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Systematic Review

Context-Aware Systems Architecture in Industry 4.0: A Systematic Literature Review

Arlindo Santos [1,*], Claudio Lima [2], Tiago Pinto [2,3], Arsénio Reis [2,3] and João Barroso [2,3]

1 School of Public Management, Communication and Tourism, Polytechnic Institute of Bragança, Campus de Santa Apolónia, 5300-253 Bragança, Portugal
2 School of Science and Technology, University of Trás-os-Montes and Alto Douro, Quinta de Prados, 5000-801 Vila Real, Portugal; claudiol@utad.pt (C.L.); tiagopinto@utad.pt (T.P.); ars@utad.pt (A.R.); jbarroso@utad.pt (J.B.)
3 INESC TEC, University of Trás-os-Montes and Alto Douro, Quinta de Prados, 5000-801 Vila Real, Portugal
* Correspondence: acsantos@ipb.pt

Featured Application: This review highlights interoperability, automation, and decision-making as critical requirements for context-aware systems in the manufacturing domain that integrate the principles of Industry 4.0. It discusses relevant patterns and technologies, identifies context gaps, emphasises ontologies' importance, and proposes directions for future research.

Abstract: Technological evolution has driven the integration of computing devices in various domains, giving rise to heterogeneous and dynamic intelligent environments; together with market pressure, these pose challenges in formulating an architecture that takes advantage of contextual knowledge. In terms of architectural design, we are witnessing a transition from a centralised, monolithic view of systems to a decentralised view that incorporates the vertical and horizontal dimensions of the production environment. Therefore, this review aimed to (i) identify the requirements, (ii) find out about the representation models and context inference techniques, and (iii) identify architectural technologies, norms, models, and standards. The results observed in 25 articles made it possible to identify interoperability, automation, and decision-making as convergence points and observe the adoption of ontologies as a research area for context representation. In contrast, the discussion of context inference techniques remains open. Finally, this study presents recommendations for the design of a context-aware systems architecture that incorporates the principles of Industry 4.0 and facilitates the development of applications.

Keywords: information system architectures; Industry 4.0; context-aware; smart manufacturing; cyber–physical systems; review

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1. Introduction

In recent decades, technological integration has been natural, omnipresent, indistinguishable, and extensive in physical spaces, achieving the vision of the future described by Mark Weiser [1]. When used to improve human activities in different spaces, ubiquitous computing transforms them into intelligent environments [2]. This ubiquity can assist users in the most diverse forms, such as in the context of the ambient assisted living (AAL) concept [3–6]. In the industrial scenario, technology improves the production efficiency, supporting workers with relevant information to carry out their tasks from the perspective of the ambient assisted working (AAW) concept [7].

By making informed decisions, modern production organisations can respond innovatively and quickly to market changes, gaining a competitive advantage [8]. However, faced with increasingly global, competitive, and dynamic markets, modern organisations are forced to reformulate their strategic actions quickly, as product life cycles are becoming increasingly short and consumers are more demanding and attentive to issues such as sustainability and personalisation [9]. These issues require a rapid organisational response to the context [10].

From this perspective, enterprise information systems (EIS) are a company's leading information technology (IT) assets and help it to organise, plan, schedule, and control its business processes competitively. However, modern information systems produce and transact vast volumes of data, and decision-makers often need help in finding the correct information in the right place, time, and format [11,12]. Therefore, it becomes crucial for business applications to have context information [13].

The diversity of industrial scenarios makes it difficult to adopt a single model that assertively guides architectural design, including context awareness in complex business environments as a relevant functional requirement. In addition, engineers and system designers need to obtain guidelines for the design of the architectures of context-aware systems in the Industry 4.0 (I4.0) domain. These assumptions motivated this systematic review of architectures that support context-aware systems in I4.0, particularly in the "Factory of the Future" (FoF) project, which includes the University of Trás-os-Montes e Alto Douro and the company Continental Advanced Antenna, based in Vila Real-Portugal, that is one of Europe's leading specialists and manufacturers of antennas for vehicles (Continental AA).

Section 2 of this document outlines the theoretical background underlying this review. Section 3 details the methodology used in this study. The systematic review results are presented in Section 4, followed by an analysis and discussion in Section 5. Finally, Section 6 summarises the study's conclusions and suggests directions for future research.

2. Background

Integrating context-aware capabilities within I4.0 frameworks presents an opportunity to enhance operational efficiency and decision-making processes. Therefore, this section delves into the theoretical background supporting this systematic review, providing an in-depth exploration of key concepts of I4.0 and context-aware systems.

2.1. Industry 4.0

I4.0 refers to the Fourth Industrial Revolution, characterised by the integration of information and communications technology (ICT) into industrial processes [14–16], and government entities and industries have acted to take advantage of the benefits that this new wave of innovation represents [17]. The presentation of the I4.0 concept occurred during the Hannover Fair in 2011 as a German strategic initiative to take on a pioneering role in manufacturing industries [18]. Now, many countries have public programs devoted to I4.0 [19], which refers to a set of technologies applied to the industrial sector, such as Internet of Things (IoT), cyber–physical computing (CPS), artificial intelligence (AI), cloud computing, and big data, among others.

Among the technologies presented above, according to Pivoto et al. [20], CPS and the Industrial Internet of Things (IIoT) concept play an essential role in the emergence of the I4.0 paradigm, and researchers are exploring it to accompany the digital transformation in the industrial sector. In recent years, the trend towards customer-oriented production has driven the evolution towards cyber–physical production systems (CPPS) based on CPS. This includes autonomous, cooperative, and interconnected actors at all production levels and adopts an open and loosely coupled architecture, rather than following the traditional ISA-95 automation pyramid [21]. In addition, the digital twin (DT) concept, one of the leading technologies for the implementation of CPS [22], requires the creation of a virtual and exact copy of a physical object or system, including its properties and its environment [23], and constantly synchronises with its physical system through continuous data transfer [24].

The focus of I4.0, according to Kagermann et al. [18], lies in achieving horizontal, vertical, and end-to-end integration in an ecosystem where physical and virtual actors, humans, and machines live. The horizontal integration of these actors promotes collaboration and integration between different entities within the value chain, enabling continuous communication and coordination while providing a complete solution to departments. End-to-end integration refers to systems, processes, and data integration throughout the value chain or production system, which integrates the different stakeholders.

Later, in 2019, automation, interoperability, and sustainability were introduced as strategic fields presented by the Platform for I4.0 in the document "2030 Vision for Industrie 4.0" [25], which describes this new global and digital ecosystem that is more dynamic, collaborative, and focused on data. Other works have discussed the concepts, characteristics, and principles that effectively materialise innovations in global industry. Roblek et al. [26], Posada et al. [27], and Lu [28] listed five main characteristics associated with achieving the objectives of I4.0: the digitisation and personalisation of production; automation and adaptation; human–machine interaction; value-added services and businesses; and interoperability. In addition, Hermann et al. [29] identified four design principles: interconnection, information transparency, decentralised decisions, and technical assistance. Finally, Lu [28] stated that the principles of I4.0 are interoperability, virtualisation, decentralisation, real-time updating, service orientation, and modularity.

The popularity of the I4.0 paradigm has grown in recent years, creating the conditions for its implementation [30]. Although I4.0 was introduced a decade ago, there are many barriers, like new employee skills, data security and privacy, system standardisation, and high investments, mainly in medium-sized enterprises (SMEs) [31], and a lack of understanding of the benefits of I4.0 [32]. Consequently, according to Kadir and Broberg [33], in the majority of manufacturing companies, particularly those in developing economies, I4.0 remains more of an aspiration than a reality.

2.2. Context Awareness

The term "context-aware" was first used by Schilit et al. [34] to refer to the location and identity of people or objects in the vicinity and changes to these objects. Other definitions emphasise using context information to provide relevant services, where relevance depends on the characteristics of the users and task performance [35]. Currently, the availability of sensors and the extensive use of smart devices allow for the development of systems that can sense the environment, recognise specific contexts, and must know the context to adapt rapidly and change situations [36]. This scenario occurs in the physical industrial space, which integrates technologies and actors (people and machines) to execute various tasks to achieve common goals.

Characterised as intelligent, spaces that incorporate context awareness use knowledge of the physical and virtual worlds' context to help perform tasks and make informed decisions that can improve the effectiveness and efficiency of the production process [37]. In addition, concepts such as smart factories are emerging, which use context awareness to assist people and optimise tasks based on data from the physical and virtual worlds [38]. Furthermore, Alexopoulos et al. [39] argue that incorporating the concept of context will make it possible to support operators, supervisors, and coordinators in decision-making on the factory floor in real time, considering the whole rather than a fragmented view of the system and specialised knowledge. In industry, context knowledge can be used to increase the visibility of operations and their performance in a factory environment, thereby promoting one of the principles of Hermann et al. [29]—transparency. Therefore, developing context-aware applications and systems is a promising way to enable CPPS to properly exploit the dynamic manufacturing environment while ensuring sustainable quality and high performance [40].

However, the context-aware solutions in this scenario also face challenges. Firstly, a comprehensive understanding of context, including its principles, modelling, and reasoning, must be effectively incorporated into the solutions developed [41]. Secondly, the dynamic nature of these industrial spaces requires continuous insight and the seamless adaptation of applications to changing conditions [42]. Finally, developers need adequate guidance and support in creating context-aware systems, particularly in integrating multiple data sources and delivering personalised services at the right time and in the right place and format [43].

Another challenge for systems that incorporate contextual knowledge is selecting strategies that facilitate the development of applications capable of using contextualised information. Santos et al. [44] observed that, although many commercial companies offer IT solutions for user assistance, providing context-based content and functionalities, two fundamental issues persist in the industry. The first is the lack of a generalised and unique definition of the concept of context, which varies according to the domain [45], and the second is the limited incorporation of this concept into industrial projects [46,47]. This is due to the lack of architectures, methods, and techniques to support documentation, analysis, and context optimisation, which hinders the intensive development of context-aware systems [48]. Considering that industrial spaces integrate properties of ubiquitous computing and act as smart spaces that aggregate smart objects [49], the projects discussed by Santos et al. [44] related to context-aware systems and ubiquitous computing can offer relevant architectural perspectives that facilitate the rapid development of applications.

2.3. Systems Architecture for Industry 4.0

To address the new challenges posed by I4.0, the European Commission [50] has identified the need for advances in production architectures to incorporate the response to new dynamic market requirements. The new I4.0 requirements necessitate changes to ISA-95 and IT [51,52], which require a decentralised and distributed control approach to enable flexibility and the rapid control of manufacturing operations [53,54]. In this sense, it is essential to define an architecture to highlight the concepts and relationships resulting from the new perspective proposed by the I4.0 paradigm [55]. Architecture design, in the context of the software engineering field of study, is at a high level and seeks to meet functional and non-functional requirements and identify the structural elements and their interfaces, as well as the behaviour of the components [56]. In addition, decision-makers can also choose architectural standards, technologies, applications, modules, and programming languages, and the result of decisions about the architecture influences the non-functional characteristics of the system and many of its quality attributes [57]. Moreover, the 4 + 1 framework [58] can help to outline an architecture using five simultaneous views (logical, process, physical, development, and scenario).

Production environments and the concepts surrounding them are complex, and reference models are needed to describe and guide the construction of architectures for information systems in this domain [15]. To this end, a systematic review by Nakagawa et al. [59] identified and presented six architectural reference models for I4.0: the academic models SITAM and LASFA, the Japanese conceptual architecture model IVRA, and the commercial architecture model IBM Industry 4.0. Regarding breadth and adoption, the two most detailed reference models are the Reference Architectural Model Industrie 4.0 (RAMI 4.0) and the Industrial Internet Reference Architecture (IIRA) [60]. In addition to standardised architectures, specific non-standard architectures for CPS have also been proposed in the literature, the best known of which is the 5C framework proposed by Lee et al. [22], which has been referenced and described in several review articles [20,61–63].

2.3.1. The 5C Framework

In the industrial domain, the 5C framework is known within cyber–physical systems [22] to provide step-by-step guidance in developing and deploying CPS to support industrial production. It is based on layers and starts with the involvement of intelligent sensors at level I. Level II introduces self-awareness into the machines, level III (cyber level) acts as the central information hub, and there is a decision support system at level IV. Level V (configuration level) provides feedback from the cyberspace to physical space, facilitating supervisory control to make machines self-configuring and self-adapting.

Lee et al. [22] state that the 5C framework can automate and centralise data processing, health status assessment, and prognosis, covering all the necessary stages, from data acquisition, processing, and presentation to users to decision-making support.

2.3.2. RAMI 4.0 Architecture

The RAMI 4.0 architecture [64] was proposed to meet the requirements of I4.0 [65] based on the current production environment standards, aiming to meet different specifications in a single three-dimensional structure involving vertical and horizontal integration and one-to-one interaction. The three axes define all aspects of I4.0, allowing elements to fit within this three-dimensional vision. RAMI 4.0 enables the exploration and implementation of I4.0 concepts, facilitating step-by-step migration to the world of I4.0.

This architecture proposes three axes: (1) hierarchical levels based on IEC 61512-1 and IEC 62264-1, (2) life cycle and value stream dimensions according to IEC 62890, and (3) a digitisation dimension with six layers [66]. Axis 1 defines the interconnection model of all the elements of the production system, including information, people, machines, and the functionalities that represent the I4.0 environment. Axis 2 meets the requirements of I4.0 as it considers improvements throughout the life cycles of products, machines, and factories, and it is used to visualise and normalise the relationships of I4.0 components with the life cycles of products and equipment along a value chain [67]. Axis 3 presents the architecture model in six abstract levels of interoperability [68]: business, functional, information, communication, integration, and asset.

2.3.3. IIRA Architecture

The Industrial Internet Consortium developed the IIRA [69], a domain-independent, industry-oriented architecture that encompasses manufacturing, health, energy, smart cities, and more. The United States is leading in the global adoption of IoT in the industrial context, under the name IIoT [54].

In short, the proposal has three (3) levels: (1) the edge tier acquires data from the physical space; (2) the platform tier receives, processes, and forwards control commands from the enterprise tier to the edge tier; provides device management functions; and also offers services such as data query and analysis; (3) the enterprise tier implements domain-specific applications and decision support systems and also provides interfaces to end users.

3. Methodology

We conducted this systematic literature review of context-aware systems architectures in the I4.0 domain following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) method [70], applying the protocol with explicit descriptions of each stage to be carried out [71]. These included (1) research questions, (2) a search strategy, (3) inclusion and exclusion criteria, (4) review procedures, and (5) an analysis of the results.

This review aimed to describe context-aware systems architectures for I4.0 to obtain guidelines for architecture design in the context of the Continental AA located in Vila Real, Portugal and to promote the adoption of I4.0 principles. The aim was to objectively select articles that focused on the study and design of architectures. While the methodological approach to software engineering, according to the Software Engineering Institute [72], begins with the gathering of requirements and constraints and describing the environment and only considers the description of architectural styles and patterns at the end, in this systematic review, we opted to use a reverse methodology: we first sought to identify the architectures, and, only afterwards, based on these, we identified the requirements and other relevant characteristics.

3.1. Research Questions

The research objective focused on identifying studies that focused on designing support architectures for industrial production environments that adopt the I4.0 paradigm and simultaneously incorporate context information. In summary, this systematic literature review aimed to answer the following questions:

- RQ1—What requirements are supported by the context-aware systems architectures for I4.0?
- RQ2—What are the context modelling and inference techniques presented?
- RQ3—What software architecture models and standards are used?

3.2. Research Strategy

In the preliminary phase, a set of terms was established to guide the systematic review process. As shown in Table 1, the parameters, the research concept was first identified, followed by a description of the artefact in which the concept was applied, the domain of applicability, and the appropriate research tool selection.

Table 1. Research parameters.

Parameter	Value
concept	context-aware
artefact	architecture
domain	Industry 4.0
tool	Google Scholar

3.3. Inclusion and Exclusion Criteria

In the context of systematic reviews and PRISMA, inclusion and exclusion criteria are applied to determine which studies are eligible. Here, this was based on the criteria listed in Tables 2 and 3.

Table 2. Inclusion criteria.

Criterion
Date range: 2013–2022
Language: English
Databases: ACM, Springer, Elsevier, IEEE, Wiley Online Library, Taylor & Francis

Table 3. Exclusion criteria.

Criterion
Articles without access to the full version or an abstract
Articles associated with other domains
Articles that do not explicitly incorporate the context-aware concept or do not describe an architecture

3.4. Review Procedures

Figure 1 shows the flowchart according to the PRISMA methodology and then describes the steps explicitly.

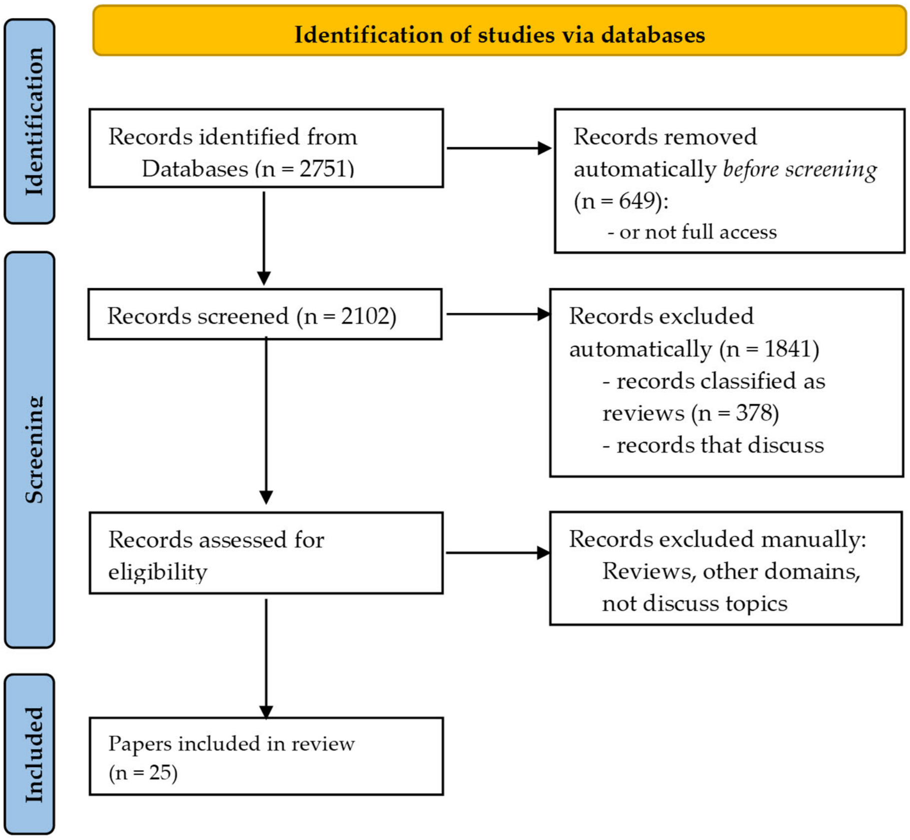

Figure 1. Flowchart of the systematic review.

1. We identified records by using the Google Scholar search tool. Search filters were applied, including a specific date range, a preference for the English language, and all types of articles, including review articles. At this stage, a NodeJS script automated the extraction of 2751 records (see Supplementary Materials for the dataset).
   Expression:
   (architecture) ("industry 4.0" OR "industrie 4.0") "context aware"
2. Records for which full access to the content was not possible, did not provide an abstract, or were not classified as journals or conference articles were automatically excluded. After this step, 649 records were ignored.
3. The titles of each record were automatically analysed, and we excluded 378 records that included the words "review(s)", "survey", and "systematic". At the end of this step, 1724 records remained.
4. Records that explicitly included terms associated with other application domains and unrelated to the manufacturing sector were excluded from the review. Considering that this systematic review focused on the I4.0 paradigm, we eliminated records that

did not include the concepts associated with and identified by Hermann et al. [29] and the term "context" in the title or abstract. After this process, 1463 records were eliminated, leaving 261 that were subjected to manual evaluation.

5. At this stage, we first manually read the abstracts of each article identified, and then we read the articles that required a more in-depth analysis for decision-making. We excluded articles classified as literature reviews (30), articles focused on areas of study that did not contribute to the design of the architecture and the respective discussion of the context-aware concept (119), articles related to other domains of applicability (63), articles with the absence or duplication of software architectures (12), and articles with no discussion of the concept of context (8), and articles (4) were also excluded due to the impossibility of obtaining relevant information for the state-of-the-art review. In the end, 25 articles remained.

4. Results

After the systematic review procedures following the PRISMA method, the 25 articles listed in the table below were obtained (Table 4); these are ordered by publication year.

Table 4. List of the results of the systematic review using the PRISMA method.

ID	Title	Author	Year
1	Towards situation-aware adaptive workflows: SitOPT—A general purpose situation-aware workflow management system	[73]	2015
2	A context-aware assistance system for maintenance applications in smart factories based on augmented reality and indoor localization	[74]	2015
3	An architecture to support responsive production in manufacturing companies	[75]	2016
4	Requirements and languages for the semantic representation of manufacturing systems	[76]	2016
5	Engineering insights from an anthropocentric cyber-physical system: A case study for an assembly station	[77]	2016
6	SAMBA: A self-aware health monitoring architecture for distributed industrial systems	[78]	2017
7	Towards a conceptual framework of OSH risk management in smart working environments based on smart PPE, ambient intelligence and the Internet of Things technologies	[79]	2017
8	CASOA: An Architecture for Agent-Based Manufacturing System in the Context of Industry 4.0	[80]	2018
9	A Multi-agent System Approach for Management of Industrial IoT Devices in Manufacturing Processes	[81]	2018
10	Artificial Intelligence for Cloud-Assisted Smart Factory	[82]	2018
11	A cyber-physical context-aware system for coordinating human-robot collaboration	[83]	2018
12	An industrial Internet of Things-based platform for context-aware information services in manufacturing	[39]	2018
13	Control as a Service Architecture to Support Context-aware Control Application Development	[84]	2019
14	An event-driven integrative framework enabling information notification among manufacturing resources	[55]	2019
15	Implementing self-* autonomic properties in self-coordinated manufacturing processes for the Industry 4.0 context	[85]	2020
16	Intelligent assistant system as a context-aware decision-making support for the workers of the future	[49]	2020
17	A microservice architecture for predictive analytics in manufacturing	[86]	2020
18	A digital twin-enhanced system for engineering product family design and optimisation	[87]	2020
19	Semantic communications between distributed cyber-physical systems towards collaborative automation for intelligent manufacturing	[88]	2020
20	Context-Based Resilience in Cyber-Physical Production System	[89]	2021
21	The HORSE framework: A reference architecture for cyber-physical systems in hybrid smart manufacturing	[90]	2021
22	Agent-Based Distributed Data Analysis Industrial Cyber-Physical Systems	[91]	2022
23	Context-aware scheduling and control architecture for cyber-physical production systems	[92]	2022
24	Integrating process management and event processing in smart factories: A systems architecture and use cases	[93]	2022
25	Extending the Intelligent Digital Twin with a context modelling service: A decision support use case	[94]	2022

5. Analysis and Discussion

Based on the systematic review results (Table 4), we analysed 25 articles to answer the three research questions (Section 3.1). We present this analysis and discuss the subsequent results in the following section.

5.1. Requirements of the Architectures Researched

The analysis of the 25 scientific articles identified three clusters that focused on the high-level requirements most frequently mentioned in the literature. We present the interoperability, automation, and decision-making requirements and their relevance in the following subsections. At the other extreme, sustainability—a topic that is widely discussed today and highlighted by the Industrie 4.0 platform [25]—as well as security and privacy are requirements with little discussion and no criteria for evaluation.

5.1.1. Interoperability

According to Modoni et al. [55], one of the functional requirements listed relates to the need for the architecture to enable interconnection with factory stakeholders and facilitate interoperability. Belkadi et al. [49] present an architecture that promotes interoperability exclusively with the factory's legacy systems, such as the manufacturing execution system (MES) and enterprise resource planning (ERP), to extract knowledge, perform calculations, or carry out some simulations.

Sánchez et al. [85], citing Pedone and Mezgár [95], refer to the fact that interoperability between stakeholders makes it possible to increase the flexibility and adaptability of production systems. They also state that, according to Liao et al. [17], the principle of interoperability associated with I4.0 allows stakeholders to exchange information. With this principle in mind, Sánchez et al. [85] propose an approach to solving the integration and interoperability challenges of I4.0 using a five-level structure called the 5C stack: connection, communication, coordination, cooperation, and collaboration.

A physical space incorporates physical and computational artefacts, where machines and humans collaborate to perform various tasks, and, according to Pirvu et al. [77], an architecture must support the integration of heterogeneous environments. Additionally, Cagnin et al. [81] suggest that it is necessary to apply specific techniques to coordinate, communicate with, and recognise heterogeneous devices. It is important to remember that the ecosystem incorporates variations in production modules or equipment, which may have different functionalities, sizes, or configurations [74], and the amount of data generated, both structured and unstructured, adds further challenges in promoting interoperability [87]. Furthermore, from the perspective considered by Traganos et al. [90], we must consider the heterogeneity of the technologies involved.

Finally, we have real scenarios described by Nikolakis et al. [83], in which robots and humans coexist and collaborate to carry out tasks, highlighting the need to coordinate the work of these players. In concordance with this topic, the design of the HORSE architecture, presented by Traganos et al. [90], and the architecture proposed by Nikolakis et al. [83] support hybrid manufacturing processes.

5.1.2. Automation

The I4.0 paradigm presents the prospect of smart factories that automatically adjust to changes, as described by Flatt et al. [74]. In this new, dynamic environment, applications are designed to ensure the automation of processes and coordinate and manage the execution of tasks by autonomous devices, as indicated by Cagnin et al. [81]. In addition, Sánchez et al. [85] point out that I4.0 requires high levels of autonomy to ensure that manufacturing processes meet production objectives, requiring advanced coordination, cooperation, and collaboration levels so that those involved in the manufacturing process can communicate and interoperate effectively. Pirvu et al. [77] complement this view and argue that architectures should promote the adaptable and dynamic division of labour between components. Thus, the distribution of functions should not be established at the design stage but should vary between different degrees of automation, from fully manual to fully automated.

For future research, Alexopoulos et al. [39] propose an enhanced architecture for the configuration and operation of CPS to support the automatic and semi-automatic optimisation of production systems. To this end, it will be essential to provide cognitive and configuration capabilities, especially in the upper layers of the architecture, through the implementation of machine learning techniques.

5.1.3. Decision-Making

Decision support systems have a high reasoning capacity to provide users with appropriate information to support complex decision-making. These systems attempt to automate various tasks to provide possible solutions to a problem; however, according to Belkadi et al. [49], the human being selects, accepts, modifies, or rejects the decision. Moreover, according to Belkadi et al. [49], we have three fundamental requirements in decision support: (i) the need to adapt access to knowledge according to the experience profile; (ii) the fact that decision-making involves not only knowledge of the problem but also the impact of the action; (iii) and real-time assistance because the worker is in permanent contact with the machine and needs to react quickly to specific events.

The Human-in-the-Loop paradigm, addressed in the proposals by Bagozi et al. [89] and Lim et al. [87], refers to integrating human intelligence and decision-making into automated systems. This approach is increasingly important as industries transition to more automated and intelligent systems while recognising the critical role of human expertise and supervision. However, according to Lim et al. [87], this paradigm poses a challenge as operators handle multiple resources and will be overloaded, and bottlenecks will arise on the shop floor. As an alternative, the authors propose a DT model that can be transformed into a flexible system that facilitates autonomous processing.

Decentralised decision-making is one of the basic principles set out by Hermann et al. [29] and Marques et al. [75], who state that decentralised decision-making allows for autonomy and flexibility, promoting optimization, and each entity has its own decision-making space, influenced by the decisions of other entities. This strategy reduces the dependence on a single decision-making centre, leading to faster processes and a greater ability to respond to the dynamic demands of the market. Cognitive capabilities are essential to support decision-making without human intervention, which could be obtained through machine learning techniques given the amount of information collected and aggregated from various data sources [39], enabling operators to make certain decisions. The system will learn from the operator [85]. Finally, the main challenge for Alexopoulos et al. [39] lies in the system's ability to link data from different sources and generate new data sets that can be used to support decision-making, rather than simply processing and storing data.

5.2. Context Modelling and Inference Techniques

5.2.1. Modelling Techniques

The context life cycle begins with acquiring data from different sources. In this sense, the architecture of Alexopoulos et al. [39] collects data from the physical and virtual space (e.g., ERP, MES) to infer the context of the production environment on the shop floor. It promotes a holistic and dynamic view, considering the different entities, such as tools, machines, parts, products, and personnel, and information related to production orders. Seiger et al. [93] add the benefits and importance of integrating business process management (BPM) systems to enrich the knowledge of the context of production processes, providing a structured framework for capturing and analysing related information. Other authors, such as Belkadi et al. [45], only consider using data from the organisation's legacy systems.

As shown in Figure 2, 72% of papers use ontologies to represent the context, 12% use object-based methods, and the rest (16%) do not explain the technique used. Pirvu et al. [77] explain this preference for ontologies because they play a crucial role in interoperability between different actors. Alexopoulos et al. [39] consider the high formal expressiveness and the possibility of applying rules to make inferences. In addition, for Negri et al. [76], ontologies facilitate automatic reconfiguration, creating a common vocabulary and enabling the sharing and reuse of knowledge.

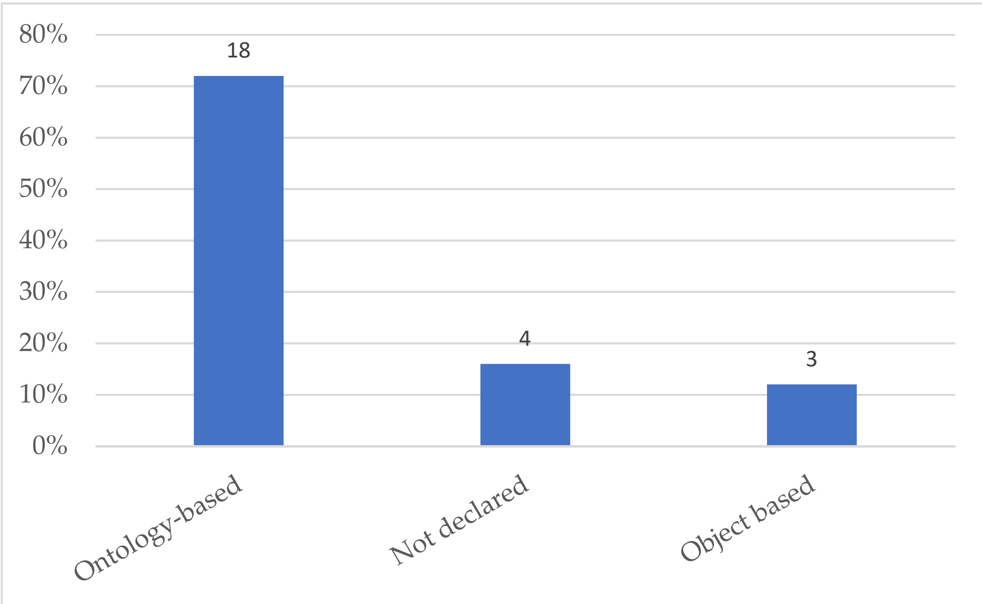

Figure 2. Comparative list of context representation models.

Using ontologies can simplify context modelling, especially in ecosystems with diverse and abundant resources. Ontologies provide a unified framework for the description of domain-specific knowledge, ensuring better interoperability and greater flexibility [82]. Heterogeneous data sources can be integrated through semantic queries in complex environments to improve decision support [87]. This perspective is corroborated by Tang et al. [80], advocating for ontology usage to represent context to aid the decision-making process. Considering the dynamic characteristics, the architecture proposed by Flatt et al. [74] increases the adaptability by using ontologies and contextual inference technologies. It is, therefore, essential to develop an architecture based on ontologies that allow the creation of inference engines and automated decision-making applications, enabling them to understand the environment, as described by Wemlinger and Holder [96], cited by Podgórski et al. [79].

Finally, the literature discusses different context scales. Traganos et al. [90] consider the existence of two spatial levels of context: local and global. Local involves observing the physical state of a workstation, receiving and analysing sensor signals, and notifying local modules and the global module. Meanwhile, the global context awareness module monitors the general state of the environment to ensure safety. The SAHM proposal [78] also considers this perspective and acts locally and globally.

5.2.2. Context Inference

Looking at the results in Figure 3, different inference techniques are adopted in 52% of papers, with the rule-based technique taking precedence (32%). Other techniques mentioned include machine learning (8%), AI, and statistical methods with 1%. The same technique is applied by Belkadi et al. [49] by applying inference rules to obtain additional data and learn about the user's current context, while Alexopoulos et al. [39] use a rule-based data pre-processing module to generate local (audio/visual) alerts.

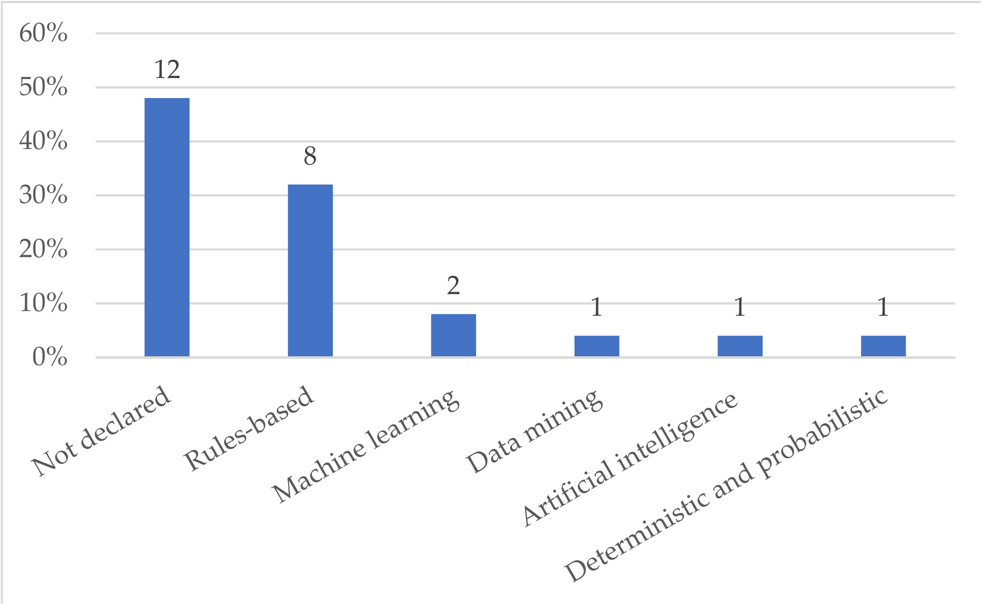

Figure 3. Comparative list of context inference techniques.

Various works explore the predictive capacity to support and optimise maintenance [86,87] or specific tasks [91] by context-aware systems. Alexopoulos et al. [34] argue that data mining algorithms help to predict future scenarios to meet this need. With the proliferation of software systems equipped with AI, the role of these systems is evolving from reactive to proactive, and they provide contextualised support to operators [97]. With the continuous development and updating of methods and tools for the processing of large volumes of industrial data, combined with cloud-based platforms and the integration of AI, we can see the applicability of these technologies in preventive maintenance, data reconstruction, and contextual knowledge services in factories [82].

5.3. Architecture Technologies, Norms, Models, and Standards

5.3.1. Technologies

The software architect designs the architecture to meet functional and non-functional needs. From this perspective, most current systems are based on monolithic software solutions that restrict the flexibility, adaptability, and scalability and add complexity to the maintenance task [86]. The multiplicity of technologies associated with I4.0 and incorporated into the solution means that, according to Traganos et al. [90], it takes a technology-agnostic approach to architectural design.

According to Figure 4, and regarding the technologies that guided the development of the architectures identified in the 25 articles, the first grouping includes CPS (64%), IoT (56%), and cloud computing (52%). Another grouping includes CPPS (28%) and edge computing (28%) and, finally, IIoT (24%), digital twins (16%), and fog computing (12%). This is an expected result given that the inclusion criteria only allowed articles whose titles or abstracts contained concepts associated with I4.0 as identified by Herman et al. [29].

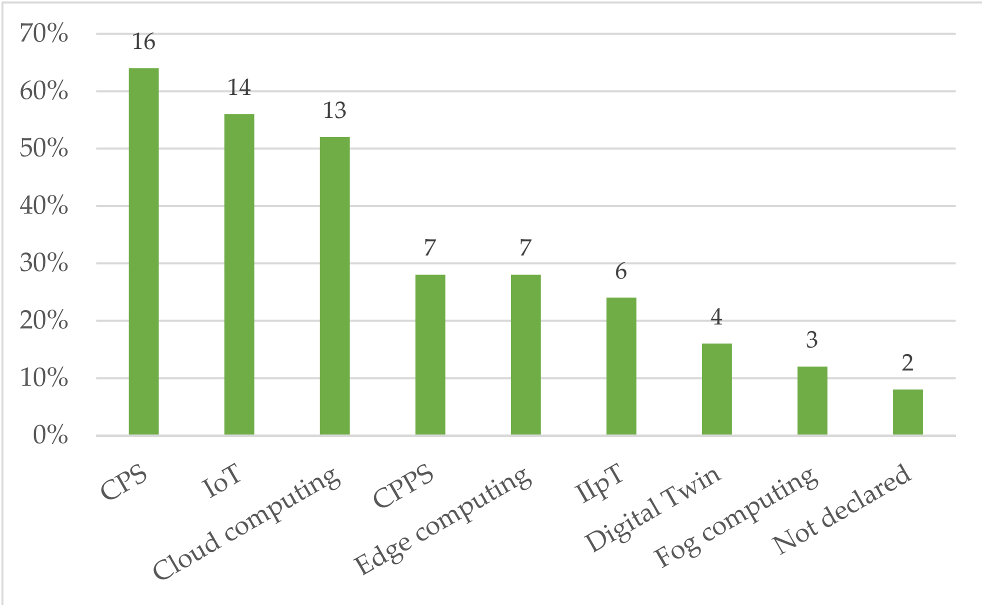

Figure 4. Comparative list of technologies referenced in examined papers.

CPS and other technologies, such as IoT, are considered the key to achieving the convergence of the physical and digital worlds, increasing the quality and personalisation of production [75]. Researchers identify and discuss IIoT and CPPS because IoT devices are integrated into the industrial environment and CPS support production processes. On the other hand, Leitão et al. [98], cited by Modoni et al. [55], states that I4.0 relies on the combination and interaction of many existing and new technologies around these two concepts, IIoT and CPPS.

CPS incorporates decentralisation, modularity, and scalability as fundamental attributes, intending to enhance the effectiveness of production processes, both internal and external [75]. It is a critical element of I4.0, as the central infrastructure for the development of solutions based on decentralised networks of cyber–physical entities [91]. In the analysis of the selected studies, we can observe the broad application of CPS, since the effective control of the industrial space also requires characteristics associated with context services, which are essential to enable flexible systems, according to Nikolakis et al. [83].

Instead of ISA-95, the CPS concept provides a series of features, such as flexibility, scalability, and adaptability, to respond promptly to changes in customer requirements. However, according to Wan et al. [92], the development of such a system remains a challenge. One of these challenges concerns the need for programmers to foresee all possible scenarios.

Another prominent trend in autonomous systems for Gartner is DT, which represents an essential part of CPS and can provide decision support to improve product life cycle management workflows [87]. Modoni et al. [55] present an example of this concept in an architecture that includes a layer to mirror and synchronise the real factory space in the digital space. Sahlab et al. [94] present three characteristics listed by Ashtari Talkhestani et al. [99] and associated with the DT to enable mirroring and ensure synchronisation between the physical and digital: (i) it must be synchronised with its physical twin, (ii) there must be active data acquisition, and (iii) there must be some executable models.

In the physical space, sensors transmit data in real time via IoT systems, using established communication protocols to ensure the reliability and consistency of the information. As the volume of data generated grows exponentially, cloud computing and edge computing techniques are used to process sensor information before storing it in databases for future analysis [87]. According to the literature, this is the layered organisation model, proposed in 13 papers [39,55,73,75,80–82,84,86,87,90,91,93], and only three papers [86,90,91] investigate the application of software architectures that make it possible to optimise the use of data flowing between the three layers—the edge, fog, and cloud. Traganos et al. [85] argue that the logical view, from the perspective of Kruchten [58], of the framework needs to be revised, considering that performance and time constraints are decisive factors in allocating cloud services. Thus, services that require minimal response times, especially those running locally, should be assigned to local infrastructures, possibly in combination with fog computing.

Integrating CPS into innovative production environments requires a balance of analytical intelligence and decision-making capabilities between the different computing layers (edge, fog, and cloud) and the use of appropriate technological solutions [91]. In recent years, according to the same authors, there has been a growing need to transfer the vast volume of data acquired by numerous IoT devices to cloud computing platforms, where they are stored and processed by AI algorithms to extract valuable knowledge. Despite the advantages of using the cloud to store data and run advanced analysis algorithms, its use can be costly and inadequate to ensure responsiveness due to network latency and connectivity limitations. Therefore, the challenge lies in distributing intelligence across different computing platforms, and the fog layer reduces the network costs by appropriately selecting the most efficient peripheral devices [86].

5.3.2. Standards and Reference Models

The new configuration of industrial production generated by the advent of I4.0 requires changes to the automation pyramid (ISA-95), and Cupek et al. [52] argue that this standard is no longer canon in industrial IT systems. On the contrary, Marques et al. [75] consider that this standard can be applied to architectures through the total virtualisation of the pyramid, offering the ability to design flexible production processes. In addition, it contributes to the realisation of the total virtualization process, optimising the extraction of knowledge for comprehensive reasoning, the visualisation of factory reconfiguration, and decentralised decision-making.

According to Figure 5, several standards and models are identified in the papers studied, 48% of which do not reference standards or models. Among those referenced are RAMI 4.0 (36%), 5C (20%), the IIRA (12%), IEC 62264 (12%), ISA-95 (8%), IEC 61499 (8%), and ISO 23247 (4%). We highlight that, among the reference models designed by the industry—RAMI 4.0 and the IIRA—these are cited in 36% of the articles.

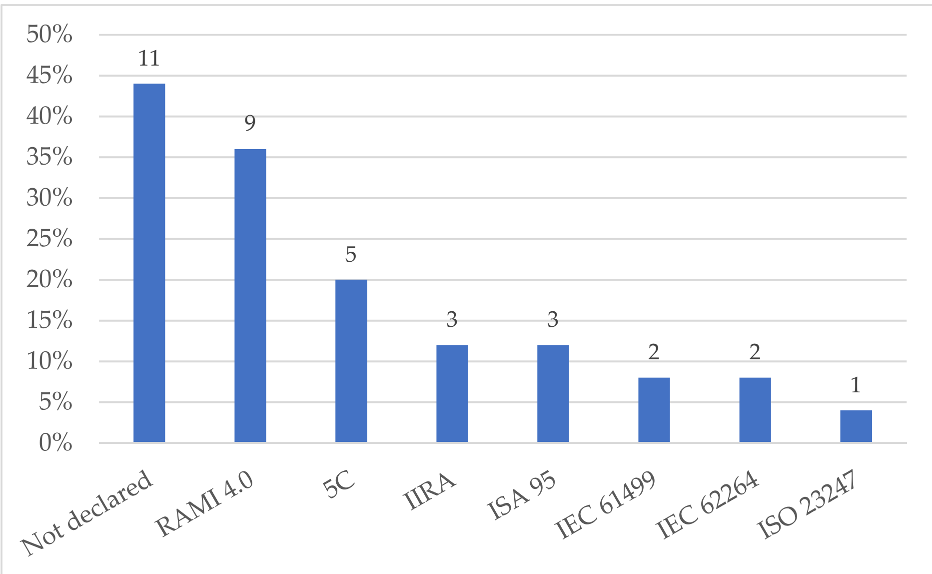

Figure 5. Comparative list of architecture standards and models.

The 5C reference model proposed for the implementation of CPS is referenced in 20% of the papers [39,55,75,88,90]; however, its adoption is nil. The justification presented by Modoni et al. [55] is that the model does not consider interoperability between resources. The standard high-level architecture, RAMI 4.0, is highlighted and used explicitly in the work by Alexopoulos et al. [39]. Although the names of the high-level layers coincide with the nomenclature of the IIRA architecture, the HORSE project [90] uses RAMI 4.0 and the IIRA as references.

An examination of the papers reveals the different standards applied in the architectures. The IEC 62264 standard is referred to in [76,89,90] and adopted by RAMI 4.0 at the hierarchy level. It is an international standard for the integration of enterprise control systems based on ISA-95 that presents a functional hierarchy for manufacturing control to guide the layering of systems architectures [90]. The implementation of the IEC +61499 standard, discussed by Nikolakis et al. [83] and Marques et al. [75], facilitates the control of CPS components and regulates manufacturing operations, while the ISO 23247 standard, used by Sahlab et al. [94], aims to provide a formal description of the reference architecture of the DT, the representation of manufacturing elements, and the exchange of information.

5.3.3. Architecture Standards

This analysis shows that the architectures predominantly adopt a structural model based on layers, with each layer performing operations that progressively come closer to the set of instructions at the machine level, as illustrated in Figure 6. In the topmost layer, components are dedicated to operations related to the user interface, i.e., applications. On the other hand, in the deepest layer, components interact with the physical domain of the plant. The intermediate layers, often referred to as middleware, play a crucial role by providing the core of the system and the support services that the other layers need. This layered methodology proves to be effective in managing the development of highly complex systems, allowing the segregation of independent features and functionalities [39]. According to Muccini and Moghaddam [100], cited by Seiger et al. [93], these architectural configurations are among the most recurrent ones implemented in the IoT domain. As indicated by these authors, the reference architectures, namely the IIRA and RAMI 4.0, incorporate elements from various high-level perspectives and can be broken down into six main layers: business, functional, information, communication, integration, and physical.

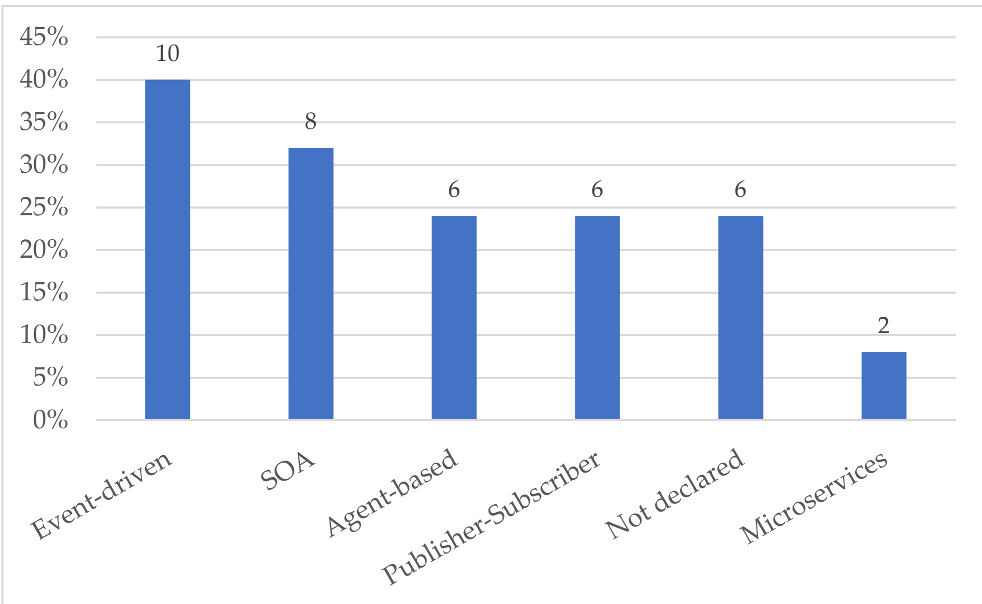

Figure 6. Comparative list of architecture standards.

In analysing various studies on high-level software architecture patterns, there is a predominance in adopting the event-driven model (40%). This preference is attributed to the dynamic nature of the scenarios in which the systems are inserted and the constant occurrence of events. This is followed by the service-oriented architecture (SOA), which accounts for 32% of the implementations analysed. The SOA stands out for its ability to offer a modular structure, facilitating the integration and flexibility of services. At the subsequent level, agent-based standards and the publisher–subscriber model (24%) were identified because they are recognised for their effectiveness in managing asynchronous communications and distributing information between decoupled components. Finally, microservices appear as an emerging trend that has evolved from SOA principles; they add granularity and capacity to provide more flexible development, deployment, and scalability of services.

In the contemporary industrial context, the ability to respond in real time is imperative for the players involved, which requires them to react quickly to events triggered by other players [49]. In this context, the architectures designed by Marques et al. [75] and Wan et al. [92] aim to increase the ability to react to unexpected occurrences. The pervasive insertion of IoT devices in industrial scenarios gives the event-based pattern a prevalence in architectures that stand out for their effectiveness, as Alexopoulos et al. [39] report. The event orchestration and composition approach suggested by Lyu et al. [84] also promotes remarkable adaptability, reactivity, and autonomy.

Regarding strategies for the implementation of the event-based standard, Nikolakis et al. [83] and Flatt et al. [74] propose a context-sensitive service layer that forwards events to subscribing clients to provide the required information. At the same time, Wieland et al. [73], Alexopoulos et al. [39], and Seiger et al. [93] make it possible to integrate events from the physical layer.

With technological progress in the SOA, there is the possibility of a progressive transition from a centralised to a distributed architecture in industrial automation [77]. The SOA is emerging as a promising solution for interoperability between devices, attributing this capacity to its intrinsic properties, which include message-based communication, flexible coupling, and the adoption of open standards [76]. Lyu et al. [84] also point out that the SOA provides a solid foundation for the promotion of flexibility. The abstraction of IoT devices facilitates access to and the execution of operations. It has been recognised and adopted by Cagnin et al. [81], Seiger et al. [93], and Flatt et al. [74] to provide services to external entities, minimising the complexity resulting from heterogeneity. On the other hand, Nikolakis et al. [77] proposed an architecture capable of offering contextual services to third parties via RESTful, intending to make information available. Similarly, Alexopoulos et al. [39] implemented services for applications in the business layer, and Wieland et al. [73] integrated the sensor layer and the situation recognition layer, demonstrating the versatility and applicability of the SOA and its associated technologies in optimising communication and interoperability in complex systems.

In a highly distributed context, incorporating agent-based technologies emerges as an innovative control paradigm that can efficiently overcome field challenges. As elucidated by Tang et al. [80], this approach is beneficial in managing the complexities intrinsic to personalised systems. In addition, the modularity and distribution inherent in this pattern provide the essential abstraction for the delineation of various operational states, mirroring the system's behaviour and facilitating adaptation to the heterogeneity of the physical environment.

CPS offers a balance of intelligence capabilities for data analysis and decision-making at different levels. In this context, implementing autonomous agents adds the ability to make decisions and ignores the need to consider fixed hierarchical structures [91]; see also

Modoni et al. [55]. Additionally, to enhance cooperation between the components of an IIoT network, a practical approach is to conceive the network as a distributed cooperative system based on agents. Furthermore, according to Tang et al. [74], agents promote the self-configuration and modification of the system, providing a more comprehensive range of decisions to respond to the external environment.

To address the inherent challenge of interoperability between interconnected resources, the architecture proposed by Modoni et al. [55] applies the publisher–subscriber standard. This approach uses a unified data model to formulate subscription requests and subsequent notifications. The research carried out by Queiroz et al. [91] evaluated the implementation of this standard to facilitate the uninterrupted receipt of relevant information, with a view to initiating specific actions reactively or proactively. This procedure aims to optimise frequently occurring asynchronous interactions, helping to reduce the volume of messages exchanged. Tang et al. [80] provide stakeholders with a negotiation mechanism under the publisher–subscriber scheme. In addition, adopting communication protocols such as the WebSocket-based Message Bus [90] and MQTT [39] integrates the publishing and subscription functionality.

Finally, as another pattern identified, microservices reduce the granularity and offer greater flexibility compared to the SOA. In distributed applications, Nikolakis et al. [86] suggest using microservices coupled with docker containers because this granularity makes it easier to model, develop, and maintain applications. Lyu et al. [84] added microservices to support control functionalities and associated each microservice with a service from the logical and physical layers.

6. Conclusions and Future Work

In the context of this systematic review, the aim was to deepen our understanding and contribute to developing context-aware software architectures to support the production system of the Continental AA company, which is in line with the principles of I4.0 and the integration of context knowledge. This analysis contributed practical insights into the development of architectures and prototype applications for the testbed of the production system of Continental AA [38,101,102]. This study also facilitated the identification of numerous significant works, including those by Alexopoulos et al. [103], who, in 2016, presented an architecture that incorporates the concept of context awareness into the manufacturing environment and then, in 2018, implemented and evaluated it in a real-world scenario [39]. This strategy is widely accepted in the academic literature and industrial practice, and, while a minority complete this cycle, others, such as Sánchez et al. [85], aim in future work to use their architectures in real-world applications to proceed with the evaluation. We also refer to the work of Traganos et al. [90], which involved different countries and factories in Europe and their evaluation, and the work of Sánchez et al. [85] due to the amount of data involved or Queiroz et al. [91] due to the time invested in the testing phase.

In this work, the theoretical foundations were analysed in Section 2, followed by a systematic literature review in Section 3, culminating in the 25 articles analysed to answer the three research questions.

Concerning the first research question (RQ1—requirements that the architectures support), interoperability, automation, and decision-making are important and align with the principles of I4.0. In the manufacturing environment, these three requirements are interrelated and make it easier to operate the production environment fully. Computational or physical entities populate the space, and humans need the addition of interoperability, the automation of production processes, and new challenges for more efficient and effective decision-making. A concern also emerged regarding responding to issues of technical functionality to deal with the complexity of the manufacturing environment and the emerging principles of the I4.0 paradigm, because non-functional requirements such as scalability, adaptability, and performance were constantly highlighted.

The second research question (RQ2) sought to elucidate the dynamics underlying context representation and inference. It was concluded that interoperability is promoted by applying ontologies for context representation, corresponding to 72% of the choices. Additionally, there needs to be a model for the representation of context that favours interoperability between different systems and the ability to add new attributes, which enhances the model complexity while increasing the readability, scalability, intelligence, and user-centricity to accelerate the realisation of truly flexible, adaptive, and efficient smart factories. Moreover, according to our analysis, the design of context modelling is crucial, because it has direct implications for the quality attributes of software: adaptation, flexibility, and interoperability. We also highlight the local and global concepts presented by Traganos et al. [90], which can have different dimensions of representation, inference, and dissimilation. On the other hand, context inference also emerges as an open field of study, because 48% of the articles did not refer to this topic, and 32% chose to apply the rule-based model. This issue requires the selection of algorithms and is influenced by the computational and storage capacities of the computing nodes, the complexity of the context being analysed, the volume of data to be processed, and the time requirements, among others. Thus, in different scenarios, we must use different inference techniques according to the granularity of the impact of the decision-making outputs, and we should consider the concept of Human-in-the-Loop, which is popular in these studies.

To find an answer to the third research question (RQ3), we identified the technologies, standards, reference models, and software architecture patterns discussed in each paper. The proposals emphasise the integration of CPS (64%) and IoT (56%) technologies and also assign a role to cloud computing (52%). In addition, technologies such as DT (16%) and fog computing (12%) are still at an early stage of exploration and adoption. Regarding reference models, there was a preference for RAMI 4.0 (36%) over the IIRA (12%), while the 5C model (20%) was only mentioned and not adopted. These results align with the inclusion and exclusion criteria applied in the systematic review, considering that RAMI 4.0 is oriented towards I4.0, the IIRA supports the interoperability of IIoT systems, and 5C does not consider interoperability between resources. It is worth noting the identification of several implemented standards (ISA-95, IEC 61499, IEC 62264, ISO 23247) that support production processes and the design of architectures to guide the functional development of the system. We emphasise that 5C is mentioned but not used, while RAMI 4.0 and the IIRA were used mainly in the architectures proposed by Alexopoulos et al. [39] and in the HORSE project [90], and none wrote about the consideration of this strategy, which suggests compatibility issues. However, organisations can apply them together to guide their systems and processes, benefiting from the advantages of both without encountering major technical or conceptual obstacles. The analysis suggests that architecture design should be layered, distributed, and modular, and the software architecture patterns proposed to facilitate system development are event-driven strategies (40%), SOAs (32%), agent-based strategies (24%), publisher–subscriber models (24%), and microservices (8%), which play a crucial role in promoting applications that are loosely coupled, responsive, scalable, flexible, autonomous, and capable of operating in real time.

We propose the exploration of future lines of research aimed at (i) exploring distributed computing and storage between the three layers of the cloud, fog, and edge; (ii) the study of decision-making algorithms in micro-moments; (iii) the creation of a representation model for micro-contexts using ontologies; and (iv) the development of inference techniques adapted to micro-contexts. In addition, it is crucial to recognise the importance of the concept of ubiquitous computing, which offers valuable perspectives for the evolution of industry and the future of factories [49], as well as considering relevant projects in the area, such as those mentioned by Santos et al. [44], to ensure effective integration. Another consideration is AI [39], which, in recent years, has gained increased popularity in a wide range of applications [104].

Finally, we identified some barriers referenced in the 25 examined papers. First, security and privacy were two quality attributes that were discussed infrequently (5), and no papers evaluated them. These concepts assume crucial importance in industrial sectors because data are, in some cases, valuable, of high volume, and sensitive. Second, corporate policy restrictions are important, such as cloud solutions, which are not accepted in some cases due to security concerns, while fog concepts could achieve greater acceptance in this sector.

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References

1. Weiser, M. The Computer for the 21st Century. *Sci. Am.* **1991**, *265*, 94–104. [CrossRef]
2. Steventon, A.; Wright, S. *Intelligent Spaces: The Application of Pervasive ICT*; Springer Science & Business Media: Berlin/Heidelberg, Germany, 2010.
3. Calvaresi, D.; Cesarini, D.; Sernani, P.; Marinoni, M.; Dragoni, A.F.; Sturm, A. Exploring the ambient assisted living domain: A systematic review. *J. Ambient Intell. Humaniz. Comput.* **2017**, *8*, 239–257. [CrossRef]
4. Dohr, A.; Modre-Opsrian, R.; Drobics, M.; Hayn, D.; Schreier, G. The Internet of Things for Ambient Assisted Living. In Proceedings of the 2010 Seventh International Conference on Information Technology: New Generations, Las Vegas, NV, USA, 12–14 April 2010; pp. 804–809.
5. Koleva, P.; Tonchev, K.; Balabanov, G.; Manolova, A.; Poulkov, V. Challenges in designing and implementation of an effective Ambient Assisted Living system. In Proceedings of the 2015 12th International Conference on Telecommunication in Modern Satellite, Cable and Broadcasting Services (TELSIKS), Nis, Serbia, 14–17 October 2015; pp. 305–308.
6. Reis, A.; Paulino, D.; Paredes, H.; Barroso, J. *Using Intelligent Personal Assistants to Strengthen the Elderlies' Social Bonds: A Preliminary Evaluation of Amazon Alexa, Google Assistant, Microsoft Cortana, and Apple Siri, Proceedings of the Universal Access in Human–Computer Interaction. Human and Technological Environments: 11th International Conference, UAHCI 2017, Held as Part of HCI International 2017; Part III, Vancouver, BC, Canada, 9–14 July 2017*; Springer: Berlin/Heidelberg, Germany, 2017; pp. 593–602.
7. Reis, A.; Rocha, T.; Barroso, J.; Carvalho, D. The Ambient Assisted Working (AAW) concept: Assistance according to I4.0 Technical Assistance design principle. In Proceedings of the 15th International Conference on PErvasive Technologies Related to Assistive Environments, Association for Computing Machinery, New York, NY, USA, 29 June–1 July 2022; pp. 316–318.
8. Clemons, J. The Anatomy of Smart Manufacturing. Available online: https://www.forbes.com/sites/forbestechcouncil/2018/03/19/the-anatomy-of-smart-manufacturing/ (accessed on 8 June 2022).
9. Kotler, P.; Kartajaya, H.; Setiawan, I. *Marketing 5.0: Technology for Humanity*; John Wiley & Sons: Hoboken, NJ, USA, 2021; ISBN 978-1-119-66851-0.
10. Hribernik, K.; Cabri, G.; Mandreoli, F.; Mentzas, G. Autonomous, context-aware, adaptive Digital Twins—State of the art and roadmap. *Comput. Ind.* **2021**, *133*, 103508. [CrossRef]
11. Kubina, M.; Varmus, M.; Kubinova, I. Use of big data for competitive advantage of company. *Procedia Econ. Financ.* **2015**, *26*, 561–565. [CrossRef]

12. Sadiku, M.N.O.; Ajayi-Majebi, A.J.; Adebo, P.O. Big Data in Manufacturing. In *Emerging Technologies in Manufacturing*; Sadiku, M.N.O., Ajayi-Majebi, A.J., Adebo, P.O., Eds.; Springer International Publishing: Cham, Switzerland, 2023; pp. 95–107. ISBN 978-3-031-23156-8.
13. El Kadiri, S.; Grabot, B.; Thoben, K.-D.; Hribernik, K.; Emmanouilidis, C.; von Cieminski, G.; Kiritsis, D. Current trends on ICT technologies for enterprise information systems. *Comput. Ind.* **2016**, *79*, 14–33. [CrossRef]
14. Lasi, H.; Fettke, P.; Kemper, H.-G.; Feld, T.; Hoffmann, M. Industry 4.0. *Bus. Inf. Syst. Eng.* **2014**, *6*, 239–242. [CrossRef]
15. Thoben, K.-D.; Wiesner, S.; Wuest, T. "Industrie 4.0" and Smart Manufacturing—A Review of Research Issues and Application Examples. *Int. J. Autom. Technol.* **2017**, *11*, 4–16. [CrossRef]
16. Wang, S.; Wan, J.; Li, D.; Zhang, C. Implementing Smart Factory of Industrie 4.0: An Outlook. *Int. J. Distrib. Sens. Netw.* **2016**, *12*, 3159805. [CrossRef]
17. Liao, Y.; Deschamps, F.; Loures, E.d.F.R.; Ramos, L.F.P. Past, present and future of Industry 4.0—A systematic literature review and research agenda proposal. *Int. J. Prod. Res.* **2017**, *55*, 3609–3629. [CrossRef]
18. Kagermann, H.; Wahlster, W.; Helbig, J. (Eds.) *Recommendations for Implementing the Strategic Initiative INDUSTRIE 4.0*; Industrie 4.0 Working Group: Frankfurt, Germany, 2013.
19. Folgado, F.J.; Calderón, D.; González, I.; Calderón, A.J. Review of Industry 4.0 from the perspective of automation and supervision systems: Definitions, architectures and recent trends. *Electronics* **2024**, *13*, 782. [CrossRef]
20. Pivoto, D.G.S.; de Almeida, L.F.F.; da Rosa Righi, R.; Rodrigues, J.J.P.C.; Lugli, A.B.; Alberti, A.M. Cyber-physical systems architectures for industrial internet of things applications in Industry 4.0: A literature review. *J. Manuf. Syst.* **2021**, *58*, 176–192. [CrossRef]
21. Moghaddam, M.; Cadavid, M.N.; Kenley, C.R.; Deshmukh, A.V. Reference architectures for smart manufacturing: A critical review. *J. Manuf. Syst.* **2018**, *49*, 215–225. [CrossRef]
22. Lee, J.; Ardakani, H.D.; Yang, S.; Bagheri, B. Industrial Big Data Analytics and Cyber-physical Systems for Future Maintenance & Service Innovation. *Procedia CIRP* **2015**, *38*, 3–7. [CrossRef]
23. Negri, E.; Fumagalli, L.; Macchi, M. A Review of the Roles of Digital Twin in CPS-based Production Systems. *Procedia Manuf.* **2017**, *11*, 939–948. [CrossRef]
24. Parrott, A.; Warshaw, L. *Industry 4.0 and the Digital Twin*; Deloitte University Press: New York, NY, USA, 2017.
25. Plattform Industrie 4.0. *2030 Vision for Industrie 4.0*; Federal Ministry for Economic Affairs and Energy (BMWi): Berlin, Germany, 2019.
26. Roblek, V.; Meško, M.; Krapež, A. A complex view of industry 4.0. *SAGE Open* **2016**, *6*, 2158244016653987. [CrossRef]
27. Posada, J.; Toro, C.; Barandiaran, I.; Oyarzun, D.; Stricker, D.; de Amicis, R.; Pinto, E.B.; Eisert, P.; Döllner, J.; Vallarino, I. Visual Computing as a Key Enabling Technology for Industrie 4.0 and Industrial Internet. *IEEE Comput. Graph. Appl.* **2015**, *35*, 26–40. [CrossRef]
28. Lu, Y. Industry 4.0: A survey on technologies, applications and open research issues. *J. Ind. Inf. Integr.* **2017**, *6*, 1–10. [CrossRef]
29. Hermann, M.; Pentek, T.; Otto, B. Design principles for industrie 4.0 scenarios. In Proceedings of the Annual Hawaii International Conference on System Sciences, Koloa, HI, USA, 5–8 January 2016; Volume 2016-March, pp. 3928–3937.
30. Pereira, A.C.; Romero, F. A review of the meanings and the implications of the Industry 4.0 concept. *Procedia Manuf.* **2017**, *13*, 1206–1214. [CrossRef]
31. dos Reis, F.B.; Júnior, A.S.C. Industry 4.0: An investigation of benefits and barriers with managers of Brazilian manufacturers adopters. *J. Eng. Technol. Manag.* **2024**, *71*, 101786. [CrossRef]
32. Cordeiro, R.F.; Reis, L.P.; Fernandes, J.M. A study on the barriers that impact the adoption of Industry 4.0 in the context of Brazilian companies. *TQM J.* **2024**, *36*, 361–384. [CrossRef]
33. Kadir, B.A.; Broberg, O. Human well-being and system performance in the transition to industry 4.0. *Int. J. Ind. Ergon.* **2020**, *76*, 102936. [CrossRef]
34. Schilit, B.; Adams, N.; Want, R. Context-aware computing applications. In Proceedings of the Mobile Computing Systems and Applications—Workshop Proceedings, Santa Cruz, CA, USA, 8–9 December 1994; pp. 85–90.
35. Abowd, G.D.; Dey, A.K.; Brown, P.J.; Davies, N.; Smith, M.; Steggles, P. Towards a better understanding of context and context-awareness. In *Handheld and Ubiquitous Computing: First International Symposium, Proceedings of the Handheld and Ubiquitous Computing (HUC 1999), Karlsruhe, Germany, 27–29 September 1999*; Springer: Berlin/Heidelberg, Germany, 1999; Volume 1707, pp. 304–307. [CrossRef]
36. Ranganathan, A.; Campbell, R.H. An infrastructure for context-awareness based on first order logic. *Pers. Ubiquitous Comput.* **2003**, *7*, 353–364. [CrossRef]
37. Monteiro, P.; Lima, C.; Pinto, T.; Nogueira, P.; Reis, A.; Filipe, V. *Context-Aware Applications in Industry 4.0: A Systematic Literature Review, Proceedings of the Distributed Computing and Artificial Intelligence, Special Sessions I, 20th International Conference, Guimarães, Portugal, 12–14 July 2023*; Mehmood, R., Alves, V., Praça, I., Wikarek, J., Parra-Domínguez, J., Loukanova, R., de Miguel, I., Pinto, T., Nunes, R., Ricca, M., Eds.; Springer Nature: Cham, Switzerland, 2023; pp. 301–311.

38. Monteiro, P.; Pereira, R.; Nunes, R.; Reis, A.; Pinto, T. Context-Aware System for Information Flow Management in Factories of the Future. *Appl. Sci.* **2024**, *14*, 3907. [CrossRef]
39. Alexopoulos, K.; Sipsas, K.; Xanthakis, E.; Makris, S.; Mourtzis, D. An industrial Internet of things based platform for context-aware information services in manufacturing. *Int. J. Comput. Integr. Manuf.* **2018**, *31*, 1111–1123. [CrossRef]
40. Scholze, S.; Barata, J. *Context Awareness for Flexible Manufacturing Systems Using Cyber Physical Approaches, Proceedings of the Technological Innovation for Cyber-Physical Systems: 7th IFIP WG 5.5/SOCOLNET Advanced Doctoral Conference on Computing, Electrical and Industrial Systems, DoCEIS 2016, Costa de Caparica, Portugal, 11–13 April 2016*; Springer: Berlin/Heidelberg, Germany, 2016; pp. 107–115.
41. Li, X.; Eckert, M.; Martinez, J.F.; Rubio, G. Context Aware Middleware Architectures: Survey and Challenges. *Sensors* **2015**, *15*, 20570–20607. [CrossRef]
42. Alagar, V.; Mohammad, M.; Wan, K.; Hnaide, S.A. A Framework for Developing Context-aware Systems. *EAI Endorsed Trans. Context-Aware Syst. Appl.* **2014**, *1*, e2. [CrossRef]
43. Augusto, J.C.; Quinde, M.J.; Oguego, C.L.; Giménez Manuel, J. Context-aware systems architecture (CaSa). *Cybern. Syst.* **2022**, *53*, 319–345. [CrossRef]
44. Santos, A.; Lima, C.; Reis, A.; Pinto, T.; Nogueira, P.; Barroso, J. *Design of Context-Aware Information Systems in Manufacturing Industries: Overview and Challenges, Proceedings of the Distributed Computing and Artificial Intelligence, Special Sessions I, 20th International Conference, Guimarães, Portugal, 12–14 July 2023*; Mehmood, R., Alves, V., Praça, I., Wikarek, J., Parra-Domínguez, J., Loukanova, R., de Miguel, I., Pinto, T., Nunes, R., Ricca, M., Eds.; Springer Nature: Cham, Switzerland, 2023; pp. 322–331.
45. Bazire, M.; Brézillon, P. Understanding context before using it. In *Modeling and Using Context, Proceedings of the 5th International and Interdisciplinary Conference, CONTEXT 2005, Paris, France, 5–8 July 2005*; Springer: Berlin/Heidelberg, Germany, 2005; pp. 29–40. [CrossRef]
46. Perera, C.; Zaslavsky, A.; Christen, P.; Georgakopoulos, D. Context aware computing for the internet of things: A survey. *IEEE Commun. Surv. Tutor.* **2014**, *16*, 414–454. [CrossRef]
47. Rosenberger, P.; Grafinger, M.; Gerhard, D.; Hennig, M.; Dumss, S. The CASAD Matrix Method: Introduction of a Technique for the Documentation, Analysis, and Optimization of Context-Aware Systems. *Procedia CIRP* **2020**, *91*, 427–432. [CrossRef]
48. Alegre, U.; Augusto, J.C.; Clark, T. Engineering context-aware systems and applications: A survey. *J. Syst. Softw.* **2016**, *117*, 55–83. [CrossRef]
49. Belkadi, F.; Dhuieb, M.A.; Aguado, J.V.; Laroche, F.; Bernard, A.; Chinesta, F. Intelligent assistant system as a context-aware decision-making support for the workers of the future. *Comput. Ind. Eng.* **2020**, *139*, 105732. [CrossRef]
50. European Commission. *Horizon 2020 Work Programme 2016–2017*; ENRD: European Network for Rural Development: Brussels, Belgium, 2016.
51. Apilioğulları, L. Digital transformation in project-based manufacturing: Developing the ISA-95 model for vertical integration. *Int. J. Prod. Econ.* **2022**, *245*, 108413. [CrossRef]
52. Cupek, R.; Ziebinski, A.; Huczala, L.; Erdogan, H. Agent-based manufacturing execution systems for short-series production scheduling. *Comput. Ind.* **2016**, *82*, 245–258. [CrossRef]
53. Lafortune, S. On decentralized and distributed control of partially-observed discrete event systems. In *Advances in Control Theory and Applications*; Springer: Berlin/Heidelberg, Germany, 2007; pp. 171–184.
54. Pedrielli, G.; Matta, A.; Alfieri, A.; Zhang, M. Design and control of manufacturing systems: A discrete event optimisation methodology. *Int. J. Prod. Res.* **2018**, *56*, 543–564. [CrossRef]
55. Modoni, G.E.; Trombetta, A.; Veniero, M.; Sacco, M.; Mourtzis, D. An event-driven integrative framework enabling information notification among manufacturing resources. *Int. J. Comput. Integr. Manuf.* **2019**, *32*, 241–252. [CrossRef]
56. Kruchten, P.; Capilla, R.; Dueñas, J.C. The Decision View's Role in Software Architecture Practice. *IEEE Softw.* **2009**, *26*, 36–42. [CrossRef]
57. Zimmermann, O. Architectural Decisions as Reusable Design Assets. *IEEE Softw.* **2011**, *28*, 64–69. [CrossRef]
58. Kruchten, P. The 4+1 View Model of Architecture. *IEEE Softw.* **1995**, *12*, 45–50. [CrossRef]
59. Nakagawa, E.Y.; Antonino, P.O.; Schnicke, F.; Capilla, R.; Kuhn, T.; Liggesmeyer, P. Industry 4.0 reference architectures: State of the art and future trends. *Comput. Ind. Eng.* **2021**, *156*, 107241. [CrossRef]
60. Shadravan, A.; Parsaei, H.R. A Review of Reference Architectures for Industry 4.0 and Their Impacts in Smart Manufacturing. In Proceedings of the 1st World Congress on Industrial Engineering and Operations Management, Detroit, MI, USA, 9–11 October 2024.
61. Sony, M. Design of cyber physical system architecture for industry 4.0 through lean six sigma: Conceptual foundations and research issues. *Prod. Manuf. Res.* **2020**, *8*, 158–181. [CrossRef]
62. Tavčar, J.; Horváth, I. A Review of the Principles of Designing Smart Cyber-Physical Systems for Run-Time Adaptation: Learned Lessons and Open Issues. *IEEE Trans. Syst. Man Cybern. Syst.* **2019**, *49*, 145–158. [CrossRef]

63. Wu, X.; Goepp, V.; Siadat, A. Concept and engineering development of cyber physical production systems: A systematic literature review. *Int. J. Adv. Manuf. Technol.* **2020**, *111*, 243–261. [CrossRef]
64. Hankel, M.; Rexroth, B. *The Reference Architectural Model Industrie 4.0 (RAMI 4.0)*; Zvei: Frankfurt, Germany, 2015; Volume 2, pp. 4–9.
65. Wegener, D. *German Standardization Roadmap on Industry 4.0*; DKE German Commission for Electrical, Electronic & Information Technologies: Offenbach, Germany, 2020.
66. Nagorny, K.; Scholze, S.; Colombo, A.W.; Oliveira, J.B. A DIN Spec 91345 RAMI 4.0 Compliant Data Pipelining Model: An Approach to Support Data Understanding and Data Acquisition in Smart Manufacturing Environments. *IEEE Access* **2020**, *8*, 223114–223129. [CrossRef]
67. Pisching, M.A.; Pessoa, M.A.; Junqueira, F.; dos Santos Filho, D.J.; Miyagi, P.E. An architecture based on RAMI 4.0 to discover equipment to process operations required by products. *Comput. Ind. Eng.* **2018**, *125*, 574–591. [CrossRef]
68. Binder, C. *Introduction to the "RAMI 4.0 Toolbox"*; Josef Ressel Center for User-Centric Smart Grid Privacy, Security and Control: Salzburg, Austria, 2020; Volume 43, pp. 1–27.
69. Lin, S.-W.; Miller, B.; Durand, J.; Joshi, R.; Didier, P.; Chigani, A.; Torenbeek, R.; Duggal, D.; Martin, R.; Bleakley, G. *Industrial Internet Reference Architecture*; Industrial Internet Consortium: Boston, MA, USA, 2015.
70. Moher, D.; Liberati, A.; Tetzlaff, J.; Altman, D.G. Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *Int. J. Surg.* **2010**, *8*, 336–341. [CrossRef]
71. Xiao, Y.; Watson, M. Guidance on Conducting a Systematic Literature Review. *J. Plan. Educ. Res.* **2017**, *39*, 93–112. [CrossRef]
72. Kazman, R.; Klein, M.; Clements, P. *ATAM: Method for Architecture Evaluation*; Carnegie Mellon University, Software Engineering Institute: Pittsburgh, PA, USA, 2000.
73. Wieland, M.; Schwarz, H.; Breitenbücher, U.; Leymann, F. Towards situation-aware adaptive workflows: SitOPT—A general purpose situation-aware workflow management system. In Proceedings of the 2015 IEEE International Conference on Pervasive Computing and Communication Workshops (PerCom Workshops), St. Louis, MO, USA, 23–27 March 2015; pp. 32–37.
74. Flatt, H.; Koch, N.; Röcker, C.; Günter, A.; Jasperneite, J. A context-aware assistance system for maintenance applications in smart factories based on augmented reality and indoor localization. In Proceedings of the 2015 IEEE 20th Conference on Emerging Technologies & Factory Automation (ETFA), Luxembourg, 8–11 September 2015; pp. 1–4.
75. Marques, M.; Agostinho, C.; Poler, R.; Zacharewicz, G.; Jardim-Gonçalves, R. An architecture to support responsive production in manufacturing companies. In Proceedings of the 2016 IEEE 8th International Conference on Intelligent Systems (IS), Sofia, Bulgaria, 4–6 September 2016; pp. 40–46.
76. Negri, E.; Fumagalli, L.; Garetti, M.; Tanca, L. Requirements and languages for the semantic representation of manufacturing systems. *Comput. Ind.* **2016**, *81*, 55–66. [CrossRef]
77. Pirvu, B.-C.; Zamfirescu, C.-B.; Gorecky, D. Engineering insights from an anthropocentric cyber-physical system: A case study for an assembly station. *Mechatronics* **2016**, *34*, 147–159. [CrossRef]
78. Siafara, L.C.; Kholerdi, H.A.; Bratukhin, A.; TaheriNejad, N.; Wendt, A.; Jantsch, A.; Treytl, A.; Sauter, T. SAMBA: A self-aware health monitoring architecture for distributed industrial systems. In Proceedings of the IECON 2017—43rd Annual Conference of the IEEE Industrial Electronics Society, Beijing, China, 29 October–1 November 2017; pp. 3512–3517.
79. Podgórski, D.; Majchrzycka, K.; Dąbrowska, A.; Gralewicz, G.; Okrasa, M. Towards a conceptual framework of OSH risk management in smart working environments based on smart PPE, ambient intelligence and the Internet of Things technologies. *Int. J. Occup. Saf. Ergon.* **2017**, *23*, 1–20. [CrossRef]
80. Tang, H.; Li, D.; Wang, S.; Dong, Z. CASOA: An Architecture for Agent-Based Manufacturing System in the Context of Industry 4.0. *IEEE Access* **2018**, *6*, 12746–12754. [CrossRef]
81. Cagnin, R.L.; Guilherme, I.R.; Queiroz, J.; Paulo, B.; Neto, M.F.O. A Multi-agent System Approach for Management of Industrial IoT Devices in Manufacturing Processes. In Proceedings of the 2018 IEEE 16th International Conference on Industrial Informatics (INDIN), Porto, Portugal, 18–20 July 2018; pp. 31–36.
82. Wan, J.; Yang, J.; Wang, Z.; Hua, Q. Artificial Intelligence for Cloud-Assisted Smart Factory. *IEEE Access* **2018**, *6*, 55419–55430. [CrossRef]
83. Nikolakis, N.; Sipsas, K.; Makris, S. A cyber-physical context-aware system for coordinating human-robot collaboration. *Procedia CIRP* **2018**, *72*, 27–32. [CrossRef]
84. Lyu, M.; Benfenatki, H.; Biennier, F.; Ghodous, P. Control as a Service Architecture to Support Context-aware Control Application Development. *IFAC-PapersOnLine* **2019**, *52*, 1085–1090. [CrossRef]
85. Sánchez, M.; Exposito, E.; Aguilar, J. Implementing self-* autonomic properties in self-coordinated manufacturing processes for the Industry 4.0 context. *Comput. Ind.* **2020**, *121*, 103247. [CrossRef]
86. Nikolakis, N.; Marguglio, A.; Veneziano, G.; Greco, P.; Panicucci, S.; Cerquitelli, T.; Macii, E.; Andolina, S.; Alexopoulos, K. A microservice architecture for predictive analytics in manufacturing. *Procedia Manuf.* **2020**, *51*, 1091–1097. [CrossRef]

87. Lim, K.Y.H.; Zheng, P.; Chen, C.-H.; Huang, L. A digital twin-enhanced system for engineering product family design and optimization. *J. Manuf. Syst.* **2020**, *57*, 82–93. [CrossRef]
88. Lu, Y.; Asghar, M.R. Semantic communications between distributed cyber-physical systems towards collaborative automation for smart manufacturing. *J. Manuf. Syst.* **2020**, *55*, 348–359. [CrossRef]
89. Bagozi, A.; Bianchini, D.; Antonellis, V.D. Context-Based Resilience in Cyber-Physical Production System. *Data Sci. Eng.* **2021**, *6*, 434–454. [CrossRef]
90. Traganos, K.; Grefen, P.; Vanderfeesten, I.; Erasmus, J.; Boultadakis, G.; Bouklis, P. The HORSE framework: A reference architecture for cyber-physical systems in hybrid smart manufacturing. *J. Manuf. Syst.* **2021**, *61*, 461–494. [CrossRef]
91. Queiroz, J.; Leitão, P.; Barbosa, J.; Oliveira, E.; Garcia, G. Agent-Based Distributed Data Analysis in Industrial Cyber-Physical Systems. *IEEE J. Emerg. Sel. Top. Ind. Electron.* **2022**, *3*, 5–12. [CrossRef]
92. Wan, G.; Dong, X.; Dong, Q.; He, Y.; Zeng, P. Context-aware scheduling and control architecture for cyber-physical production systems. *J. Manuf. Syst.* **2022**, *62*, 550–560. [CrossRef]
93. Seiger, R.; Malburg, L.; Weber, B.; Bergmann, R. Integrating process management and event processing in smart factories: A systems architecture and use cases. *J. Manuf. Syst.* **2022**, *63*, 575–592. [CrossRef]
94. Sahlab, N.; Braun, D.; Köhler, C.; Jazdi, N.; Weyrich, M. Extending the Intelligent Digital Twin with a context modeling service: A decision support use case. *Procedia CIRP* **2022**, *107*, 463–468. [CrossRef]
95. Pedone, G.; Mezgár, I. Model similarity evidence and interoperability affinity in cloud-ready Industry 4.0 technologies. *Comput. Ind.* **2018**, *100*, 278–286. [CrossRef]
96. Wemlinger, Z.; Holder, L. The COSE Ontology: Bringing the Semantic Web to Smart Environments. In *Toward Useful Services for Elderly and People with Disabilities, Proceedings of the 9th International Conference on Smart Homes and Health Telematics, ICOST 2011, Montreal, QC, Canada, 20–22 June 2011*; Abdulrazak, B., Giroux, S., Bouchard, B., Pigot, H., Mokhtari, M., Eds.; Springer: Berlin/Heidelberg, Germany, 2011; pp. 205–209.
97. Haindl, P.; Buchgeher, G.; Khan, M.; Moser, B. Towards a reference software architecture for human-AI teaming in smart manufacturing. In Proceedings of the ACM/IEEE 44th International Conference on Software Engineering: New Ideas and Emerging Results, Pittsburgh, PA, USA, 21–29 May 2022; pp. 96–100.
98. Leitão, P.; Karnouskos, S.; Ribeiro, L.; Lee, J.; Strasser, T.; Colombo, A.W. Smart Agents in Industrial Cyber–Physical Systems. *Proc. IEEE* **2016**, *104*, 1086–1101. [CrossRef]
99. Ashtari Talkhestani, B.; Jung, T.; Lindemann, B.; Sahlab, N.; Jazdi, N.; Schloegl, W.; Weyrich, M. An Architecture of an Intelligent Digital Twin in a Cyber-Physical Production System. Available online: https://openurl.ebsco.com/contentitem/doi:10.1515/auto-2019-0039?sid=ebsco:plink:crawler&id=ebsco:doi:10.1515/auto-2019-0039 (accessed on 7 February 2024).
100. Muccini, H.; Moghaddam, M.T. IoT Architectural Styles. In *Software Architecture, Proceeding of the 12th European Conference on Software Architecture, ECSA 2018, Madrid, Spain, 24–28 September 2018*; Cuesta, C.E., Garlan, D., Pérez, J., Eds.; Springer International Publishing: Cham, Switzerland, 2018; pp. 68–85.
101. Pereira, R.; Lima, C.; Pinto, T.; Reis, A. Virtual Assistants in Industry 4.0: A Systematic Literature Review. *Electronics* **2023**, *12*, 4096. [CrossRef]
102. Nunes, R.; Pereira, R.; Nogueira, P.; Barroso, J.; Rocha, T.; Reis, A. Wearable Devices for Communication and Problem-Solving in the Context of Industry 4.0. In *HCI International 2023—Late Breaking Papers, Proceedings of the 25th International Conference on Human-Computer Interaction, HCII 2023, Copenhagen, Denmark, 23–28 July 2023*; Duffy, V.G., Krömker, H.A., Streitz, N., Konomi, S., Eds.; Springer Nature: Cham, Switzerland, 2023; pp. 583–592.
103. Alexopoulos, K.; Makris, S.; Xanthakis, V.; Sipsas, K.; Chryssolouris, G. A concept for context-aware computing in manufacturing: The white goods case. *Int. J. Comput. Integr. Manuf.* **2016**, *29*, 839–849. [CrossRef]
104. Villar, E.; Martín Toral, I.; Calvo, I.; Barambones, O.; Fernández-Bustamante, P. Architectures for Industrial AIoT Applications. *Sensors* **2024**, *24*, 4929. [CrossRef]