, and organize the received events.

These measures help reduce errors in interpreting the information and increase the reliability of the indicators presented by the platform. The implementation of the intelligent system demonstrated the importance of the backend as a central element of the proposed digital transformation. By integrating machine data, processing it, storing it, and making it available in real time, the solution creates a technological foundation for continuous production monitoring and for future stages of advanced analysis. This structure also enables the subsequent application of data mining techniques, pattern identification, anomaly analysis, and support for dynamic production replanning. Overall, the developed backend contributes to the consolidation of a modular, scalable, and data-driven architecture. The separation between data collection, processing, persistence, and availability facilitates system maintenance and allows for its expansion to new machines, lines, production orders, or event types.

As a result, the system no longer relies exclusively on manual records and now has a structured historical database for analysis and decision-making. In addition to data persistence, the backend is also responsible for enforcing the system's business rules. These rules involve interpreting the received data, associating the data points with their respective machines and production orders, identifying the operational status of the equipment, and preparing the information to be presented to users. As a result, the backend acts as an intermediate intelligence layer, transforming raw data from the operation into organized and useful information for monitoring production. Another key aspect was the handling of industrial indicators. Based on the stored and processed data, the backend provides information related to productivity, machine status, production history, recent events, and production order tracking.

This data serves as the basis for the performance indicators used on the platform, enabling supervisors and managers to monitor operations with greater precision and faster response times. To meet the need for continuous updates, the backend was also designed with real-time communication mechanisms. This strategy allows changes in machine status, new data collections, or relevant events to be sent to client interfaces without relying solely on manual queries or periodic refreshes. Real-time communication is especially important in an industrial context, as it allows operational deviations, downtime, and order completions to be identified more quickly. During production campaigns or indicator tracking. Thus, the intelligent system applied to the manufacturing environment now offers greater traceability, operational visibility, and support for data-driven decision-making.

V. CONCLUSION

The proposal to develop an intelligent system represents a significant step forward for digital transformation in the industrial sector at the Manaus Industrial Hub (PIM). The flowchart presented in the results, Figure 6, illustrates a structured and efficient architecture, beginning with data collection by IoT devices, machines, and sensors, which continuously monitor production processes in real time. The use of REST APIs for collecting and validating information ensures data reliability, security, and standardization, allowing backend services to process business rules and facilitate integration across different industrial sectors. Storage in a PostgreSQL database combined with integration with corporate systems provides greater traceability, organization, and interoperability of production information. In addition, the generation of indicators, historical data, and events in real time enables more accurate analyses and efficient support for decision-making. Dashboards and client systems make data accessible in a visual and intuitive way, contributing to increased productivity, reduced failures, and the optimization of industrial resources. Thus, the proposed system strengthens smart manufacturing, promoting greater competitiveness, automation, and operational efficiency in modern industries within the context of real-time digital transformation.

VI. AUTHOR'S CONTRIBUTION

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VIII. REFERÊNCIAS

- [1] Selim, A., Skender, F., & Ali, I. (2021). A systematic review of big data, areas of digital transformation, and Industry 4.0 trends in 2021. *International Scientific Journal Vision*, 6 (2), 27-41.
- [2] Nica, E., & Stehel, V. (2021). Internet of Things sensor networks, artificial intelligence-based decision-making algorithms, and real-time process monitoring in sustainable Industry 4.0. *Journal of Self-Governance and Management Economics*, 9 (3), 35-47.
- [3] Jagatheesaperumal, SK, Rahouti, M., Ahmad, K., Al-Fuqaha, A., & Guizani, M. (2021). The combination of artificial intelligence and big data for Industry 4.0: applications, techniques, challenges, and future research directions. *IEEE Internet of Things Journal*, 9 (15), 12861-12885.
- [4] Neustein, A., Mahalle, PN, Joshi, P., & Shinde, GR (Eds.). (2023). *AI, IoT, Big Data, and Cloud Computing for Industry 4.0*. Springer.
- [5] Henrique Amaral, C., Cabral Leite, J., da Silva Ribeiro, PF, Soares Silva, Í. R., Silva Parente, R., Nunes Dirane, E., & Barros Mendonça, PH (2024). Development of a gateway prototype for data collection and transmission in material handling systems - Gate Move 4.0. *GeSec: Revista de Gestão e Secretariado*, 15 (9).
- [6] Gurcan, F., Boztas, GD, Dalveren, GGM, & Derawi, M. (2023). Strategies, practices, and trends in digital transformation: a large-scale retrospective study based on machine learning. *Sustainability*, 15 (9), 7496.
- [7] Miklosik, A., & Evans, N. (2020). The Impact of Big Data and Machine Learning on Digital Transformation in Marketing: A Literature Review. *Ieee Access*, 8, 101284-101292.
- [8] Cheng, L. (2022). Decision modeling and evaluation of corporate digital transformation using data mining. *Mobile information systems*, 2022 (1), 2380100.
- [9] Aceto, G., Persico, V., & Pescapé, A. (2019). A Survey of Information and Communication Technologies for Industry 4.0: State of the Art, Taxonomies, Prospects, and Challenges. *IEEE Communications Surveys & Tutorials*, 21 (4), 3467-3501.
- [10] Ma, Z., Xiao, M., Xiao, Y., Pang, Z., Poor, HV, & Vucetic, B. (2019). Highly Reliable, Low-Latency Wireless Communication for the Internet of Things: Challenges, Fundamentals, and Enabling Technologies. *IEEE Internet of Things Journal*, 6 (5), 7946-7970.
- [11] Sishi, M., & Telukdarie, A. (2025). Adoption of data-driven automation techniques to create smart key performance indicators for business optimization. *Applied System Innovation*.
- [12] Omisola, JO, Shiyabola, JO, & Osho, GO (2023). A KPI-driven decision intelligence model: using integrated dashboards to enhance strategic operational control in advanced manufacturing. DOI: <https://doi.org/10.54660/IJFMR>, 1-93.
- [13] Eweje, A., & Ohaegbu, F (2021). Advances in modern data stack architectures for scalable data integration and business intelligence.
- [14] Oloruntoba, O. (2025). Architecture of Resilient Multi-Cloud Database Systems: Distributed Ledger Technology, Fault Tolerance, and Cross-Platform Synchronization. *International Journal of Research Publication and Reviews*, 6 (2), 2358-2376.
- [15] Agoro, H. (2023). Improving production planning with data science techniques.
- [16] Skėrė, S. (2024). A Decision Support Method for Dynamic Production Planning in Small and Medium-Sized Enterprises (Doctoral Dissertation, Kaunas University of Technology).
- [17] Kolade Ajeigbe, EC (2024). Data analysis for informed decision-making in manufacturing.
- [18] Becker, T., Blocher, A., Bűcker, I., Drewel, M., Faath, A., Harland, T., ... & Zeller, V. (2017). *Industrie 4.0 Maturity Index [Eng.]: Managing the Digital Transformation of Businesses*. Herbert Utz Verlag.

- [19] Schuh, G., Anderl, R., Dumitrescu, R., Krüger, A., e ten Hompel, M. (Eds.). (2020). Industry 4.0 Maturity Index: Managing the Digital Transformation of Businesses - 2020 Update. Acatech, Deutsche Akademie der Technikwissenschaften eV.
- [20] Zeller, V., Hocken, C., & Stich, V. (agosto de 2018). Acatech Industry 4.0 Maturity Index – a multidimensional maturity model. In the IFIP International Conference on Advances in Production Management Systems (pp. 105-113). Cham: Springer International Publishing.
- [21] Ryalat, M., Franco, E., Elmoaqet, H., Almtireen, N., & Al-Refai, G. (2024). The integration of advanced mechatronic systems in Industry 4.0 for smart manufacturing. Sustainability, 16 (19), 8504.
- [22] Wagire, AA, Rathore, APS, & Jain, R. (2020). Exploring the pillars of Industry 4.0 using latent semantic analysis. In Smart Manufacturing and Energy Sustainability: Proceedings of ICIMES 2019 (pp. 711-719). Singapura: Springer Singapore.
- [23] Stephanopoulos, G., & Han, C. (1996). Intelligent Systems in Process Engineering: A Review. Computers & Chemical Engineering , 20 (6-7), 743-791.
- [24] Grosan, C., Abraham, A., Jain, LC e Kacprzyk, J. (2011). Smart systems (Vol. 17, pp. 261-268). Berlim: Springer.
- [25] Shafique, K., Khawaja, BA, Sabir, F., Qazi, S., & Mustaqim, M. (2020). The Internet of Things (IoT) for Next-Generation Smart Systems: A Review of Current Challenges, Future Trends, and Prospects for Emerging 5G-IoT Scenarios. IEEE access , 8 , 23022-23040.
- [26] Firouzi, F., Nassif, S., & Chakrabarty, K. (2020). Smart Internet of Things.
- [27] Klipa, D., Ristić, I., Radonjić, A., & Scepanović, I. (2022). Big data and artificial intelligence. International Journal of Management Trends: Key Concepts and Research , 1 (1), 3-14. Klipa, D., Ristić, I., Radonjić, A., & Scepanović, I. (2022).
- [28] Rose, K., Eldridge, S., & Chapin, L. (2015). The Internet of Things: An Overview. The internet society (ISOC) , 80 (15), 1-53.
- [29] Li, S., Xu, L. D., & Zhao, S. (2015). The internet of things: a survey. Information systems frontiers, 17(2), 243-259.
- [30] Mukhopadhyay, SC, & Suryadevara, NK (2014). The Internet of Things: Challenges and Opportunities. The Internet of Things: Challenges and Opportunities, 1–17.
- [31] Holler, J., Tsiatsis, V., Mulligan, C., Karnouskos, S., Avesand, S., & Boyle, D. (2014). Internet of Things. Academic Press.
- [32] Goldschmidt, R., Passos, E., & Bezerra, E. (2015). Data mining. Elsevier Brasil.
- [33] Goldschmidt, R. e Passos, E. (2005). Data Mining: A Practical Guide. Publicação Profissional do Golfo.
- [34] Mikut, R., & Reischl, M. (2011). Data mining tools. Wiley interdisciplinary reviews: data mining and knowledge discovery , 1 (5), 431-443.
- [35] Mining, WID (2006). Introduction to Data Mining. Multimedia Database Mining, Time Series Mining e, 2006.
- [36] Sharma, L., & Garg, PK (Eds.). (2021). Artificial Intelligence: Technologies, Applications, and Challenges.
- [37] Ding, W., Abdel-Basset, M., Hawash, H., & Ali, AM (2022). Explainability of Artificial Intelligence Methods, Applications, and Challenges: A Comprehensive Review. Information Sciences , 615 , 238-292.
- [38] Helm, JM, Swiergosz, AM, Haeberle, HS, Karnuta, JM, Schaffer, JL, Krebs, VE, ... & Ramkumar, PN (2020). Machine learning and artificial intelligence: definitions, applications, and future directions. Current reviews in musculoskeletal medicine, 13 (1), 69-76.
- [39] Ustundag, A., & Cevikcan, E. (2018). Industry 4.0: Managing the Digital Transformation (p. 286). Cham: Springer.
- [40] Gadre, M., & Deoskar, A. (2020). Industry 4.0 – Digital Transformation, Challenges, and Benefits. International Journal of Future Generation Communication and Networking , 13 (2), 139-149.