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Interoperable data extraction and information enrichment system to support smart manufacturing: an experimental application on CNC machining lines of a healthcare product

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Abstract

Paper aims: This research develops an expert system for interoperable data acquirement and information enrichment in the manufacturing lines of a healthcare product, ensuring the correct data and information sharing and supporting the decision-making process.

Originality: The research contributes to creating and developing a novel method of knowledge representation that systematises the data collection and creates semantic relationships that allow the analysis of the productive performance of healthcare product manufacturing through semantic rules and inference engines.

Research method: The Interoperable Data Extraction and Information Enrichment system 4.0 (IDEIEs 4.0) was developed using an ontological approach and experimentally applied in an implantable Vascular Access Catheterindicated production process, which involves a machining controlling process.

Main findings: The developed system application pointed out the reduction of human mistakes in the data collecting, errors in the production control and data loss due to the digital automatic and interoperable collection process that brings precision in data collection and security in their storage.

Implications for theory and practice: The solution presented here can be used as a starting point for new directions of research to support the decision-making process with extra and formalised information, improving product quality, flexibilities the manufacturing process and reducing the time wasted.

Keywords

Industry 4.0. Healthcare Product. Data Collecting. Semantic Interoperability. Machining.

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1. Introduction

In the last years, the fourth industrial revolution has instigated the industry to rethink its manufacturing processes to connect the shop floor with the administrative and management levels of the company, providing quick and assertive decisions (Büchi et al., 2020). It is the new concept of Smart Factories, which is defined by the National Institute of Standards and Technology (NIST) as "[...] fully integrated, collaborative manufacturing systems that respond in real-time to meet changing demands and conditions in the factory, in the supply network, and customer needs" (Lipman et al., 2018). Fully integrated and collaborative manufacturing needs to establish an effective data flow management that relies on the acquisition and evaluation of the data and information extracted from the shop floor to process and extract new information and knowledge to support the decisions or optimisation of the manufacturing system. (Adamczyk et al., 2020; Silva et al., 2018).

The healthcare product manufacturing industry is one of the most important industries since it is directly connected with human lives and welfare (Awad et al., 2021). As this industry is strictly related to human lives, production and quality control require a rigorous and systematic analysis process to settle manufacturing issues and meet the requirements of healthcare regulatory bodies (Arden et al., 2021; Beckers et al., 2021; Cheng, 2003). Therefore, healthcare industries are looking for technologies that bring enrichment and fast data processing via semantically interoperable systems to keep up with this competitive market and bring more benefits to its customers (Curi de Moura Leite et al., 2017; Ottonicar & Valentim, 2019).

This issue is not limited to the healthcare industries, but it is necessary for different sectors, as discussed in the research of (Liao et al., 2017). Based on this context, manufacturing industries must develop a technological infrastructure capable of supporting the high data flow through different development teams and multiple data systems, seeking to better attend to the market demands (Canciglierie et al., 2021). This point is a typically semantic interoperability problem defined by the capability of autonomous systems' to communicate through standards and to guarantee the correct exchange of information to maintain their meanings throughout the process (Ke-Qing et al., 2010; Moura, 2011). The most common way to support semantic interoperability is to research integrated solutions by defining common information models formally well-defined and their relationships (Pereira et al., 2021; Szejka et al., 2017).

Semantic web technologies, inference capability and machine understandability are good candidates for providing a formal information structure and their relationships. Related works such as Interoperable Manufacturing Knowledge System-IMKS (Chungoora et al., 2013), Semantic Annotation applied to PLM (Liao et al., 2016), OntoSTEP-NC (Danjou et al., 2016), and Semantic Interoperable Smart Manufacturing System-SISMS (Adamczyk et al., 2020) indicate that there is a tendency to explore the use of semantic web ontology languages to model the knowledge of product and manufacturing in core concepts. Therefore, this scenario requires a well-defined ontology and interoperable structure between the phases and areas of the development process to ensure the correct exchange and application of data in the production process (Buranarach et al., 2016; Curi de Moura Leite et al., 2017; Szejka et al., 2017).

Based on this context, this research proposes an Interoperable Data Extraction and Information Enrichment System to improve production control and decision-making processes across the manufacturing system by automatically processing the production performance data. The system was experimentally tested in a healthcare manufacturing industry to identify the main contributions, limitations and improvements. The research contributes to (i) creating and developing a novel method of knowledge representation that systematises the data collection and (ii) creating semantic relationships that allow the analysis of the productive performance of healthcare product manufacturing through semantic rules and inference engines.

The paper presents in Section 2 the theoretical foundations to support the conceptual proposal and Section 3 brings the system proposed development. Section 4 explores the experimentation of the system in the real healthcare industry and discusses the main results. Finally, Section 5 presents the conclusions and future perspectives.

2. Theoretical foundations for Data Extraction and Information Enrichment

This section explores the main theoretical foundations to support the proposal of the interoperable data extraction and information enrichment system. Subsection 2.1 investigates the main concepts of the Industrial Internet of Things and the emergent technologies to support Data and Information Extraction. Subsection 2.2 explores the main issues to overcome semantic interoperability, and subsection 2.3 presents the technologies to formalise and enrich the information to support the decision-making in smart manufacturing processes.

2.1. Industrial Internet of Things (IIoT)

Industry 4.0 proposes the extension of a traditional manufacturing system to a fully integrated and intelligent manufacturing system, based on the connectivity of the machines, platforms used in the industry and artificial intelligence, improving the efficiency of the factories management (Rüßmann et al., 2015). Different Manufacturing Industries, including the healthcare industry, seek to achieve higher industrial performance by integrating processes and product connectivity (Dalenogare et al., 2018). Internet of Things (IoT) has emerged as a solution to connect physical devices with the digital world forward the digital transformation.

Specifically, for the manufacturing cluster, the Industrial Internet of Things (IIoT) is an extension that uses the internet of things in industrial sectors and applications. IIoT focuses on machine-to-machine and/or human-to-machine connection, big data analytics and prediction or detection techniques (Hazra et al., 2021). It empowers modern-day technologies by expanding the Internet competency to the sensing nodes and transmitting to the edge devices (Ai et al., 2018). The integration of multiple IIoT solutions to improve decision-making, production and cost control, production waste and so on are considered Cyber-Physical Systems (CPS) (Lu et al., 2020; Zhuang et al., 2021). IIoT and CPS encompass industrial applications, including robotics, medical devices, and software-defined production processes (Hazra et al., 2021).

IIoT focuses on networking architecture and smart sensors (vibration, torque, tension, current, so on) applications to extract information from the physical assets on the shop floor (Yang et al., 2016). CPS complements the IIoT solutions since it is responsible for connecting the physical assets (IIoT sensors, controller, communication hardware) from the shop floor with the cyber world (monitoring systems, control systems, optimisation systems, simulation systems, etc.) (Hu et al., 2018). However, both IIoT and CPS can not analyse and process the extracted data and make it available for other applications in an understandably way to machines and/or humans. Furthermore, as discussed by (Lelli 2019), Industry 4.0 demands a convergence of meaning for the various concept and emphasis on the actuator aspects of the devices. Therefore, the information collected from several IIoT, and CPS devices must be stored in a well-defined structure to avoid misinterpretation and mistakes. In addition, the data stored must be evaluated and enriched with extra information and knowledge from various sources to support decision-making, optimise the manufacturing process, save energy, and improve system performance (Bahrin et al., 2016; Hazra et al., 2021; Lelli, 2019).

2.2. Semantic Interoperability

Semantic interoperability, one of the key concepts of Industry 4.0, is the ability of two or more systems to exchange information and to use the information that has been shared without losing the meaning associated with them (Lakka et al., 2019). The information and knowledge developed in design activities are based on Design for Function, Design for Assembly and Disassembly, Design for Manufacturing, Computer-Aided Design, Computer-Aided Manufacturing, etc, and must be exchanged through different steps of the production process. Additionally, the products are complex in the healthcare industry and require specific protocols, standards, and regulations to be manufactured (Liyanage et al., 2015). This scenario forces to improve the information exchange between product design and the manufacturing process.

Autonomous systems can communicate, sharing information through interconnectivity, ensuring that information is shared between different areas without misunderstandings. It is essential in industrial processes since there are problems with accessing and sharing information from different sources and taxonomy (Moura, 2011; Palmer et al., 2018). In addition, semantic interoperability can support integration and information exchange across different manufacturing systems (Liyanage et al., 2015).

The most common way to support semantic interoperability is to research integrated solutions by defining common information models formally well-defined and their relationships (Adamczyk et al., 2020; Palmer et al., 2018; Pereira et al., 2021; Szejka et al., 2017). According to Szejka et al. (2017), it is possible to describe and share data in a systematic and structured way by using an ontological approach. Ontology is a knowledge representation model that brings the simplified abstraction of knowledge structured through classes and individuals (Chungoora et al., 2013; Palmer et al., 2016).

2.3. Ontology-driven semantic interoperability

Ontology has been developed to provide machine-processable semantics of information sources that can be communicated between systems or human entities (Alaya & Monteil, 2015; Buranarach et al., 2016; Chungoora et al., 2013; Palmer et al., 2018), and intelligent systems also use it for the interoperation of heterogeneous systems. As a result, ontology has become a significant concept for Intelligent Information Integration, Internet Information Retrieval, Knowledge Management, and the Semantic Web (Imran & Young, 2016; Pereira et al., 2021).

The basic elements that compose ontologies are classes, relationships, axioms, individuals, and functions. Classes represent the set of individuals with characteristics in common; they are organised in taxonomies through appropriate relationships, representing the interaction between the elements of the classes. Axioms are true conditions to check ontology consistency. Finally, individuals are the elements that belong to the classes, and they are used to represent specific elements (Noy & Rubin, 2008).

Semantic rules can restrict the meaning of relationships and the properties of individuals. Using the Semantic Web Rule Language (SWRL), it is possible to create these rules, inferring new values and relationships, capable of producing results automatically (Farias et al., 2016). The SWRL language permits combining semantic rules with ontologies developed in Web Ontology Language (OWL), making it possible to process information by applications. Through SWRL, users can write their semantic rules from the classes, data properties, objects and individuals represented in the ontology, allowing the inference of new knowledge about such individuals through the application of an inference engine (Effendi & Sarno, 2017; Szejka & Canciglieri Junior, 2017; Young et al., 2007).

The inference reasoner performs the inference within the knowledge base of an ontology, that is, from semantic rules and an ontological base, the engine will cross the data, generating new knowledge from predetermined conditions (Dziekaniak, 2010).

3. Conceptual proposal of Interoperable Data Extraction and Information Enrichment System (IDEIEs 4.0)

The conceptual proposal of the Interoperable Data Extraction and Information Enrichment System (IDEIEs 4.0) was divided into two subsections. The first subsection explores the research opportunity and methodology used to achieve the conceptual solution. The second subsection explores the architecture of IDEIEs 4.0, and all processes involved with it.

3.1. Research opportunity

Smart Manufacturing systems must be flexible to offer new products in a short lead-time with competitive prices while ensuring higher quality levels and customisation (Adamczyk et al., 2020). This scenario requires rapid and accurate production control to ensure the correct product's manufacturing and thousands of heterogeneous data and information are created by product engineers, manufacturing engineers, production control planning analysts, machines, maintenance systems, etc. (Chungoora et al., 2013; Mabkhot et al., 2020; Palmer et al., 2018).

This study is applied research and has a qualitative approach; it explored the literature review to provide greater familiarity with a specific problem. In addition, some related works corroborate the problem discussed in this paper, and the authors propose solutions. Regarding data and information extraction, some related works (Koohang et al., 2022; Lelli, 2019; Sworna et al., 2021) suggest the use of IIoT sensors to extract some data from the production process, such as cycle time, spindle current, spindle speed, tooling vibration and so on. Analysing the extracted data and information makes it possible to predict when the tool will fatigue and break or when the machine needs to be calibrated or adjusted. In addition, several related works (Adamczyk et al., 2020; Pereira et al., 2021; Silva et al., 2018; Szejka & Canciglieri Junior, 2017) endorse the application of ontology and semantic rules for information and knowledge enrichment.

According to this context, Figure 1 summarises the technical research procedures adopted in this research. Detail “A” of Figure 1 shows the studied concepts used to support the development of the IDEIEs 4.0 architecture. In Detail, “B” of Figure 1 categorises the main functions necessary to overcome the problem.

For the research solution's experimental development, the following resources were employed: 1) Excel was used to create and export semantic rules in Semantic Web Rule Language (SWRL); 2) BonitaSoft was used to model the procedures performed by the proposed system of IDEIEs 4.0; 3) Protégé was used for the knowledge representation through the ontology representation; and 4) Apache NetBeans and Apache Jena were used to creating the dashboard that presents the results and running the inference engine.

3.2. Design of the System architecture

This research proposes the IDEIEs 4.0 to improve the production control and decision-making process throughout the manufacturing system by automatically processing the production performance data presented in Section 1. According to the related works and research opportunity, the IDEIEs 4.0 was designed based on two main structures: (1) Data and Information Extraction (Detail “1” of Figure 2) and (2) Information enrichment and analysis process (Detail “2” of Figure 2).

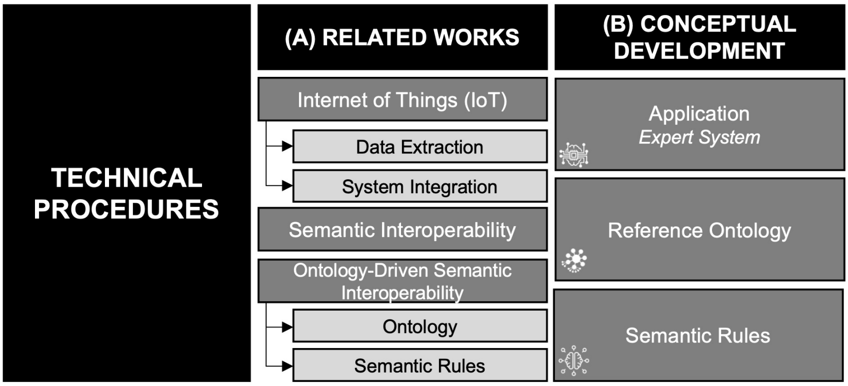

Figure 1. Research technical procedures.

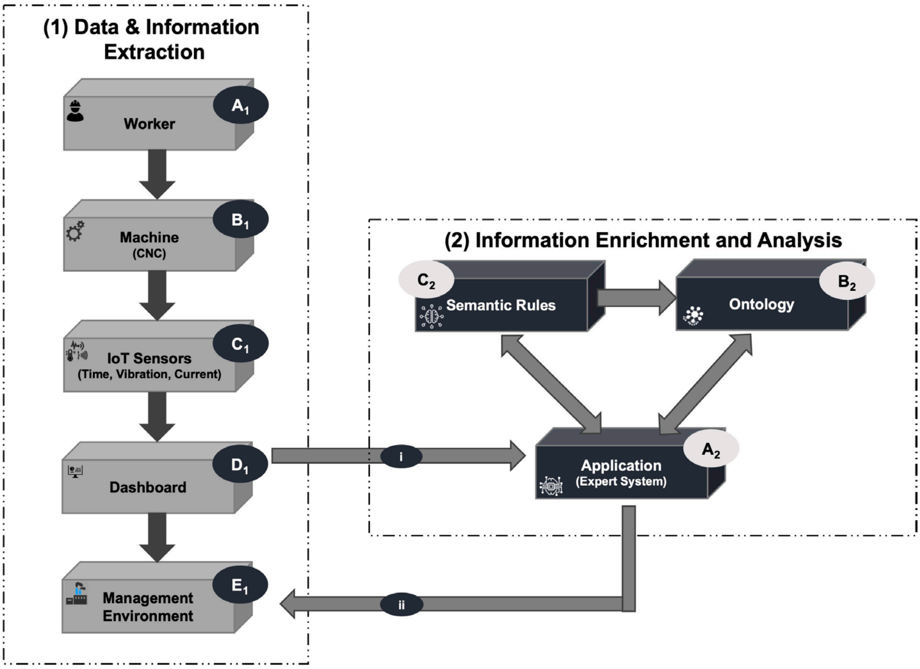

Figure 2. Architecture of Interoperable Data Extraction and Information Enrichment System 4.0 (IDEIEs 4.0).

The Data and Information Extraction of IDEIEs 4.0 is not only constituted of the IIoT technologies, but it considers the manufacturing ecosystem with workers and machines. Therefore, all information might impact the manufacturing and the decision-making process.

The manufacturing system can be formally modelled in reference ontologies and specialised according to specific information about the product, material, manufacturing process, machines, etc. (Szejka et al., 2017). Furthermore, using the semantic rules is possible to establish the relation across different manufacturing process phases and infer improvement in the production process supporting the company and the worker decisions (Adamczyk et al., 2020; Pereira et al., 2021).

According to the architecture proposed in IDEIEs 4.0, the Data and Information Extraction (Detail "1" of Figure 2) has 5 phases:

- Worker (Detail "A_1" of Figure 2) is the CNC machine operator. It is responsible for setting up the equipment and developing the G code to perform the part manufacturing;

- **Machine** (Detail "B_1" of Figure 2) is the CNC machine. There are different types of CNC machines, such as Lathe CNC Machine, Milling CNC Machine, Drilling CNC Machine, Grinding CNC Machine, Laser cutting CNC Machine, etc. All information about this equipment and its manufacturing process must be extracted and modelled in the ontologies to support the production process;

- **IoT Sensors** (Detail "C_1" of Figure 2) – Different sensors are installed inside the machine to measure/extract different data from the equipment like cycle time, cutting time, cutting speed, tooling vibration, etc. Additionally, some data may be extracted directly from the CNC machine. All this data and information are automatically driven to the machining dashboard that uses the process for the analysis and information enrichment processes;

- **Dashboard** (Detail "D_1" of Figure 2) - Once the machining has ended, the machined workpiece will be measured manually, and its data and the machine data listed before will be sent to the Dashboard. It is a virtual platform that can show the machine's performance indicators in an accessible way. The expert system connected to the dashboard (Detail "i" of Figure 2) collects the necessary information for analysis and information enrichment to support the decision-making process in the Management Environment;

- **Management Environment** (Detail "E_1" of Figure 2) – The management environment is the last phase of IDEIEs 4.0. It is responsible for triggering necessary action in the manufacturing process according to the analysis of the information from the Dashboard and the Expert System.

Additionally, according to the architecture proposed in IDEIEs 4.0, the Information Enrichment and Analysis process (Detail "2" of Figure 2) has three phases that are:

- ***Application*** (Detail "A_2" of Figure 2) – the system's application depicted is an expert system that is responsible for instantiating the data in the ontology and analysing the results of the inference engine according to the semantic Rules Application. The results allow the application to check if there are any inconsistencies in the inferences. But, if there is any inconsistency that cannot be automatically corrected, the management environment must contact the responsible for the machine to correct it manually. After the application of the inference engine on the ontology, the generated knowledge will be sent back to the Management Environment (Detail "ii" of Figure 2), which will analyse and take necessary actions for the manufacturing process (Detail "E_1" of Figure 2);

- ***Ontology*** (Detail "B_2" of Figure 2) - This element gathers and structures concepts to formally represent, in an elementary form, the product design and manufacturing taxonomy from different perspectives. The concepts are modelled in common logic-based formalism (OWL);

- ***Semantic Rules*** (Detail "C_2" of Figure 2) - The language used to create semantic rules in this research is the Semantic Web Rule Language (SWRL). This language is the most common among other existing languages, allowing the combination of rules with ontologies developed in Web Ontology Language (OWL). SWRL allows users to write reasoning rules about the individuals represented in the ontology, making it possible to infer new knowledge about individuals by applying an inference engine. When the antecedent conditions are true, the consequent conditions are also true.

According to the concepts presented, Figure 3 was created to improve the comprehension of the Information Enrichment and Analysis process and their relations among Application, Ontology and Semantic Rules.

The Application (Detail "A_2" of Figure 3) receives the data and information about the machining and machined parts from the dashboard that was acquired from the IoT sensors. The data and information are translated into individuals through a data and information treatment to the Instance Generation (Detail "V" of Figure 3).

In Detail "C_2" of Figure 3, semantic rules are established by analysing relevant information about this manufacturing process and identifying cause and effect factors during the machining process. With the semantic rules established in the Ontology (Detail "B_2" of Figure 3) that represent the manufacturing process knowledge, the inference engine (Detail "Y" of Figure 3) will be applied and using the created semantic rules (Detail "X" of Figure 3), resulting in the inference of new knowledge (Detail "Z" of Figure 3), that it will be important to support the decision-making process to improve the manufacturing process.

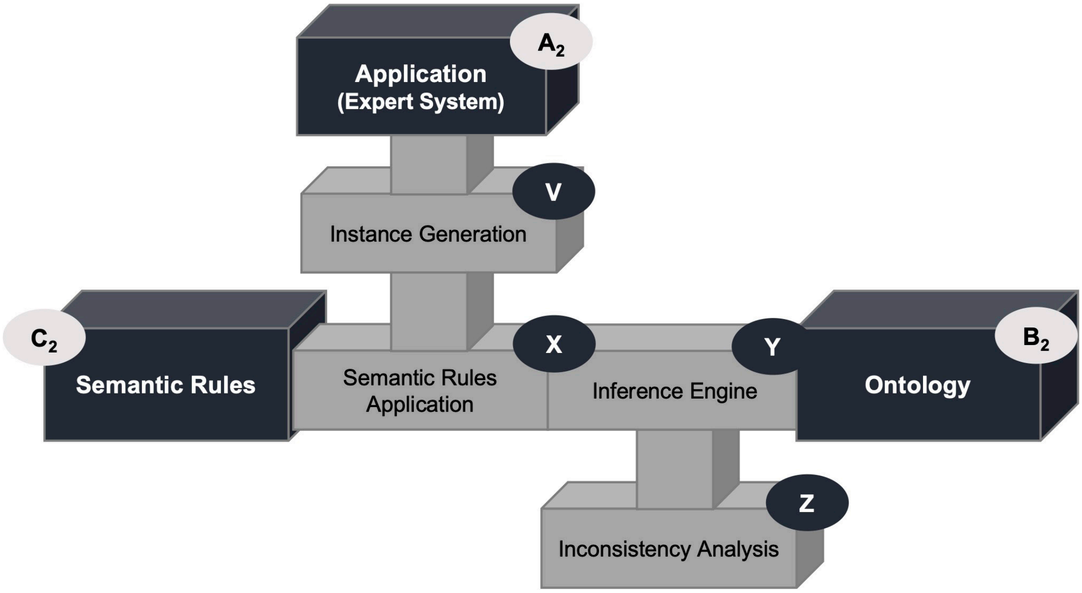

Figure 3. Information Enrichment and Analysis process (IEA 4.0).

4. Experimental case

The experimental case was carried out at the Erasto Gaertner Bioengineering Institute (*Instituto de Bioenegenharia Erasto Gaertner - IBEG*), a manufacturer of implantable Vascular Access Catheterindicated for people with long term treatment, located in Curitiba, Brazil. The catheters, shown in Detail "A" of Figure 4, are produced through machining processes on a CNC machine named Ergomat TND 200 series that is illustrated in Detail "B" of Figure 4.

In the current process, the data extraction from the machining process is made manually by the specialised technicians, which may cause misunderstandings during the data documentation. The company uses these data to make important decisions for production control and the indicator's evaluation. If the data is not accurate, the administrative environment can take wrong decisions about production, which harms the company and its customers.

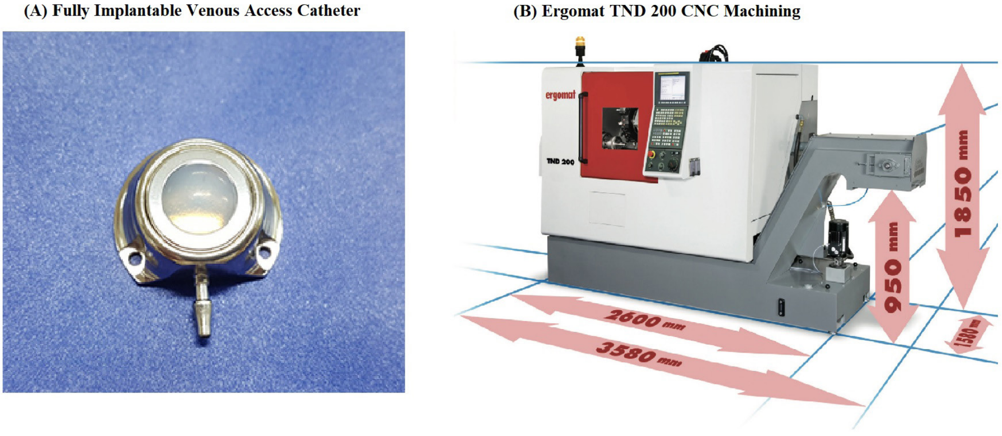

Figure 4. Product and CNC Machining of experimental case. Source: IBEG (Instituto de Bioengenharia Erasto Gaertner, 2021), ERGOMAT (2021).

The application of the IDEIEs 4.0 followed phase A_1 and B_1 of Figure 2 are to map the information about the Worker, Manufacturing process and Machine. Figure 5 shows, in Detail "A", the machine and technical data and the data collected about the product and manufacturing process in Detail B.

(A) Ergomat TND 200 CNC Machining datasheet

Working area		TND 200/51	TND 200/65
Swing Ø over way covers	mm		500
Swing Ø over cross slide	mm		270
Turning diameter with standard tools	mm		270
Chuck diameter	mm	210	210/250*
X Axis travel	mm		160
Z Axis travel	mm	455	400
Main spindle			
Spindle Nose Ø	mm		170
Bar capacity Ø	mm	51	65
Spindle speed max	rpm	5000	4000
Power 100% / 25%	kW	11/15	11/15
Torque 100% / 25%	Nm	71/130	90/164
Slide drives			
Rapid feed - X / Z axes	m/min		30
Turret			
Number of tool stations			12
Square shank	mm		20/20
Round shank Ø	mm		32
Tool holders - standard			direct clamping
Tool holders - optional			VDI 30
C axis			
Resolution	degrees		0,089°

(B) Manufacturing parts technical information

TUNELIZADOR	F1	TEMPO DE CICLO		MODALIDADES	8	H	347	Pçs
		1,23	MINUTOS		8	H	255	Pçs
		83	SEGUNDOS		0,5	H	16	Pçs
		TEMPO IMPRODUTIVO			7,1667	H	228,0	Pçs
		ABERTURA DE PORTA			7,5	H	238,0	Pçs
		30	SEGUNDOS		7	H	223,0	Pçs
		TEMPO TOTAL DO CICLO			8	H	254,0	Pçs
					9,1667	H	292,0	PÇS
		113	SEGUNDOS		9,6667	H	307,0	PÇS
TUNELIZADOR	F2	TEMPO DE CICLO		MODALIDADES	8	H	1694	Pçs
		17	MINUTOS		8	H	613	Pçs
		17	SEGUNDOS		0,5	H	38	Pçs
		TEMPO IMPRODUTIVO			7,1667	H	548,0	Pçs
		ABERTURA DE PORTA			7,5	H	574,0	Pçs
		30	SEGUNDOS		7	H	536,0	Pçs
		TEMPO TOTAL DO CICLO			8	H	702,0	Pçs
					9,1667	H	702,0	PÇS
		47	SEGUNDOS		9,6667	H	740,0	PÇS
ARRUELA PEQUENA	F1	TEMPO DE CICLO		MODALIDADES	8	H	129	Pçs
		3,43	MINUTOS		8	H	114	Pçs
		223	SEGUNDOS		0,5	H	7	Pçs
		TEMPO IMPRODUTIVO			7,1667	H	101,0	Pçs
		ABERTURA DE PORTA			7,5	H	106,0	Pçs
		30	SEGUNDOS		7	H	99,0	Pçs
		TEMPO TOTAL DO CICLO			8	H	113,0	Pçs
					9,1667	H	130,0	PÇS
		253	SEGUNDOS		9,6667	H	137,0	PÇS

Figure 5. Technical data from machine and manufacturing process.

Multiple sensors were installed in the CNC machine to automatically extract data and information such as Manufacturing Order Code, Raw Material Code, Production Cycle time, Production Volume, Tooling Vibration, and Energy Consumption. After this data and information extraction, the application system will present the information of the parts and the machine through the virtual dashboard in real-time. This dashboard goes to the administrative environment where the quality and productivity indicators will be checked, allowing the constant control of production, which helps more assertive and objective decisions.

4.1. Application – Expert System

The dashboard provides information to the system, making a communication bridge. The system will process the information generated by the inference engine, and the ontological base to feed the company's database. The system is connected to an ontological database that infers the data through a taxonomy developed by the editing of Protégé Software (Protégé, 2021).

The dashboard interface was developed in Apache NetBeans (2021), using JAVA language. This dashboard presents the data through graphs and tables according to the selected metrics and the Key Performance Indicators (KPIs). KPIs are tools used to measure performance and analyse the company's objectives. There are several types of KPIs, so it is necessary to analyse and study which are the best indicators to achieve the company's objective and vision. Furthermore, the indicators selected must be smart, available to be measured and be relevant to a company (Gözaçan & Lafci, 2020; Stanojković & Cvetković, 2018). IBEG company required in the research uses the following KPIs as the production control:

- *Efficiency Indicators*: the beneficial cost relationship between the results obtained and the resources used.
- *Effectiveness Indicators*: the analysis of the relationship between the results obtained and the expected results.
- *Capacity Indicators*: the relationship between production capacity and its time to produce.
- *Productivity Indicators*: the relationship between quantity and quality.
- *Quality Indicators*: the ratio between the total produced and the total of non-defective parts.

CSV (Comma-Separated-Values) file is a usual format for storing data and information is. This file model has a universal language, which facilitates to import and export of data to different applications. In the case of this research, all data and information imported from the operator and machine are in Excel software in a CSV file template. In addition, the processed information is exported in this same format.

The sensors present in the CNC machining extract data of vibration, preparation time, cycle time, cutting time and cutting speed. The data presented are originated from these sensors and are sent to populate the ontology. The Interoperable Data Extraction and Information Enrichment system 4.0 (IDEIEs 4.0) depends on the semantic rules tool, which treats the extracted information according to the ontological basis and the inference engine.

The system-generated results are exported to a Dashboard through CSV files, and the Dashboard presents information about the part and its defects, cycle time, and the machining process through forms created by the software "BonitaSoft".

4.2. Reference ontology

The determination of taxonomy and an inference engine that represented all the steps in the machining process of healthcare workpieces was necessary for the construction of the reference ontology construction. It allows the creation of the ontology model that includes information from machines, workers, applications, and dashboards.

The developed taxonomy classified the information hierarchically, allowing the development of classes and relationships in an appropriate ontology. Furthermore, each ontology class has criteria capable of grouping elements with common characteristics, generating the class hierarchy shown in Figure 6.

Figure 6 shows the ontology hierarchy composed of a parent class called "Machining", representing the company's machining process. This taxonomy follows the previous research presented in (Szejka et al., 2022; Szejka & Canciglieri Junior, 2017), and Protégé Software to model the ontology was used. In addition, Apache Jena (2021) was used to integrate the ontology in OWL with the expert system that was developed in Apache NetBeans.

The parent class has three children classes i) Production Line, ii) Product and iii) Inputs. The child class can be divided into subclasses that inherit the characteristics of the Parent Class. The Production Line class is divided into the following subclasses: Manufacturing Defects, Equipment, Worker and Indicator. The Product child class has a single subclass called Workpiece, and the Inputs child class has no subclass.

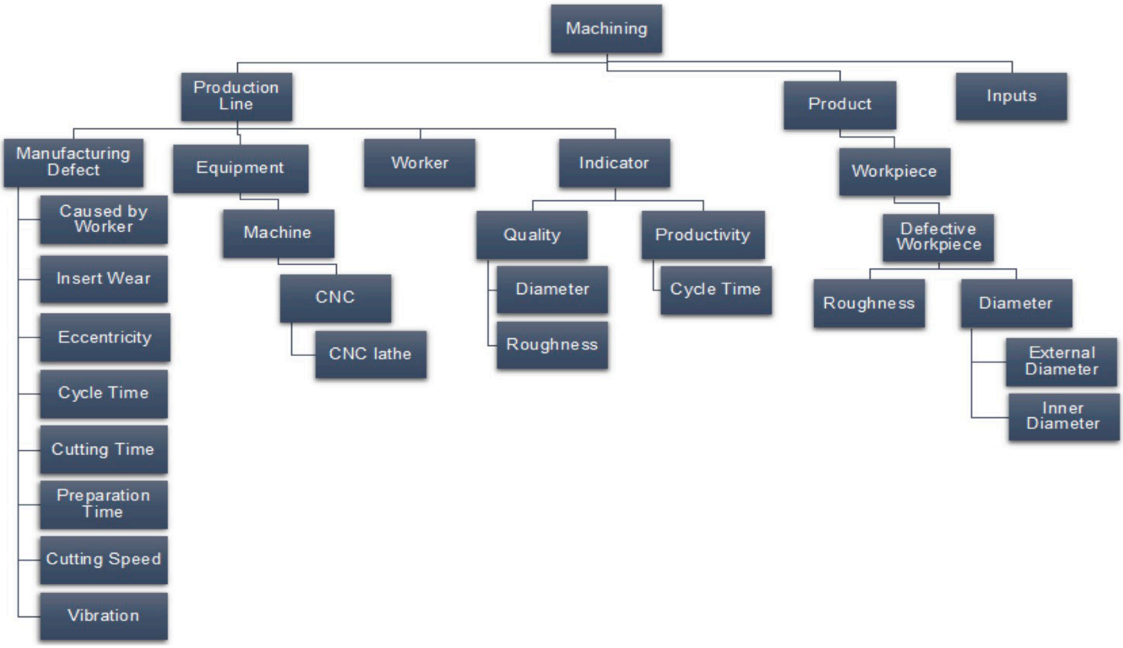

Figure 6. Taxonomy for Machining reference ontology.

The Manufacturing Defect subclass represents the Parent Class of all defects analysed in this universe that can be caused by the insert wear, the operator, the eccentricity, the cycle time, the cutting and the preparation, as well as the cutting and vibration speed since the individuals belonging to these classes are only given by the application of the rules. This subclass analyses the defects that occurred from definitions of cause and effect; for example, if the vibration value in an individual machine is greater than the defined as acceptable, this individual will belong to the subclass of vibration defect.

The Equipment subclass encompasses the equipment used in the production line of the machining process. This subclass consists of a milling machine by Computer Numerical Control and a CNC Lathe machine. The subclass Indicator is divided into Productivity Indicator (which has the Cycle Time subclass) and Quality (unfolding in Diameter and Roughness), considering that these are the parameters used to evaluate the machining quality and productivity. The worker subclass does not encompass any divisions.

The Product child class is the workpiece parent class. The Workpiece subclass encompasses a defective workpiece that unfolds Roughness defects and External and Internal Diameter defects. These are the defective information analysed in this phase, and if a part has a higher value than defined as acceptable, it should be discarded.

4.3. Semantic rules

In the analysis of quality and productivity indicators, semantic rules applied to ontologies in OWL were created to identify defective parts and the cause of the effects, which can be the machine or the operator's parameters. The semantic rules were applied through a pre-existing inference engine in the Protégé software. For this application, the rules must be established to infer data from the definition of cause-and-effect consequences between the individuals, classes, data, and properties in the ontology.

By applying these semantic rules, the knowledge is created for supporting the professionals during the decision-making process and the production control analysis through the indicators like productivity and quality and the defects that occurred in the part machining process. First, however, it is necessary to understand what needs to be inferred before the semantic rules creation to ensure the part's quality and productivity. In this way, parameters defined as an ideal must be identified so that the cause-and-effect relationship between the individuals can be defined.

For this reason, research on the machining processes was conducted, verifying the ideal parameters. They resulted in a maximum acceptable roughness of 1.6mm, an internal diameter of 12mm, and an external diameter of 20mm. After that, it was necessary to analyse the parameters that interfere negatively with the quality of the machined part: the insert wear cannot be greater than 1.5mm, the cutting speed cannot be greater than 110m/min, the maximum acceptable vibration is 187rpm, and the eccentricity of the part in the machine must be close to zero, ensuring the final quality.

The cycle time is used to analyse the productivity indicator, which means that if it is greater than 63 seconds, a problem that occurred during the machining could be caused by the operator or by the preparation time (cannot be greater than 30 seconds), or by the cutting time that has a maximum acceptable value of 33 seconds.

After defining the cause-and-effect relationships, it is possible to define and create the semantic rules using the Semantic Web Rule Language (SWRL) integrated with Protégé Software. This language allows the software to combine the rules with the ontology developed in OWL so that, with the application of an inference engine, new knowledge can be inferred.

Table 1 illustrates the semantic rules used in this experimental case. If true, all the information preceding the arrow symbol () in the body makes the following information also true and inferred. So, Rule 4 in the Table can be read as "If the machine "Y" has a cycle time value of "G", and if "G" is greater than 63, and if the machine "Y" is operated by a worker "H", and the machine "Y" has a preparation time value "I", and if "I" is greater than 30, it means and is also inferred, that the machine "Y" has a defect of preparation time, and the worker "H" caused the defect.

Table 1. Semantic rules of the experimental case.

Rule Number	Rule Description
Rule 1	*product(?X) ˆ hasRoughnessValue(?X?A) ˆ swrlb:lessThanOrEqual(?A,20) Roughness(?X)*
Rule 2	*product(?X) ˆ hasRoughnessValue(?X,?A) ˆ swrlb:greaterThan(?A, 1.6) ˆ machine(?Y) ˆ hasManufacturing(?X,?Y) ˆ hasVibrationValue(?Y,?D) ˆ swrlb:greaterThan(?D, 187) VibrationDefect(?Y)*
Rule 3	*product(?X) ˆ hasExternaDiameterValue(?X,?K) ˆ swrlb:greaterThan(?A, 5.0) ˆ hasEccentricityValue(?X,?F) ˆ swrlb:greaterThan(?F, 0) EccentricityDefect(?Y)*
Rule 4	*machine(?Y) ˆ hasCycleTimeValue(?Y,?G) ˆ swrlb:greaterThan (?G,63) ˆ operator(?H) hasMachineOperatedBy(?Y,?H) ˆ hasPreparationTimeValue(?Y,?I) swrlb:greaterThan(?I,30) PreparationTimedefect(?Y) ˆ defectCauseCausedByOperator(?H)*

This process can be automated using a program developed in spreadsheet software that exports the created rules by copying and pasting them on the Dashboard that is running the application and inference engine. Using lists in Microsoft Excel, it was possible to create a tool that allows the selection of the ontology element that corresponds to the element in the semantic rule, and its use can define the rule in the software by selecting elements in each correspondent cell. The solution facilitates the manufacturing planner's rule creation process, and in Figure 7 is possible to visualise the application.

Type	Sematic Rules									
1	Class	DataProperty	Condition	Conector	Individual/Data	Conector	Parameter	Conector	Conector	Class
	workpiece(?X)	hasExternalDiameterValue(?X,?K)	swrlb:greaterThan	(	?E	,	20	)	->	workpieceWithExternalDiameterDefect(?X)
2	Class	DataProperty	Condition	Conector	Individual/Data	Conector	Parameter	Conector	Conector	Class
	workpiece(?X)	hasRoughnessValue(?X,?K)	swrlb:greaterThan	(	?A	,	1.6	)	^	machine(?Y)
3	Class	DataProperty	Condition	Conector	Individual/Data	Conector	Parameter	Conector	Conector	Class
	workpiece(?X)	hasExternalDiameterValue(?X,?K)	swrlb:greaterThan	(	?K	,	20	)	^	hasEccentricityValue(?X,?F)
4	Class	DataProperty	Condition	Conector	Individual/Data	Conector	Parameter	Conector	Conector	Class
	machine(?Y)	hasCycleTimeValue(?Y,?G)	swrlb:greaterThan	(	?G	,	63	)	^	worker(?H)

Figure 7. Semantic Rules Automatic Creation Module.

The rules are created manually in the Excel application by defining the cause-and-effect relationships; next, the elements used in their construction were perceived, such as classes, object and data properties, conditions, connectors, individuals or data, and the parameters. As a result, four different types of rules were perceived, as shown in Table 1, and they differ in how these elements are displayed.

Using this automated tool to export and import the rules and then apply them with an inference engine in ontology, new knowledge is generated, and the inferred data are displayed in the Dashboard. According to the results, the company can analyse and make improvement decisions in the process.

In the experimental case, the inferred data are the quality indicators and are considered the results of the semantic rule application. These quality indicators analyse the part roughness, its internal and external diameter, and the productivity indicator, which analyses the machining cycle time. Additionally, they result in the indication of the problems that happened during the machining process.

4.4. Results of the experimental case application

The concept of ontology and the creation of semantic rules, different models of construction of automatic formal rules for an interoperable relationship of data were studied, forming the theoretical base for the development of an application in the manufacturing process of a health product part, ensuring the correct exchange of information between the manufacturing phases.

The knowledge representation by the ontology and formal modelling of manufacturing relationship rules were studied, allowing the determination of cause-and-effect conditions among multiple individuals of the specialised ontology. In this context, it was identified in the real process cause and effect in the machining process, for example, for a part to be considered as a parameter of quality KPI, the part diameter and roughness must be measured and analysed. Furthermore, if the dimensions are not acceptable, it is necessary to identify the root cause of this problem as the cutting speed, the tooling vibration of the machine, the eccentricity of the part in the machine, insert wear problems, and so on.

Based on the literature review and the studied machining process, the IDEIEs 4.0 was developed, focusing on automatically collecting interoperable data of the CNC machining lines, contributing to production control.

The system application shows the machining process data using forms created throughout the software "BonitaSoft" to the management environment. The data is displayed according to the selected KPIs metrics, showing the machine analysis and the part manufacturing information in a daily and weekly parameter. In addition, the inferred data from the ontology is also shown on the dashboard, displaying the quality and productivity indicators and defects during manufacturing.

The dashboard interface presents a simple configuration and easy handling for the operator, who will manually fill the questions about the part cycle with "yes" or "no" answers. The questions to be answered by the operator are:

- "Program code for machining is entered?"
- "Is the machining finished?"
- "Were the pieces measured?"
- " Did occur any inconsistencies in the application of the inference engine?"
- "Is it possible to correct the inconsistencies automatically?"

Based on these questions, Table 2 presents the manufactured parts' quality that is measured by the inner diameter, outer diameter, and roughness values. The defects of the piece are measured with multiple parameters, as shown in Table 3. The parameters are (i) defects caused by the operator, (ii) defects caused by insert wear, defects in eccentricity, (iii) defects in a cycle and cutting time, (iv) defects in preparation time and (v) defect in vibration. These data are displayed together with the date and the time of production, the operator's name, the piece number and the machine number, and they are inferred by applying an inference engine through the semantic rules.

Table 2. Results of the manufactured parts' quality.

RESULTS A							
QUALITY INDICATOR		PRODUCTIVE INDICATOR			DEFECTS		
DATE	TIME	PART	WORKER	MACHINE	INTERNAL DIAMETER	EXTERNAL DIAMETER	ROUGHNESS
06/06/2020	14:30	Part 1	Worker 1	LatheCNC1	12	20	1.6
06/06/2020	14:33	Part 2	Worker 2	LatheCNC2	12	20	1.6
06/06/2020	14:36	Part 3	Worker 3	LatheCNC3	12	20	1.6

Table 3. Results of the manufactured parts' defects.

RESULTS B							
QUALITY INDICATOR		PRODUCTIVE INDICATOR			DEFECTS		
DEFECTS CAUSED BY WORKER	INSERT WEAR DEFECTS	ECCENTRICITY DEFECTS	CYCLE TIME DEFECTS	CUTTING TIME DEFECTS	PREPARATION DEFECTS	VIBRATION DEFECTS	
DATE	TIME	PART	WORKER	MACHINE	PREPARATION TIME	CYCLE TIME	CUTTING TIME
06/06/2020	14:39	Part 1	Worker 1	LatheCNC1	60	93	33

The data displayed about the piece are internal diameter, external diameter and eccentricity, shown in Figure 8 (Detail "A"). The data presented about defects are the machine cycle and cutting time, cutting speed and vibration, as shown in Figure 8 (Detail "B"). Additionally, the weekly displayed data are the inserted wear, the number of parts produced, machine operation time, the number of problems reported, and the roughness of the samples collected.

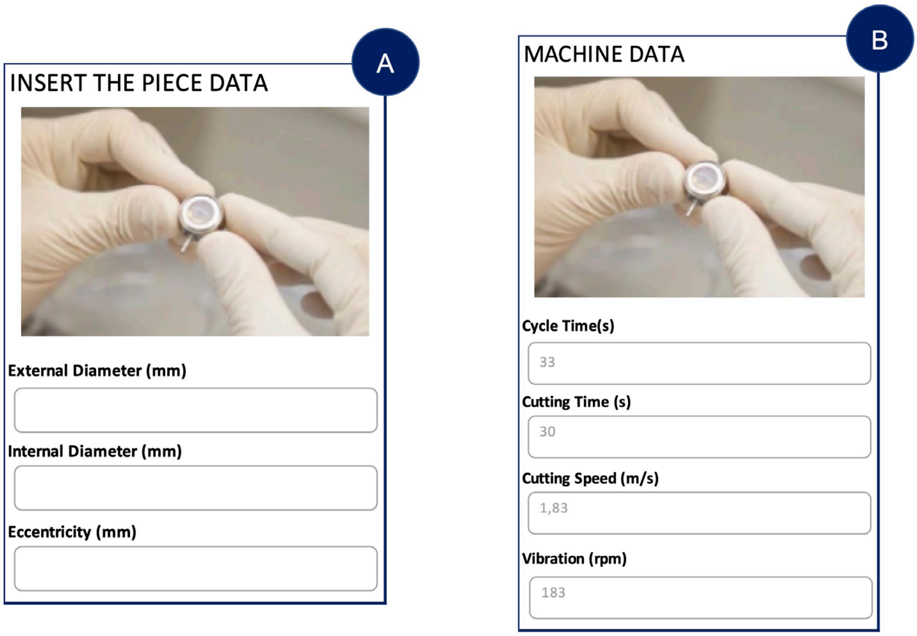

Figure 8. Data Application Results.

Before developing the system application, all data were collected manually by the operator or manufacturing planner. Also, all data were manually entered into the Enterprise Resource Planning (ERP) by typing the paper reports. This traditional method used by the Enterprise of the experimental case is the method used by several Small and Medium Enterprises (SMEs). However, it generates several human errors in data collecting, errors in the production control and data and information loss. This condition is a huge problem in the healthcare industry due to the high complexity of production control that it is necessary to conduct precise analyses of the produced parts, guaranteeing the patients' health.

Therefore, the research indicates that the developed IDEIEs 4.0 system brings qualitative benefits to the IBEG manufacturing process, highlighting: 1) the data and information extraction process is done enterally digitally, minimising the risk of mistakes, data and information misinterpretation and security in their storage; 2) the formal data and information extraction and storage allow to trace quickly manufacturing issues as production input materials, tool wear, etc; 3) information enrichment with references knowledge and inferences support the decision-making process by the administrative staff with precise information.

5. Conclusion

This article presented the development and application of the Interoperable Data Extraction and Information Enrichment System 4.0 (IDEIEs 4.0) in the healthcare product manufacturing industry. This solution contributes to (i) creating and developing a novel method of knowledge representation that systematises the data acquirement of the machining manufacturing process and (ii) creating semantic relationships that allow the analysis of the productive performance of healthcare product manufacturing through semantic rules and inference engines.

The system was developed based on a literature review concerning IoT, semantic interoperability, ontology and application of semantic rules. The literature review was important to understand the concepts involved to ensure semantic interoperability in the healthcare product manufacturing process and the possible solutions that should be applied. Based on this literature review, the IDEIEs 4.0 was conceived to formalise the information extraction from the real world and enrich with knowledge about the process. In this way, it was created and exported semantic rules for the quality and productivity indicators analysis within the manufacturing process, evaluating data and inferring new knowledge. In addition, decision-making strategies based on relationship rules and modelling languages were identified to create semantic rules through ontologies and semantic rules. Furthermore, the tool for automatic creation of semantic rules, data collection in real-time and production analysis was created, applied and evaluated through a conceptual test.

Although tested in an experimental case in the Healthcare industry, the developed system application pointed out the reduction of human mistakes in the data collecting, errors in the production control and data loss due to the digital automatic and interoperable collection process that brings precision in data collection and security in their storage. Furthermore, the system formalises data collection and analyses the production process, which helps the administrative environment in decision-making, generating benefits for producers and consumers and guaranteeing the patients' health.

The research group intends to carry out other tests to stress the platform in multiple scenarios of the Healthcare industry and explore its potential to be applied in other industrial installations as the research's continuity, aiming to improve the developed system and more accurate results.

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