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Toward the industry 5.0 paradigm: Increasing value creation through the robust integration of humans and machines☆

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ABSTRACT

This study proposes a flexible architecture under the LAsim Smart FActor Plus reference framework, fostering the integration of different related data sources—processes, products and the human dimension (operators or other agents)—to increase business value creation. The proposed architecture promotes distributed component perspectives at different levels using different types of digital assets. Integrated reusable services to build composed business applications are found to help increase business understanding and transparency. The robustness attribute is related to the concept of persistence and seeks to reduce the degree of intervention required and thus enable integration. Use cases are presented to demonstrate the advantages provided by the proposed architecture.

1. Introduction

The birth of Industry 4.0 (I4.0) has brought about an imminent need for new approaches to effective data management (Raptis et al., 2019; Williams and Tang, 2020; Bousdekis and Mentzas, 2021). Over the next few years, all manufacturing sectors are anticipated to experience a massive increase in data volume. The adoption of I4.0 technologies by industries is accompanied by a manufacturing execution data stream that grows as materials flow through the production process. Nowadays, industrial companies face the challenge of dealing with this data explosion. They lack the necessary tools, internal standards, control systems, and capabilities to effectively take advantage of these new technologies and obtain all the value enabled by I4.0-related data sources. This challenge will intensify in the coming years. Industry 4.0-enabling technologies have also promoted the evolution of all supply chain logistics processes, leading to the development of Supply Chain 4.0 (Frederico et al., 2019) and Procurement 4.0 (Bag et al., 2020).

Simultaneously, industries have not acted as mere observers of the new technological wave. There are solid indications that many manufacturers are leveraging advanced I4.0 technologies and embracing new predictive analytical methodologies to attain the business-changing predictive results they desire. The vast majority of manufacturing organizations now believe that more efficiently using and analyzing data are critical to future organizational competitiveness (Hagiu and Wright, 2020).

The industrial internet of things (IIoT), which enables huge data collection and process control without demanding a dedicated wired infrastructure, is essential as a value supplier (Malik et al., 2021). A key element of IIoT is wireless communication. Although the latter is a feature of current sensor networks, these networks are not designed with industrial systems in mind. Nevertheless, wireless communication has enabled the evolution of companies toward manufacturing organizations with less centralized control management (Hermann et al., 2016).

One main functionality of IIoT is the real-time production tracking to facilitate the vertical integration of production from the shop floor through manufacturing execution systems and toward enterprise resource planning (Mantravadi et al., 2022). The implementation of IIoT, however, exhibits a tendency to advance technological aspects at the expense of the social or human aspect, as demonstrated, among others, by Xu et al. (2018), Xu and Duan (2019), Wang et al. (2019) and Maddikunta et al. (2021). The only way to ensure the robustness and

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purpose of value creation processes is to urgently place the human being at the center of such activities (Nahavandi, 2019; Wan and Leirmo, 2023). In this direction, a new paradigm has been configured—Industry 5.0 (I5.0)—which is a long-term vision of the future of industries toward a human-centric, sustainable, and resilient manufacturing system (Leng et al., 2022a). In 2021, the European Commission proposed that the European industry should redefine its social obligations and advance this idea to ensure its long-term profitability. This strategy calls for developing resilient and sustainable cyber–physical systems (CPSs) (European Commission et al., 2021).

The relevance of CPSs is underlined in the I4.0 paradigm, in which they are essential elements (Kagermann, 2015). Cyber–physical systems are described as "systems of collaborating computational entities which are in intensive connection with the surrounding physical world and its ongoing processes, providing and using, at the same time, data-accessing and data-processing services available on the Internet" (Monostori et al., 2016, p.621). Therefore, they refer to the close connection and coordination between computational and physical resources. Cyber–physical systems are sociotechnical constructs that attempt to systematically lower the variability of value creation processes in order to improve their effectiveness and profitability (Shah and Ward, 2003; Villalba-Diez and Ordieres-Mere, 2016).

In this context, variability is defined as any divergence from the planned state of a process. Quantitatively, process variability is measured by the systematic decrease in the standard deviation associated with indicators evaluating process performance (Villalba-Diez and Ordieres-Mere, 2015). It incorporates all available data sources that are relevant to the possible variability of the chosen key performance indicators (KPIs), highlighting the significance of measuring and appreciating the value of data across the organization. The development of a uniform enterprise operational technology (OT) data architecture that incorporates numerous data sources, such as wearable and other mobile sensors, is a related component requiring the application of traditional leadership viewpoints (Doan et al., 2001). The two fundamental dimensions—social and technical—mentioned above are meant to work in harmony with each other in order to maximize value creation through the systematic identification and elimination of activities that do not create value for the customer, as well as through the pursuit of waste reduction in necessary activities (Villalba-Diez, 2017).

Furthermore, from a wider viewpoint, the aspects of robustness and resilience must be considered. The integration and reconciliation of data from different sources have their own intrinsic risks and barriers, such as data inconsistencies caused by ill-calibrated measurement devices, leakages, human flaws, and fluctuation in the energy supply, in addition to other factors inherent in any process (Prata et al., 2010). All these barriers constitute challenges that need to be carefully addressed in order to foster system robustness. The inability to measure some process variables because of high costs or technological limitations may result in additional challenges. In fact, a misalignment between different data sources originating from reference dates can induce additional noise. This also defies the robustness of the gathered integrated information, enabling the development of convenient process indicators or references. Additional effort is required to handle data integration and reconciliation in the context of I5.0 in order to determine which strategy can be used to achieve a global approximation of interoperability.

After a thorough analysis, a gap in the formulation of specific strategies to deal with the data integration process, particularly when non-stationary data sources are involved, is identified. Therefore, this study proposes a flexible architecture that not only enables integration from different data sources, both process and product related, but also incorporates the human dimension to increase business value creation.

The remainder of this paper is organized as follows. Following the introduction, Section 2 presents the state of the art, including the human aspects, where the main limitation in existing contributions is presented. Section 3 presents the research question addressed and the methodology followed to provide the answer. Interoperability issues resulting from the heterogeneity of relevant assets and inherently dynamic human behaviors are discussed in Section 4. Although ignoring low-level implementation details, Section 5 explains the platform based on the flexible architecture adopted and its key characteristics. Section 6 presents the evaluation of the platform developed, in which human integration is essential for value creation at the business level. Finally, Section 7 summarizes the knowledge collected and discusses the limitations of the work carried out.

2. State of the art

The revolution of industry 5.0 (I5.0) means that humans and machines are working together, improving the efficiency of industrial production (Xu et al., 2021; Lu et al., 2022). I5.0 is termed as the revolution in which man and machine are finding ways to improve the efficiency of the manufacturing system (Imoize et al., 2021), adding human-centric, sustainable, and resilient concepts to the industrial revolution (Ietto et al., 2022).

A business process is a collection of related actions with predetermined beginning and ending points. A workflow is a representation of how a business process flows and complies with established business standards. In the manufacturing sector, processes have largely followed two separate paths: automation- and human-centric, which are seen as somewhat complementary. Human-centered processes are typically designed to address a specific business issue. Document-centric technologies have developed into human-centric workflow software. The most effective aspect of these workflows has been team collaboration. Workflows that are focused on automating processes typically orchestrate apps and rely on rules-based automation. This type of orchestration offers a sequencing that typically stays the same even when unexpected results show up. To put it another way, the flow has a static quality that makes it challenging to deal with unforeseen problems. The ability to integrate two types of workflow is where the real value lies. Currently, this is the way that industry standards are headed (Ayachitula et al., 2007; Kong et al., 2019; Atif, 2023).

The strength of Japanese manufacturing industry might be the continuous pursuit of high quality in manufacturing by engineers and technicians on their own initiatives. This leads to the 'lean' concept and requires kaizen (continuous improvement) of Cyber Physical Production Systems (CPPS). As a complement of the existing concept of CPPS, 'Digital Triplet' (Physical World, Cyber World, Intelligent Activity World) has been proposed. The aim is to extract knowledge (including tacit knowledge) from experts and transfer it to novices (Umeda et al., 2020).

With regard to their social dimensions, highlighting the human aspect of CPSs is essential, as this presents certain challenges that are vital to the complexity of the human factor in all its variants (Liu and Wang, 2020). Some authors have suggested that the key to the integration of humans with automation is not so much in the replacement of human activities by automatons as in the cooperative symbiotization of both by utilizing the positive characteristics of both for mutual benefits (Tzafestas, 2006). This concept has crystallized into the more human-centric solution of I5.0 (Nahavandi, 2019), which aims to combine human subjectivity and intelligence with the efficiency, artificial intelligence (AI), and precision of machines in industrial production, reflecting the value of humanistic care and thus realizing the evolution toward a symbiotic ecosystem (Müller, 2020).

Human CPSs are expected to have more fault tolerance capabilities (Lu et al., 2022), which, in turn, should increase flexibility, agility, and robustness against disruptions (Nguyen Ngoc et al., 2022). The approach to the idea of human CPSs is considered from a variety of perspectives, such as advocating for a broad framework to design interactions, as presented by Fantini et al. (2020), and identifying demands from various situations (Gorecky et al., 2014). Peruzzini et al. (2020) discussed both psychological and physiological human responses when interacting with machines. Romero et al. (2016) proposed the Operator 4.0 concept, and Sun et al. (2020a) extended it by proposing the integration of the health dimension at work. These are examples of works addressing specific configurations for the integration of humans and CPSs.

When the focus is placed on I5.0, some authors make general proposals about the integration of human behavior into the AI and manufacturing contexts, such as Pathak et al. (2019) and Leng et al. (2022b), but ethical aspects need to be considered as well (Longo et al., 2020). In summary, human CPSs consider human needs as the core of industrial processes (Fukuda, 2020).

Thus, in order to adopt I5.0 for the companies, the personnel are required proper interaction with the machines as well as the operators, where the first requirement to be accomplished is data integration. Data integration initiatives are mainly used to handle data from databases, yet modern methods call for both structured and unstructured data to be considered (Prata et al., 2010). In fact, because of the large growth of data available within organizations, distributing processing to multiple locations rather than concentrating on the processing of all data is more efficient (Giatrakos et al., 2020).

Another relevant aspect is the time framework allotted for data integration. Designers are expected to adopt either batch-oriented data integration or real-time data integration; the latter requires additional interfaces across systems to complete a single business transaction.

Some authors, such as Trunzer et al. (2017), proposed principles and a list of requirements in an attempt to address all these aspects, including security and integrity. This list is as follows:

- **R1. Use a common data model.** The purpose is to create a shared understanding of combined facts.
- **R2. Provide different ways of data processing.** Different processing paradigms might be used depending on the data to be processed and the goal of the study. The chosen architecture must be able to process both streaming or real-time sensor data and events, as well as vast amounts of batch data from many sources.
- **R3. Support a variety of tools.** By establishing shared interfaces with multiple analysis tools, this criterion directly promotes flexibility.
- **R4. Make data transparently available.** Model results and parameters that are integrated with sensor data should be made available to other services. This requires the architecture to use open standards and frameworks that allow access to the entire data collection.
- **R5. Ensure data privacy and security.** Sharing data across organizational boundaries aims to guarantee security. Some regions have strict laws regarding personal data use.

Nemati et al. (2002) introduced an interesting concept called *knowledge warehouse*, which not only performs data integration but also records the entire knowledge management process. As a result, they also consider data analysis and visualization, as well as the relationships between all related phases. The idea includes some form of the common data model (R1) and offers a number of tools compatible with this new architecture (R3). However, it does not consider how real-time data (R2) are processed or how private the data are (R5). The only means through which the results and data stored are accessible is through an interface that is not clearly defined (R4).

There are some other proposals, such as *enterprise service bus* (Chappell, 2004), which allow for an indirect link instead of a point-to-point direct link between systems. This feature means a higher maintenance cost, as the number of required interfaces grows exponentially. The service-oriented bus design has a number of distinct benefits, including decoupling, transport protocol conversion, high availability, message transformation, routing, and security (Aziz et al., 2020). On the other hand, it is circumscribed in its conception and does not contemplate the acquisition of live data (R2, R3, and R4) (Trunzer et al., 2017).

The focus of current research is gradually shifting from the integration of a large number of homogeneous and heterogeneous systems, including the corresponding interfaces, to providing a knowledge model for social context-awareness and reasoning by using ontology-based context modeling (Horváth, 2022). The knowledge base to support decision-making actions include knowledge on processes, their varieties, conditions and rules for process status changes (microstages). Creating an ontology for process development capable of describing classes of basic concepts and relations used for process phases is considered an essential approach. Ontology describes the main controlled and uncontrolled factors affecting processes, which involves modeling different entities with different attributes (Skobelev and Borovik, 2017; Martynov et al., 2019). Semantic web technologies mitigate the data heterogeneity problem, however due to the data structure heterogeneity the integration of several ontologies is still a complex task.

Data and other digital objects created by and utilized for research and co-innovation need to be findable, accessible, interoperable, and reusable (FAIR) (Wilkinson et al., 2016) in order to benefit from digital capabilities while assuring transparency, reproducibility, and, ultimately, societal value (European Commission, 2018). Interoperability frameworks that define community practices for data sharing, data formats, metadata standards, tools and infrastructure play a fundamental role in the FAIR context.

To increase the opportunities for data reuse for data stakeholders and to provide users with a full functional system, data commons and FAIR principles have been suggested and used in a number of disciplines (Barker et al., 2019; Guizzardi, 2020). As data is a shared resource, it may be unified and reused in ways that are more reliable and less expensive. In order to address the issue of data interoperability on a knowledge level, common metadata standards, as bottom-up particular data knowledge, enable that data to be transmitted and interpreted easily among stakeholders. To deal with the involved heterogeneous knowledge sources, it is first required to analyze and reorganize the metadata by using object-oriented principles and then extract semantic relations among these pieces of knowledge. From here it is possible to create a unified ontology for the collaborative environment and formalize it using web ontology language (OWL) (Pang et al., 2023; Mezghani et al., 2016).

In order to create models that can promote semantic interoperability, numerous ontologies have been developed. Ontology reuse is founded on the idea that building a model from scratch by using conventional ontology design approaches takes longer and is more expensive. Ontology reuse, which generally falls under the category of "ontology learning", is the process of creating a new ontology by combining, expanding, specializing, and adapting existing ones (Pinto and Martins, 2000; Lonsdale et al., 2010). Then, using the terms of ontology as an "explanatory dictionary", a state graph of each use case enables the abstract formalization, which is the strategy adopted in this research.

In regard to data integration in industrial settings, there is a barrier to the adoption of new standards and architectures, which is derived from existing legacy systems. They are difficult to abandon, and ensuring that they keep working independently is challenging; they typically have isolated data storage systems that prevent effective decision making, data analysis, and processing (Khadka et al., 2013; Langer, 2020). The use of various data integration models (DIMs) is important in this regard, and data integration is crucial. As described by Aziz et al. (2021), the initial data integration model (DIM-I) uses a message queuing telemetry transport broker to exchange data and is based on an event-driven architecture (EDA). The Arrowhead Framework is used to implement service-oriented architecture (SOA) principles in the foundation of the second data integration model (DIM-II).

Service providers, service consumers, and service brokers are the three fundamental constituents of SOA. Registration, search, and binding actions are all parts of their communication processes. The supplier

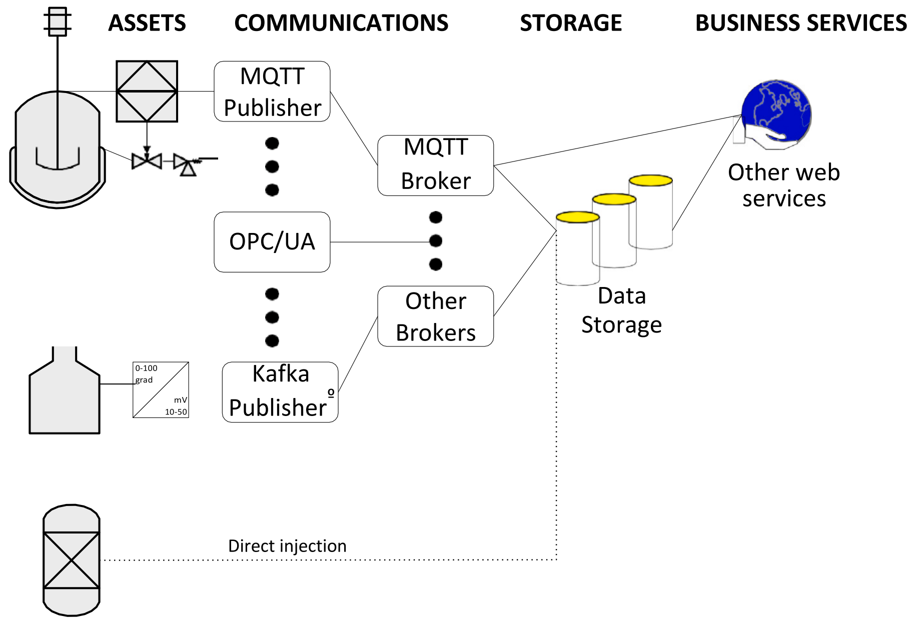


Fig. 1. Classic architecture of services typically found.

of the service sets the service description and registers it with the service broker. To find the service description, the service consumer searches for the service broker. The service consumer then uses a binding operation to consume the service from the service provider. Additionally, SOA 2.0 blends classic SOA with EDA functionality to record in-the-moment business activities. The Arrowhead Framework begins by creating adapters for non-compliant Arrowhead systems, such as Azure IoT, to integrate data between legacy systems. The EventHandler/eventhandler/publish service endpoint is used by the event provider system to consume a POST-REST-API for publishing events. The body of this POST request includes the EventType, data, and provider system information as sources. The REST endpoint must be sent by the subscriber to the EventHandler so that the service can use it to alert the subscriber when the event occurs. The classic architecture commonly found in industries is shown in Fig. 1.

Unfortunately, all the previous architectures are fully oriented to industrial systems. Data collections from systems or sensors that are wearable, mobile, have low-power batteries, and proximity communication protocols are miles ahead of previous architectures. These sensors are relevant for describing the potential human effects on production processes, which means not only human decisions but also fatigue and other characteristics. It is evident that better knowledge of business performance may be achieved by expanding data integration, including information from wearables (Sun et al., 2020a). As introduced in Sun et al. (2020b), the quality of the final product and factory productivity in manufacturing activities are significantly impacted by human variables, often represented by weariness indications. All these systems and devices are significant parts of the I5.0 concept, which requires seamless integration with traditional cyber components.

A higher level of data integration that considers both subsystems (industrial devices and operators) is essential to develop a successful and efficient human–cyber–physical symbiosis when there is interest in expanding current knowledge (Kong et al., 2018). Industrial internet of things infrastructures must focus on pervasive data connections and data-driven dynamic decision making to significantly improve company performance. For this to happen, we must have a common and coherent viewpoint.

The Reference Architecture Model for Industry 4.0 (RAMI 4.0) (Hankel and Rexroth, 2015) aims to provide the fundamental aspects of I4.0 in order to leverage the transition process from classical manufacturing systems to I4.0. The value provided by the data fusion of wearable devices is weak from both a functional and business perspective because the RAMI 4.0 model does not give adequate consideration to wearable devices in the integration layer, especially those connected with human biosensing dimensions. Aside from privacy-related concerns, data ownership issues, data silos, and a lack of interoperability, dealing with these complexities may demand having several digital twins (DTs), both for processes and for goods. To better integrate privacy aspects and mobile data sources, Sun et al. (2020b) proposed LASFA+ as a natural extension of the original LASFA reference model. The LASFA architectural model is a concept on how to approach the planning and implementation of smart factories. The model was built based on RAMI 4.0, from where it adopted the hierarchy of layers (Resman et al., 2019).

Although the concept of an administration shell or an asset administration shell (AAS) is a virtual digital representation of the Industry 4.0 (I4.0) asset that plays a pivotal role in establishing communication among I4.0 Components, to date, the granularity of information modeled in an AAS remains undefined (Ye and Hong, 2019). The LASFA model focused on one of the most important features of smart factories: the communication between systems in smart factories' distributed systems. The model facilitates an understanding of the principle of operating smart factories specifically from the data integration perspective.

It can then be concluded that there is a need for standardization of integrated business processes that involve both automated and human-driven operations. In this sense, the development of specialized standards and federated ontology merging processes have helped the transparency of new, knowledge-intensive fields with larger data volumes.

Although some preliminary work has been done in specific domains, such as e-health (Mezghani et al., 2015; Pathak et al., 2022), much more effort is required for the industrial sector to analyze the interoperability aspects of the heterogeneous collection of systems and components, including wearable devices, to increase value creation. Therefore, this study attempts to contribute to closing this gap by extending the AAS to cover I5.0 contexts to promote additional transparency levels and, therefore, new knowledge creation. The selected framework was LASFA+ and integrated reusable services based architecture. It is applied to some industrial use cases that involve such complexities, emphasizing the knowledge and value created.

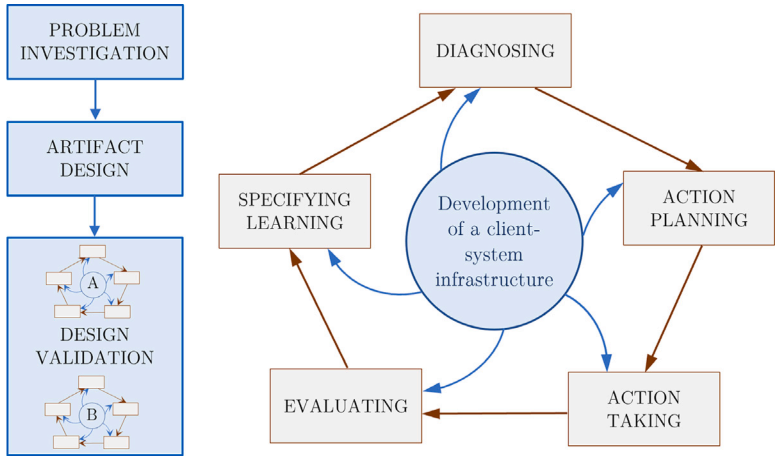


Fig. 2. Methodology schema.
Source: Adapted from Susman and Evered (1978) and Wieringa and Morali (2012).

3. Methodology

The following research question is addressed in this study:

RQ. How can robust and effective data interoperability be achieved in the integration of the human dimension with product and process data sources to increase value creation in manufacturing?

The proposal of a generic flexible architecture that answers the question is developed under the framework of a research project funded by the European Commission. The project addresses a generic demand from the industry identified from a gap in the literature, as previously described. The solution is developed under a generic approach aligned with the current technological trends in the scope of I5.0. Companies with specific problematic situation requirements participate in the project. Providing a solution to these cases leads to the refinement of the generic architecture, validates its practical efficiency and applicability, and gives clues to other researchers on how to take advantage of the proposal.

Fig. 2 shows a schematic representation of the methodology adopted. We follow an adaptation of the technical action research methodology (Wieringa and Morali, 2012), an empirically grounded approach that combines action research methodology and design science. This methodology considers two research cycles.

The main research cycle proposes a solution to a class of problems on the basis of what design science calls an instantiation artifact (March and Smith, 1995). In this case, the main research cycle addresses the research question posed. Design science is underlined by Hevner et al. (2004, p.75) as one of the two foundational paradigms of the information systems discipline, "positioned as it is at the confluence of people, organizations, and technology". Once designed and built, the artifact must be rigorously evaluated through instances of the class of problems (Peffers et al., 2007), in this case, two company-specific situations (Company A and Company B for confidentiality reasons). Finally, after the evaluation, the conclusions provide theoretical answer to the research question and its justification.

The second research cycle, concerning the evaluation of the artifact, is conducted as a direct application of the action research methodology. Two action research cycles, each one for a company-specific case, are performed, following the canonical phases as proposed by Susman and Evered (1978): diagnosis, action planning, action taking, evaluating, and specifying learning. The origins of action research date back to the mid-20th century, achieving importance in its applicability in information systems research by the end of the century (Baskerville, 1999). It is a methodology of particular value when aiming at improving human–system interaction, as it was developed in the scope of social and medical studies. The purpose behind its inception was to develop new knowledge through an improvement-based methodology grounded in planning and taking direct action in a specific system. Action research and design science are complementary, as shown by different authors (Järvinen, 2007; Lee, 2007; Sein et al., 2011; Wieringa and Morali, 2012). As previously noted, we adapt the technical action research methodology (Wieringa and Morali, 2012), which explicitly considers both research cycles, and is particularly well suited for the purpose of answering the research question posed.

The methodology followed reflects on the document structure. To design the artifact that answers the research question, hence providing an effective incorporation of the human dimension to product- and process-related data, it has to ensure interoperability among data sources, including legacy systems. Before the design of the artifact is presented, this aspect is covered. Then, the proposed platform design (artifact) is detailed, and the validation of the artifact is provided, applying the five phases of the action research cycle to two real-world problem situations (Company A and Company B) (Checkland and Holwell, 1998).

4. Interoperability

Although there are many current and emerging standards for corporate data interchange, the majority of them have been created using dissimilar techniques and without consideration of compatibility with other standards, whether they are used in the same or different scopes of usage. There is no global strategy to make these standards interoperable with one another because the majority of them were created independently (Jardim-Goncalves et al., 2006). New approaches are needed to facilitate the integration of these models and eventually achieve interoperability. There are various definitions of interoperability in the context of e-commerce. Interoperability allows information and communication technology systems to increase service compatibility and information interchange between systems (Kosanke, 2006a; Framework, Interoperability, 2004; Ralyté et al., 2008). This study adopts the definition of interoperability by the Institute of Electrical and Electronics Engineers as *"the ability of two or more systems or components to exchange information and to use the information that has been exchanged"* (Kosanke, 2006b, p.57).

Interoperability involves resolution on a number of different levels. There are four levels of interoperability, according to Chen and Daclin (2006) and ISO/TC184/SC5 (2011): technical, syntactic, semantic, and organizational.

- *Technical interoperability* is reached when services or information can be transmitted directly and successfully between communication systems or pieces of equipment and their users. Systems, platforms, and hardware/software parts that enable machine-to-machine communication are frequently linked to technical interoperability.
- *Syntactic interoperability* is defined as the ability to exchange data. Syntactic interoperability is generally associated with data formats.
- *Semantic interoperability* is the capacity to manipulate facts in accordance with the established semantics. Semantic interoperability typically has to do with how the material is defined and how people understand that content.
- *Organizational interoperability* is related to an organization's capacity to efficiently communicate and transfer relevant data (information) even while using a variety of information systems with different infrastructures and cultural contexts.

Interoperability can be viewed from several perspectives using this multidimensional idea, but to bring all these angles, approaches, and directions—many of which are sometimes at odds with one another—together, a framework is required. A set of standards and principles that specify how organizations have decided to interact with one another—or ought to agree to interact—make up the framework. The framework is used to highlight various stages (communication, data, business, knowledge, etc.). This study assumes the Interoperability Development for Enterprise Application and Software (IDEAS) Framework without a lack of generalization (Rezaei et al., 2014).

The business layer, which includes a decision model, a business model, and processes, addresses all associated concerns in the management and structure of a company. By contrast, the knowledge layer is used to combine the internal components of individual and collective (enterprise) knowledge. Although interoperability at this level involves skill compatibility and company assets (methods and tools) that support the diffusion, organization, collection, and elicitation of business knowledge, interoperability at the business level is related to the business model and to business processes. The business model defines the commercial ties that exist between companies and how they provide services and products to the market. Business processes are groups of actions designed to provide value to customers (Chen et al., 2008; Rezaei et al., 2014).

5. Platform proposal

As this study is interested in increasing the value created as a result of smart interactions, the relevant layer of the analysis is the business layer or the equivalent one in the adopted framework (if different from the ideas selected here) because the reflective analysis must remain as agnostic as possible (Saunila et al., 2019). Another critical aspect is the heterogeneity of components. This is a must in today's businesses, particularly because of the need to integrate IoT devices into data and process models. Communication between disparate endpoints, data sensing through these devices, secure data storage on centralized servers, and, finally, the processing and transmission of filtered information to the next level are the main goals of IoT. These are meant to enhance the working conditions of various personnel, lower operational costs, and lengthen the life expectancies of machines. Indeed, IIoT technology opens a new age for dealing with real-time applications in a complicated environment.

The ability to connect one or more IIoT devices and comprehend and exchange data with one another for a specific purpose is one of the most challenging problems in IIoT applications (Chen et al., 2008). The numerous IIoT devices and their functionalities in the industrial context are crucial to the creation of an interoperable IIoT-enabling technology (Fedullo et al., 2022). Severe heterogeneity and dynamic communication are two crucial qualities when addressing the interoperability problem in the IIoT domain. In actuality, each IIoT device adds a variety of technologies, resulting in issues with device comprehension during data transmission and processing. Furthermore, as the link between IIoT devices is not established until runtime, no design decision can lead to the interoperability solution (Hazra et al., 2021). Because of the broad adoption of IIoT and IoT solutions for a wide range of industrial applications, each firm began to create its own infrastructure, proprietary protocols, rules, and data formats, which are not globally standardized and thus cause industry interoperability issues. Interoperability concerns are also causing insoluble challenges from the end user's perspective, such as vendor lock-in, in which customers are forced to work with a certain vendor because of incompatible vendor communication and a non-standard cross-platform design (Kim et al., 2016). Introducing a non-interoperable solution to a typical industrial ecosystem and obstructing development are key issues in this regard.

Based on the previously described context, having a reference framework-based context for the configuration of multiple time-scale data flow processes is necessary. The reference framework must consider local sources for both process- and product-related data, but it must also be open to the external sources provided by web services from sensors, actuators, or fully integrated unit providers. Therefore, instead of obtaining just partially described datasets accounting for fragmented pieces of processes or product attributes, this study promotes a more integrated description of such processes by appropriately conducting fusions of the relevant data flows.

This study focuses on the LASFA+ reference framework, as introduced by Sun et al. (2020b) and presented in Fig. 3, in which the presence of different DTs and data streams, including those coming from wearables, is considered.

The adopted reference framework supports the creation of a flexible architecture of shared services based on the five requirements introduced in Section 2. The artifact, as it is referred to in the scope of design science, is the result of instantiating the architecture into a software platform. Programming tasks required to this instantiation are not subject to novelty themselves, whereas the architecture design incorporates novel aspects that are key to achieve the necessary effective integration of human data, product data, and process data, that provides the answer to the research question posed. As a result, this platform makes it possible to build composite applications that rely on reusable services supplied by many data sources (see Fig. 4.)

It is relevant to mention that the concept of smart cyber–physical systems (SCPSs) (Sha et al., 2008; Yao et al., 2019; Delicato et al., 2020) has been introduced because modern internet protocol-enabled sensors, actuators, and controllers are transforming industrial automation into I5.0 compliance to achieve full autonomy with minimal human intervention. In this context, some authors propose a heterogeneous architecture for SCPSs (Thakur and Sehgal, 2021). By predicting process disturbances, sensor delay, actuator delay, and conversion delay, the suggested architecture can isolate all parts of a process dynamic, such as computing, control, communication, and actuation, in which the focus is analyzing the robustness of distributed control strategies when disturbances occur.

Although a heterogeneous CPS is necessary to handle the various batch and continuous processes in a manufacturing plant and accommodate different production units, the human aspect is still not adequately addressed; the underlying hypothesis assumes that sensors are fully outfitted with reliable IP protocols and so on. Regrettably, the majority of wearable sensing technologies used to monitor humans do not operate in this way.

The focus of the proposed platform is much more related to facilitating the decision-making process on the basis of an extended understanding of the events in the process, including those impacted by human operators. Therefore, in this case, the top-level perspective is less relevant in relation to the proper interconnection between the different data flows coming from different systems and devices.

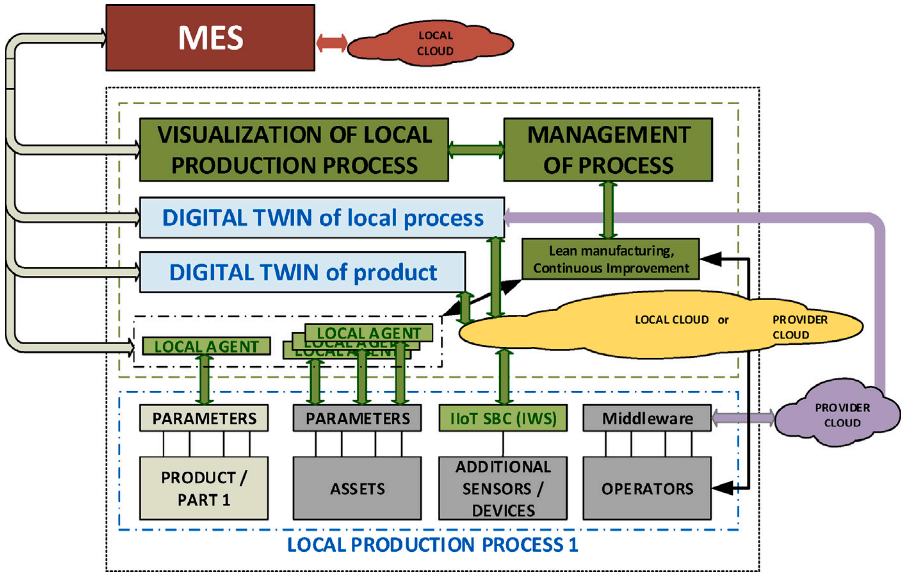


Fig. 3. LASFA+ reference model.
Source: Sun et al. (2020b).

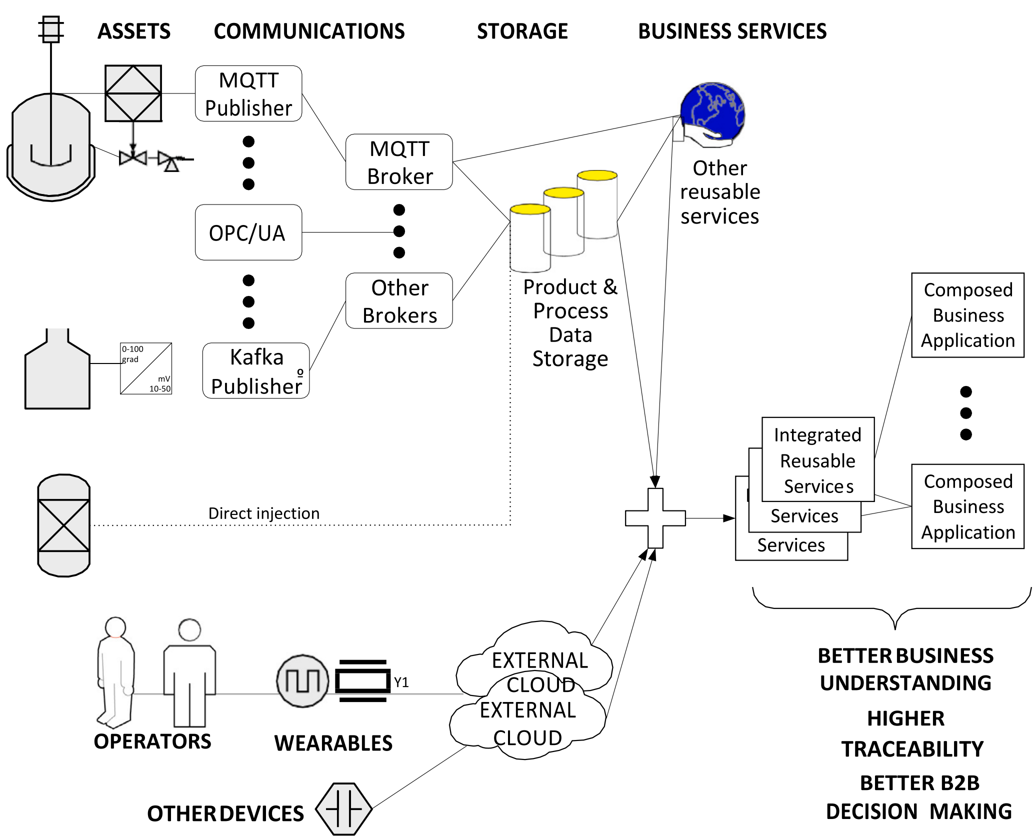


Fig. 4. Proposed architecture of shared services.

That is the data integration perspective, which seeks to promote the interoperability of different components and agents.

In the general case, data flows could be obtained from the following:

- Either databases, web services, or a combination of them describing the current manufacturing process, involving both information from the product and the assets involved in the process
- Additional IIoT devices installed to obtain relevant information not considered in the initial formulation of the process, or because of improvements to it
- IoT devices incorporated to the human operators, either for safety reasons, health, or other specific purposes
- Other IoT devices linked to additional agents or elements but are needed to understand the actual context

A major issue is that when considering interoperability at the business layer (semantic and organizational interoperability), there is no initial and complete data model because of different manufacturers, implementation times, and/or data provider(s). This concern has a significant impact on initial data integration requirement R1. As a result, a flexible architecture is required to address all relevant issues. In the case of the platform being proposed, there are specific aspects to consider that are related to integration, interoperability, and traceability.

The initial and essential step is to distill an entire relevant data model (R1), avoiding its fragmentation through operation or by the manufacturer. To this end, the configuration of a proper ontology, that is, reusing existing ones, is an essential factor in building a holistic perspective and facilitating the connection between entities; the absolute time is the key attribute in most cases, but other attributes can also be relevant.

The second critical step is to not limit the data integration approach to grouping together the interesting attributes of the selected entities and cutting off irrelevant sequences. Instead, the initial data flows are handled through proper storage and by simply using a referential approach to configure the new integrated data flows with all the necessary information. The original data from independent sources are retained in this manner, further promoting data integration requirements R2, R3, and R4 and enhancing traceability.

This effect is particularly relevant when the monitoring aspects of human operators are considered; the periods when the process is not affecting the operator can help achieve a better understanding of the variations in physiological parameters during active participation in such processes.

In the comparison of the traditional architecture and the proposed one, the benefits of the integration of IoT and IIoT are clear because highly integrated services can be built. Among integrated services involving different levels of equipment, value stream components, production lines, or even factories, a high level of composing business applications can be defined, helping managers reach increased levels of transparency and obtaining a better business understanding because more realistic what-if analyses can be performed. The proposed architecture takes full advantage of the LASFA+ reference model; having different types of digital assets, it promotes distributed component perspectives at different levels.

The combination of framework and architecture facilitates a coherent implementation of the principles mentioned above. In particular, R4, which promotes transparency in the collected data, is fully operational with the convenient ontology choice or extension, which helps meet R1. Traditionally, application architects neglect the importance of maintaining R4 in combination with R1 and R2, and they create limited services in which data integration is mainly syntactic. The entire data flow must be preserved to ensure that semantic and operational interoperability is attainable using different tools and processes, according to R3. The semantic description fueled by ontology can be achieved using the Semantic Web of Things (SWoT) (Jara et al., 2014). Privacy and security of the data (R5) are regularly ensured by the information technology infrastructure through different mechanisms, such as virtual private network access and a time-limited token.

The Semantic Web of Things includes in its vision the adoption of standards from the Semantic Web (Pfisterer et al., 2011). The Resource Description Framework and Web Ontology Language were introduced as parts of a collection of standards put in place to identify resources and encode information in order to attain this goal. The Semantic Web of Things ultimately becomes a collection of web resources that have been consistently enhanced by the additional semantic information that any adopted ontology provides to define objects and the context. The acquisition of such a new semantic meaning by the resource breaks the isolation of existing applications by vertical silos.

While ontologies and semantically organized data are thought to be static, real contexts are always changing. Providing a set of concepts that govern the dynamic interaction in addition to a static description of the world is necessary. A dynamic behavior is required not only to incorporate the most recent sensor values but also to update the meanings of various variables while constructing the connection from the observed data.

6. Platform validation

Following the methodology described in Section 3, the proposed platform, which provides an answer to the research question posed in this study, is evaluated through two action research cases. The proposed flexible platform has a configuration that depends on the specific characteristics of the cases, as projected into the integrated data model supported by the ontology. To illustrate this flexibility, we aim to show the impact of its application in two different settings, where properly linking heterogeneous data brings additional opportunities for managers to increase value creation by taking the right actions.

6.1. Company A: Inner logistics in a rebar factory

Company A manufactures customized steel rebars for construction projects. Each order encompasses engineering the bar list, manufacturing the specified bars, and shipping them to the construction site. One specificity of the entire order fulfillment process is that the bars need to be not only manufactured in a determined sequence but also bundled and loaded in the trucks so that they are delivered as needed at the construction site, favoring convenient unloading. This requirement implies the necessity of a loading buffer area, which introduces complexity because of space constraints derived from crane movement.

The primary problems that the company has are related to the highly variable truck loading procedures, which can occasionally have a negative influence on the volume of goods being produced and waiting to be delivered. In fact, this raises the possibility of specific things not being loaded onto the vehicle properly, with the corresponding disturbance in the construction site, time spent in looking for products, complaints, and the need to rearrange deliveries. Therefore, the main issue is that the organization lacks a complete understanding of the manufacturing process because loading processes are specifically planned for each operator according to their individual preferences, and there are no indicators that could aid in analysis or development.

Diagnosing. Information technology systems support the engineering, design, labeling, and scheduling of the production system. The production of rebars is fully digitalized from the beginning of the process to the last cutting, blending, or welding machine operation (see GRAITEC, 2023). However, the loading process is done based on non-systematic information owned by the crane operators. Each crane operator decides how to proceed based on their experiences. The following problems are identified:

- There is no knowledge regarding the bar bundles that have been loaded in the truck and, therefore, the loading logic followed.
- Crane operators complain about stress in their tasks because of their crucial role in the process.
- There is no detailed knowledge regarding the precise location of each bar bundle in the shop.
- There is no traceability of the loading process (who, what, when, and where).
- There is no trajectory optimization in the movement of bars from the manufacturing area to the loading area.

In conclusion, increasing value creation is necessary by incorporating the contribution of the human workforce to the truck loading process and linking it with the manufacturing process. Adding data on the crane operator's activities, location, and time and linking these with the product being handled, as well as with the resources used, are needed.

Fig. 5. General Perspective of the shopfloor of company A, with some specific details about the product and operators.

Action planning. A product tracking system is deployed to achieve the desired integration of humans and machines in the manufacturing control system. Operators carry appropriate devices that not only provide information necessary for product and process tracking but also help monitor physical conditions. A summary of the list of actions to be performed is as follows:

- Identification, acquisition, and deployment of the required devices and sensors
- Development of the information system required to access each element
- Development of the information system capable of integrating all the necessary data sources to provide product and process tracking and traceability
- Development of the necessary system and user interfaces

Action taking. The first decision is highly relevant because it concerns the identification of the necessary devices and sensors. Most industries perform product tracking with conventional procedures using data matrix codes, bar codes, or other recognized codifications, as outlined by Ustundag and Cevikcan (2018). Codification and the reading system have to work preferably with a handheld scanner when products need to be moved through non-predetermined paths. A mobile scanner is therefore necessary to accommodate the need to scan components of various sizes and from various locations throughout the shop floor. Identifying individual item sets is just one of the components of the knowledge to be gathered. Knowing the crane and the operator's movements is also required to analyze the paths and understand the best practices associated with the different operators and periods.

In this case, the tracking was implemented through ultra wide band (UWB) technology, in which an external service provider deployed the workshop infrastructure (antennas, tags, and industrial computer). The provider also implemented the data capture process in high frequency and its handling through its own platform, delivering a web service (API/REST). Data corresponding to the operator's physical condition (blood pressure and heart rate) are collected to assess the fatigue and stress levels associated with crane operators while performing their tasks. This information is gathered through an Android app connected by Bluetooth Low Energy to wearable IoT devices (smart bands) and ingested into an InfluxDB system.

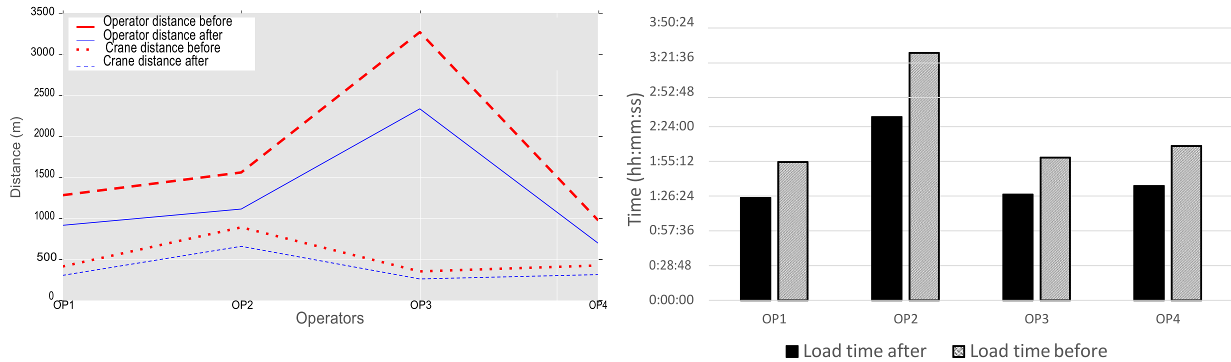
Data from crane positions and crane operators are recorded and linked to the product ID and to the relevant production order and truck being delivered to create a formal understanding of the process. This means that information from production processes and products is required, combined with external and internal web services, according to the LASFA+ framework.

To provide a clearer picture of the setup for Company A, Fig. 5 displays the general perspective of the shop floor with several product types, including rebars (Fig. 5a) and big-bags with smaller items (Fig. 5b). UWB antenna locations are artificially denoted by lines that are superimposed and end at the antenna locations in the upper wall (Fig. 5c). While his position is being recorded, the crane operator (Fig. 5d) scans the bar code of the product to be lifted.

Evaluating. Once the system is fully functional, the following information can be verified:

- Checking that all the bar bundles that need to be loaded in the truck are actually loaded before shipping
- The loading sequence followed
- How many times and when a bar bundle has been moved until the truck has been loaded
- The total distance covered (operator and crane) carrying a product
- Whether the crane carrying a product has passed over the head of another crane operator
- Monitoring of the operator's basic vital signs (enabled by wearable sensors)

To evaluate the effectiveness of the proposal in increasing process value creation, three KPIs are selected: distance covered per operator, distance covered per crane, and loading time. Taking advantage of the possibilities offered by the new system, the managers of the factory were able to identify successive sources of process improvements, and they presented the following reductions in KPIs in the project report: a 35% reduction in loading time, a 35% reduction in distance covered per operator, and a 40% reduction in distance covered per crane. Regarding operator stress monitoring, the physical data did not show measures that might lead to concluding anomalies in this respect. Although no change was induced by the new system, reaching this conclusion through the possibility of integrating physical information and linking it with the workload was positively valued by the managers. It also opened the way to periodically perform stress assessments. Figs. 6(a) and 6(b) compare the two distance KPIs and the load time KPI before and after the implementation of the new system, taking data from four operators. Improvements in the three measures are significant in all the cases, showing the positive impact of the intervention.



(a) Effect on integrated performance. (b) Effect on operator performance.

Fig. 6. Benefits of the decisions made based on system usage.

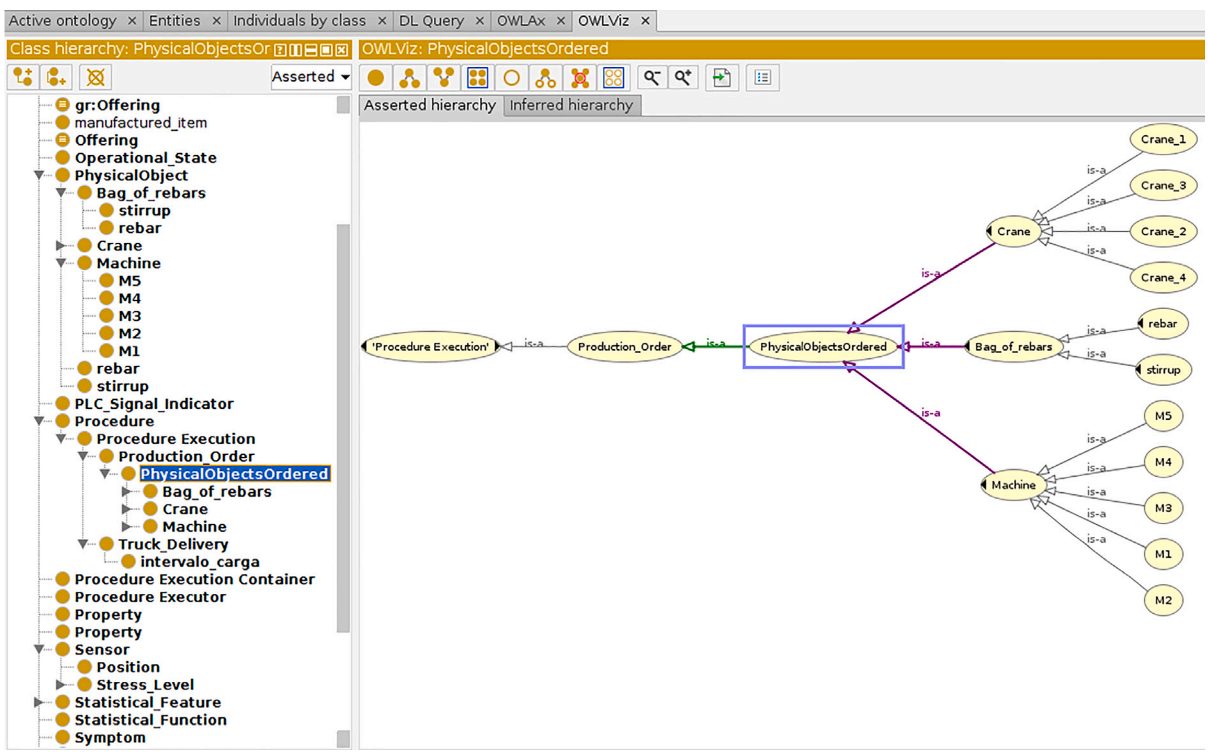


Fig. 7. Class interrelationship.

Specifying Learning. The proposed flexible architecture, which fully enables the integration of all the different data sources and data streams, is required in evaluating this case.

The benefit of information integration is that completely tracking a product is possible, including delays in intermediate storages and the sequence of loading into the truck, which is critical for segmented unloading at the construction site. In addition, management information can be collected, facilitating the identification of the same type of element, such as the duration of loading at the beginning or end of a shift, or the strategies adopted by different crane operators. It can also be extended to monitor the physical variations per worker over time when health safety is a concern.

When utilizing the architecture proposed in this paper, consideration must be given to the five data integration requirements that we outlined in Section 2. As also discussed there, an ontology that links all entities, concepts, and relationships is needed to address R1 conveniently. The authors have analyzed the logic of the process related to the inner logistics of rebars when considering delivery processes. The logic behind such a process was described using Protégé tool (Musen, 2015), as indicated in Fig. 7.

As different types of data flows are involved, data processing is not monolithic, neither in its operation nor in time. It intrinsically requires data access capabilities at different times and for different purposes, that is, R2. Therefore, it requires recording independent locations of assets (cranes and crane operators) because depending on the specific KPI computations, path considerations can be required. This is the case for loading and unloading items, in which the coordinates of the crane and the operator crane using the handheld scanner are at a close distance by that time. The identification of loading/unloading events enables the calculation of distances and durations for different items as useful KPIs that would be almost impossible to obtain without data integration from different sources. These are just examples of integrated reusable services, in which the intrinsic advantage is that different entities can be handled independently. Robustness is enforced because these integrated reusable services do not depend on manual processes that fail because of a lack of regularity.

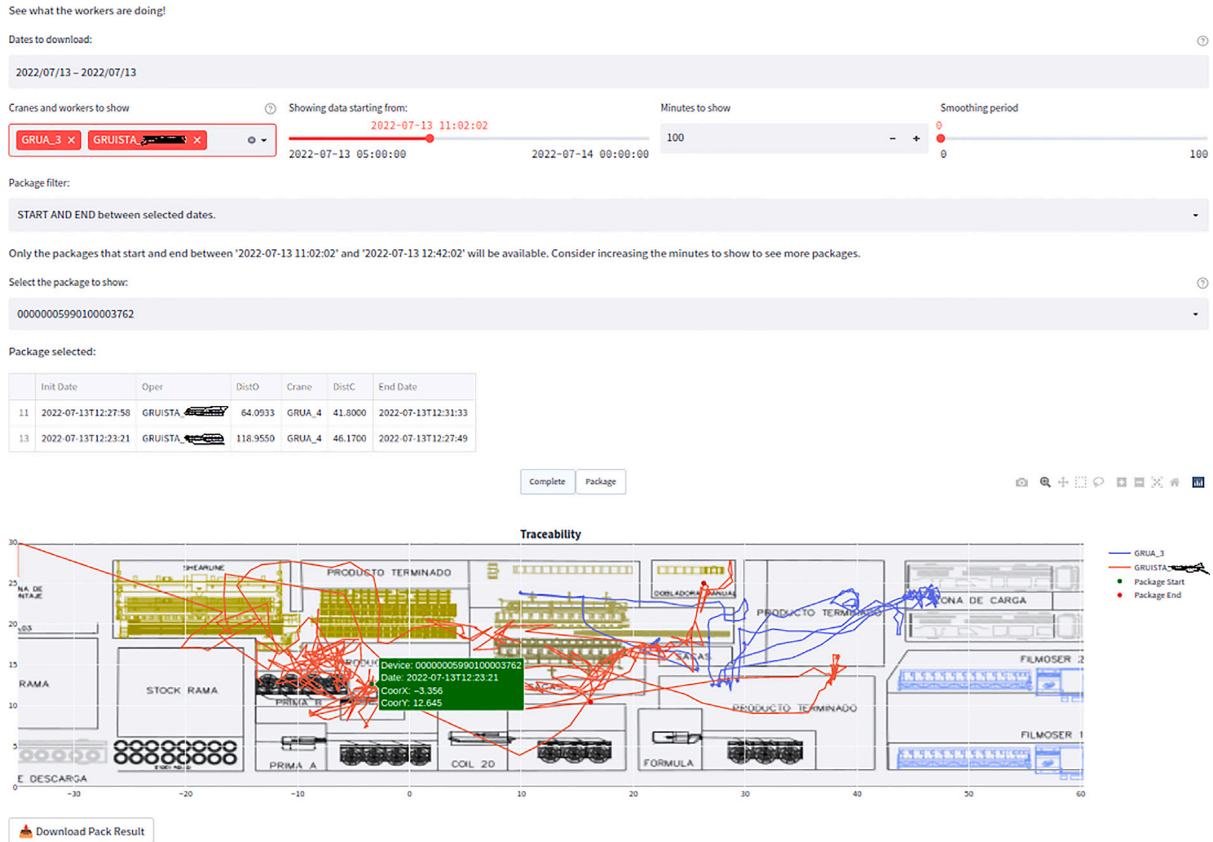


Fig. 8. Integrative UX for the crane + operator inner logistic system. The operator's name was blurred, and the company name and logo were removed.

Based on these integrated services, higher-level composed business applications can be elaborated, enabling, for example, an integrated traceability system of operations over time. It can be used as an analytic system providing pieces of evidence for every single item delivered to the construction site in case of customer complaint (see Fig. 8). In addition to the classical movement plot, it integrates information related to when and where the operator loaded one specific package. This high-level business application enables both a detailed analysis at the item level and the integration of machine learning (i.e., deep learning), which extracts information patterns from the emerging diagrammatic images (Kim et al., 2022).

6.2. Company B: Ergonomics and process variability in an automotive component supplier

Company B is an automotive component supplier. It manufactures cross-car-beams for a well-known automobile brand. The factory produces 15 different references. From a high-level perspective, the process can be understood as a sequence of different manufacturing cells, some of them working in parallel. The different parts are processed in large presses and Computer Numerical Control machines, also following thermal treatments, and assembling stages. As the company supplies components for both left- and right-driving countries' car models, there are two stages of automatic inspection. Because of the slenderness of the component, the different parts involved, and the strict dimensional tolerances, quality control requires both robotic arm laser measurements and human-based validation. Such quality checks are carried out at the end of the production lines.

Diagnosing. As it is usual in the automotive sector, Company B follows lean manufacturing principles and methodologies. However, contrary to what is expected in this paradigm, there are problems resulting from the high variability in the process throughput. Inspection stages prior to packing and sending show spikes in the workload, which implies extra costs. In addition, ergonomic and work safety issues are a matter of concern. The following issues are identified:

- The manufacturing cost per unit served is very high, compromising the benefits obtained. The cost per piece at manual inspection is significant because of the high number of workers needed. This is identified as a problematic stage.
- There are complaints regarding unhealthy conditions in the inspection stages because of the time spent with the arms over the shoulders holding and carrying voluminous items.
- There is risk of collision (there are precedents, which are fortunately not critical) because of the proximity between manual transport paths and forklift trajectories.
- There are significant deviations in the actual versus planned number of pieces inspected per shift.
- Shop floor managers have detailed information about each manufacturing operation at each work center. However, throughput variability can only be analyzed per shift level, and delving into the details of what happens per item is not possible.

In conclusion, an integrated product–operator–process view is lacking, preventing an analysis of operator arm fatigue levels and the identification of the root causes of the variability. Incorporating human workforce operation data to the manufacturing control system and linking the product, operator, and process data are necessary to reduce variability, thereby increasing value creation. Inconsistencies in the process arise when analyzing the integrated information. It is only through a series of action research cycles that the root cause can be identified. For the sake of legibility, this subsection is presented following a single linear cycle.

Action planning. As in the case of Company A, incorporating and integrating human data into the manufacturing control system through UWB tags and smart wearables have been decided. The UWB tags are

Fig. 9. Detail of an operator with the wearable attached measuring the angle of the arm, and the local display informing her.

intended to track operator location and identify when the pickup of pieces takes place while also avoiding possible collisions with forklifts (with a UWB tag attached, too). The wearable devices are aimed at monitoring the time spent by each operator with the arm over the shoulder, linking the data with the manufacturing control system so that it is possible to know the piece being inspected at the time of the arm being in that position. The steps to be followed are the same as those in the previous subsection.

Action taking. After the selection, implementation, and adaptation of the proposed platform to the specificities of the setting, the new system begins to provide useful data. Once data from the different sources—i.e., operators, pieces, and resources—are linked, and reports become available, some inconsistencies appear; for example, the number of pieces inspected and the times the operators spend with their arms in the fatigue position do not match. Moreover, linking the times at which the operators have their arms raised with the pieces that are being processed according to the manufacturing control system is not possible. All these findings motivate successive actions and intervention cycles until the root cause is identified.

After checking and ruling out various possible ergonomic explanations, we focus on the dynamics of the robotized inspection. It is found that there is a significant number of pieces that do not pass the inspection and are sent to the causing cell or work center for the necessary corrections to be made. The root cause is that, after undergoing a rework operation, the reference of the piece remains the same, so from the perspective of the control system, the rework has not taken place. Furthermore, if the piece has to be inspected many times before matching all the specifications, it counts as only one piece inspected, although the operators have raised their arms many times because inspections are necessary. Therefore, the quality problems of many work centers are hidden, no corrective action is adopted, and the situation persists. Variability in the final inspection is a consequence of quality problems in some manufacturing stages. The problem is solved by assigning a new reference each time the piece has to be reworked. The data then become coherent, and the failure rates of the different manufacturing stages are determined. The findings lead to a whole new manufacturing process improvement initiative based on lean manufacturing techniques.

The image in Fig. 9 depicts an operator in the human inspection area wearing the sensor responsible for determining the arm's angle with regard to the vertical and monitoring the total time per shift with the arms up, which is limited by worker regulations. The data collection software was extended to provide operators with information about the measures. When the angle exceeds 90 degrees, the text turns red.

Evaluating. The benefits of the incorporation and integration of human data exceed expectations because of the identification of quality problems enabled by the new system. The company reports in the project that the number of workers in the inspection stage is reduced from 24 operators at the beginning of the project to 12 operators at the end. The 12 operators who are not necessary in the inspection stage are reassigned to other areas. There is also an increase in the efficiency of the forklifts, leading to a reduction in their number from 15 to 12, with the corresponding cost savings. Once the operators are aware of the possibilities of the new monitoring, they will propose an analysis of the impact of the micro-operations they perform on the arm angle.

Different KPIs are monitored during the entire process. Two illustrations are represented in Fig. 10. Fig. 10(a) shows the significant improvement in the operator's performance, not only in increasing the number of pieces inspected per shift but also in reducing variability considerably. Fig. 10(b) illustrates how the intervention reduces the number of times the operators hold their arms up, and drastically strengths the relation with the number of pieces inspected in a shift.

Specifying Learning. The case of Company B shows the viability of the platform to handle actual production situations and underlines the importance of incorporating and integrating human data into the control system both for process and ergonomic improvements. The platform's effectiveness in increasing value creation is reflected in its applicability to support the identification of process malfunctions through the incorporation of human workforce data linked to product and process data.

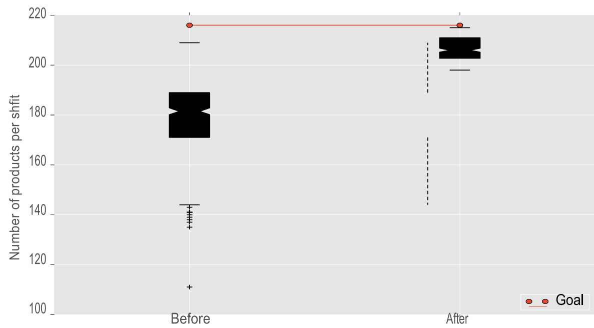
From a methodological point of view, this case reinforces the generality of the proposed platform design. It shows the interoperability among different sources of data and the capability of adapting to the manufacturing control information system in use.

7. Discussion and conclusions

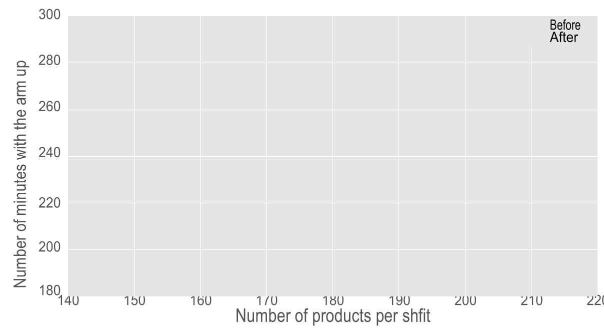
The RQ1 for this study focuses on the integration of various manufacturing data sources, including those from the operator side, in a manner that increases value generation for the processes and/or enterprises involved.

This question can be answered in a positive way by means of a flexible architecture under the LASFA+ reference framework and the application of reusable services that enable integration from data sources, both from processes and products, as well as from the human dimension (operators or other agents). This work has implemented this architecture using a software platform that enables interaction with such services. Carefully addressing the relevant requirements for data integration in a wider possible sense is proposed because flexibility and traceability are critically affected.

Linked to the first requirement, interoperability aspects are addressed, not just with regard to the technical level but considering the semantic and organizational levels as well, thanks to the adoption of an ontology. The SWoT proposal was implemented to facilitate transparent access to information sources in a given area and thus enable dynamic relationships. The preservation of the independence and integrity of the different data flows is crucial in accomplishing requirement R4.



(a) Operator performance.



(b) Relation between products and arm-up.

Fig. 10. Benefits of the decisions made based on system usage.

Two different action research cases involving product tracking, process data that require integration from different data sources, moving resources and object tracking, operator tracking, and physical monitoring have been presented. The benefits of using the proposed platform that integrates reusable services to build the specific composed business applications required by each setting have been described. The improvements in the business understanding, transparency, and success of the business actions undertaken have also been reported according to the selected methodology.

The next step can be easily predicted following the proposal made in this paper to use a merging approach to combine ontologies (see Fig. 7), in order to foster the abstraction process of integration between various data sources, with an emphasis on the interoperability of the components at different levels to support new organizational knowledge. Human behaviors associated with these processes can now be better understood, evaluated, and formalized based on the new transparency level attained as a result of the integrated analysis, and either recommended as more thorough standards or used for teaching purposes. In this sense, it can be considered as promoting the "human ontologies in Industry 5.0" field.

The main limitation of this study arises from the lack of generic rules to select the proper ontology for describing the entire data model and for assessing the integrity of the data flows because they depend not only on the specific application but also on business demands.

The authors will continue to explore organizational interoperability in depth while promoting the architecture introduced. The next challenge along this path will be to use organizational interoperability in order to foster Operational Technology (OT) capabilities in bringing additional knowledge for safety and cybersecurity. The concepts related to human ontologies in the context of I5.0, in particular, have preliminary relevance that calls for more research.

CRediT authorship contribution statement

Joaquín Ordieres-Meré: Conceptualization, Investigation, Funding acquisition. **Miguel Gutierrez:** Methodology, Data curation, Writing & editing. **Javier Villalba-Díez:** Formal analysis, Validation, Review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Joaquin Ordieres Mere reports administrative support, equipment, and writing assistance were provided by Agencia Estatal de Investgaci/'on through the grant MCIN/AEI/10.13039/501100011033/ to the project RTI2018-094614-B-I00. They also thank the European Union RFCS programme through grants 793505 (WISEST) and 847202 (AUTOSURVEILLANCE).

Data availability

The authors do not have permission to share data.

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