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# Data fabric and digital twins: An integrated approach for data fusion design and evaluation of pervasive systems

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ABSTRACT

Recent technological improvements have made it possible for pervasive computing intelligent environments, augmented by sensors and actuators, to offer services that support society's aims for a wide variety of applications. This requires the fusion of data gathered from multiple sensors to convert them into information to obtain valuable knowledge. Poor implementation of data fusion hinders the appropriate actions from being taken and offering the appropriate support to users and environment needs, particularly relevant in the healthcare domain. Data fusion poses challenges that are mainly related to the quality of the data or data sources, the definition of a data fusion process and evaluating the data fusion carried out. There is also a lack of holistic engineering frameworks to address these challenges. These frameworks should be able to support automated methods of extracting knowledge from information, selecting algorithms and techniques, assessing information and evaluating information fusion systems in an automatic and standardized manner. This work proposes a holistic framework to improve data fusion in pervasive systems, addressing the issues identified by means of two processes: the first of which guides the design of the system architecture and focuses on data management. It is based on a previous proposal that integrated aspects of Data Fabric and Digital Twins to solve data management and data contextualization and representation issues, respectively. The extension of the previous proposal presented here was mainly defined by integrating aspects and techniques from different well-known multi-sensor data fusion models. The previous proposal identified high-level data processing activities and was intended to facilitate their traceability to components in the system architecture. However, the previously defined stages are not completely adequate in a data fusion process and the data processing tasks to be performed in each stage are not described in detail, especially in the data fusion stages. The second process of the framework deals with evaluating data fusion systems and is based on international standards to ensure the quality of the data fusion tasks performed by such systems. This process also offers guidelines for designing the architecture of an evaluation subsystem to automatically perform data fusion evaluation in runtime as part of the system. To illustrate the proposal, a system for preventing the spread of COVID-19 in nursing homes is described that was developed using the proposed guidelines It is also illustrated by a description of how the data fusion tasks it supports are evaluated by the proposed evaluation process. The overall evaluation of the data fusion performed by this system was considered satisfactory, which indicates that the proposal facilitates the design and development of data fusion systems and helps to achieve the necessary quality requirements.

## 1. Introduction

Maximizing the benefits of any new initiative for society from social, economic, and territorial perspectives is greatly promoted by public institutions, such as the European Union. These initiatives include generating new knowledge and developing innovative solutions to promote eco-friendly production and consumption or to prevent, diagnose, monitor, treat and cure diseases [1]. Some computing paradigms such as ubiquitous [2] or pervasive computing [3] have discussed how information technology could be woven into everyday objects and settings under the Disappearing Computing vision [4] to offer new ways of supporting and enhancing people's lives beyond the traditional support offered by conventional desktop computers [1]. Pervasive computing involves intelligent environments augmented by mobile,

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wearable, and environmental sensors in a diversity of computing devices that collect data from multiple sources. These environments are also populated with actuators that can unobtrusively react to the user's needs and the environment, providing valuable computing services for a wide variety of applications [5]. The service described requires the processing of data gathered from multiple sensors to turn these data into information and combining them to obtain valuable knowledge. This knowledge can be used to assess, for example, the activity being conducted by the user, the status of the environment in which it takes place, also the users' behaviour and/or physiological or even emotional state to appropriately respond to their needs [1]. As Ackoff [6] and Chen et al. [7] claim, the term *data* refers to symbols that represent the properties of objects and events, whereas *information* is data that have been processed to increase their usefulness. The difference between data and information is functional rather than structural, and both terms are frequently used interchangeably. *Knowledge* and *understanding* refer to the use of data and information to answer questions such as *who, what, when, where*, or *how many*. Knowledge is conveyed by instructions and answers how-to questions. Understanding is conveyed by the explanations and answers *why* questions.

Healthcare is crucial in everyday life and concerns medical and public practices that frequently involve the use of devices [5]. The population in general and the elderly in particular demand multiple healthcare services such as medical examination services offered by physicians at clinics or outpatient services offered by specialists, nurses, etc. in hospitals, amongst others [8]. The demand for appropriate and efficient services is growing ever more rapidly [8] especially as a result of the COVID-19 pandemic, which has caused millions of infections and deaths, especially amongst the elderly [9]. Medical models are evolving from evidence-based medicine to precision medicine focused on medication tuned to the person needs for the prevention of COVID-19 and other illnesses [8]. The advances in different research areas and technologies, such as computing hardware, the Internet of Things (IoT), Artificial Intelligence techniques, Big Data, communication technologies, cloud computing, and system architectures have greatly contributed to making the pervasive vision a reality and even to providing additional facilities such as those related to user mobility [5,1]. Technologies such as mobile internet [8], smartphones or smartwatches and their inbuilt sensing devices, like heart rate sensors, provide more opportunities to adopt technology in pervasive healthcare applications [5], while the availability of massive data sources and datasets have also helped to take advantage of the information generated and its fusion.

The technique for handling multiple data sources is known as *data or information fusion* [5] and refers to the process of combining different data sources for using the combined information in a particular application [10]. Almost every information system now incorporates some level of data fusion as it can extract knowledge from raw data and improve data output quality [5]. This explains why it has been extensively used in pervasive healthcare applications [8,11–14]. However, poor implementation of data fusion hinders many other key data processes, including data analytics, for taking appropriate actions and offering an appropriate support to users and the needs of the environment. Despite this, data fusion is often taken for granted and its implementation is delegated to low-level programmers or database administrators [10].

Several issues make data fusion a challenging task. Most of its unsolved issues and challenges are related to data or data source quality, the data fusion process itself and its evaluation [15]. Amongst the different aspects of data fusion quality, *accuracy* is the most difficult to address [10]. Information systems in general have evolved and improved their efficiency to collect, process, store, analyse, and disseminate the enormous amount of heterogeneous data generated thanks to the adoption of approaches such as data fabric architectures [16]. Bearing in mind the recent shift from data-centric to data-driven approaches, the system architecture acquires a key role in addressing the above-mentioned challenges. However, designing a unique and generalized engineering framework has become a very complex task because of the constantly emerging problems regarding the context, quantity and quality of data, information, and knowledge. Different issues have also been identified that may impact the development of such frameworks, such as automated methods of extracting meaning from information; the selection of algorithms and techniques; the assessment of information and the evaluation of information fusion systems in an automatic and standardized manner, amongst others [15]. In this context, the aim of this work was therefore to develop a holistic framework to improve data fusion in pervasive systems to address the issues identified.

The key contribution of this work is mainly the holistic data fusion framework with which to design the system architecture, the data fusion approach and the data fusion evaluation as part of the system under development. This framework includes two dimensions:

- a *process for guiding the design* of the system architecture, known as EX-DLC, focusing on data management. This has been defined as an extension of the process described in [17] that integrates aspects of data fabric architectures [18] to deal with the management of heterogeneous data collected from different channels and sources. It also integrates aspects of Digital Twins (DT) [19] as the core to tackle the relevant challenge of information representation. EX-DLC now enhances that proposal, including specific aspects and techniques, from the framework described by Kokar et al. [28] and the process known as the *Entity Based Data Fusion (EBDF) process* [10]. We also analyse the way in which some of the properties associated with DT defined by Minerva et al. [19] are exploited by the data management process to facilitate the representativeness of the information and conduct specific fusion tasks.
- a *process for the evaluation* of data fusion systems based on ISO/IEC 25040 international standards [20], ISO/IEC 25012 [21], and ISO/IEC 25024 [61]. This process can be applied systematically and comprehensively to reduce errors and consequently the risks involved in the data fusion process, and to ensure the quality of the data fusion tasks performed by the system [10]. It also considers guidelines for designing the architecture of the evaluation subsystems that perform the evaluation automatically in runtime as part of the system at hand.

The work also describes a case study related to the healthcare domain to show the applicability of the proposal. This domain was selected due to its relevance to society and because healthcare applications are considered high-risk applications in which the accuracy of the fusion must be very high [10]. A pervasive healthcare data fusion system, intended mainly to monitor and prevent the propagation of COVID-19 in nursing homes, was designed and implemented applying the proposed framework. Although a smart and pervasive healthcare environment could become really complex, a basic prototype is presented here for the sake of simplicity. In this prototype, data is collected from multiple sensors to monitor different entities in the real world, i.e. users, staff, and nursing facilities. Actions are taken based on the inferences obtained from the modelled input data. The standardized evaluation of the accuracy and completeness of the data fusion tasks performed by the system is carried out automatically in runtime by specific evaluation components integrated in the data fusion system as part of an additional subsystem.

The document is structured as follows. Section 2 summarizes some of the background regarding the basic principles of Data Fabric architectures and introduces DT and its main characteristics. Section 3 includes the most relevant related work on data fusion and the identified gaps in the existing literature. In Section 4, the different dimensions of the data fusion framework proposed is described: a data management process and a fusion evaluation process. Section 5 describes a case study as an example of how the proposal has been used to develop a system, describing its main features and the deployment of its data management and data fusion evaluation subsystems on a cloud platform. The specification and design of the evaluation plan for the system developed are explained in Section 5.3, along with the automatic execution of the evaluation in runtime and the satisfactory results and conclusions. Finally, Section 6 details the conclusions drawn and our future work.

## 2. Background

The evolution of healthcare services is generating a huge amount of data in smart and pervasive healthcare ecosystems from different sources and subsystems, such as real-time generated device data, electronic information systems, etc. [8]. To be useful, these data and information need to be fused and contextualized. The resulting new knowledge should have the appropriate format and quality to be analysed and used to obtain conclusions and improve or save people's lives. However, failing to fuse the patients' information can have severe, even life-threatening, implications and explains why healthcare data fusion applications are considered high-risk applications in which fusion accuracy must be very high [10].

Processing all the data required by healthcare applications usually involves the tasks outlined in Fig. 1, including: data collection and transmission; data integration encompassing data cleaning and fusion; and data storage and analysis [8]. This type of process combining different data integration and storage techniques without restriction to specific architecture archetypes led to the concept of *Data Fabric* [18] that offers important advantages for data processing. However, data fabric architectures that use data lakes show certain issues regarding the contextualization, representation, and modelling of the data, which, together, are also an important data fusion requirement. Digital Twins (DT) can address these challenges by unifying and contextualizing the data obtained from physical space by creating virtual models of the related entities.

Data fabric and DT can be used to address certain data fusion issues, although other open issues also still need to be tackled. The lack of a holistic framework that clearly identifies a data fusion model, the appropriate data fusion techniques to adopt and a systematic and standardized data fusion evaluation process are especially important as part of the holistic framework that can be automatically carried out in runtime as an integral part of the data fusion system. In the following Sections, the basic aspects of Data Fabric and Digital Twins are described, as both approaches are the main foundations of this proposal. Section 3 then provides a summary of the open issues that led to our proposal.

### 2.1. Data fabric

According to Gartner [16], modern data management systems must be able to collect, integrate and deliver data to and from multiple sources and locations for a range of use cases. Data Fabric architecture can both integrate data and guide in what to add and improve. It can also address the extreme levels of diversity, distribution, scale and complexity in data assets that add tremendous complexity to the overall data integration and data management design. It is expected that by 2024 *Data Fabric-based* deployments will greatly improve the efficiency of data use while considerably reducing human-driven data management tasks.

Data Fabric [18] can be seen as a design concept for attaining reusable and augmented data integration services, called *data pipelines* [37], and semantics for flexible and integrated data delivery. It refers to a unified data management architecture and the set of capabilities that provide consistent functionalities to conveniently connect data endpoints and enhance end-to-end data management activities. It does not promote specific pipeline steps or implementation paradigms [18], although it usually employs *data lakes* to store data without modifying them or having to first structure them, to solve certain Big-Data challenges, such as those related to data silos [38], amongst others. Data Fabric has been used as an effective method of data management in several fields, including healthcare and systems of different types on different cloud computing platforms [35,39]. As discussed in Section 3, data fusion processes may be used in certain Data Fabric steps to extract higher-level information and to improve the reliability and reduce the uncertainty of the data or information obtained from multiple sources to improve its quality. However, *data lakes* by themselves cannot provide the extra content, such as structured information and new insights, i.e. the context required to turn data into the meaningful information needed to improve business operations [40]. To solve some of the problems aforementioned, Digital Twins (DT) is presented as an innovative solution because DT modelling capability can be seen as a form of

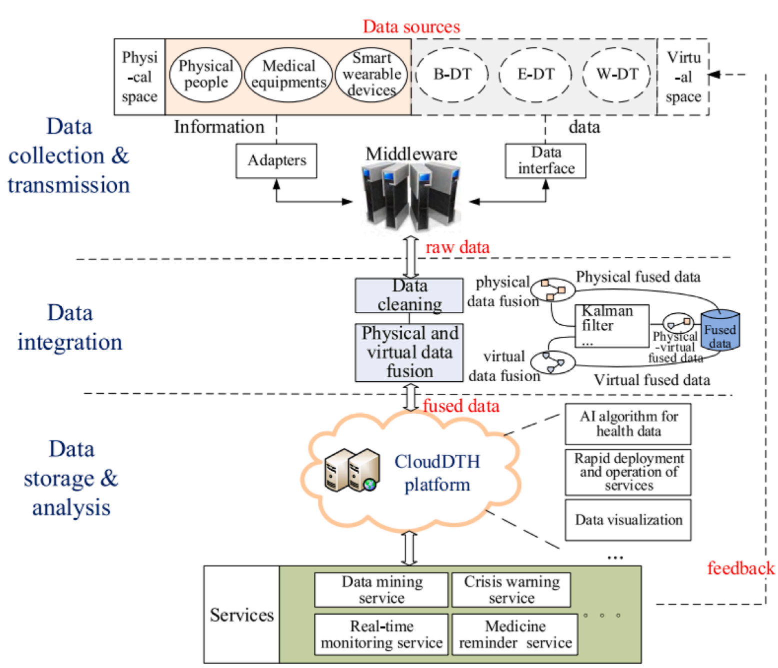



**Fig. 1.** Cloud healthcare system framework (CloudDTH) main data processing tasks (extracted from [8]).

data fusion. Some examples of Data Fabric architectures that integrate Digital Twins can be found in [41,8], while examples of adopting DT in the healthcare domain can be found in [8,42,42]. Although these works include descriptions of the system architecture, they do not provide a framework with the rationale for guiding its design.

### 2.2. Digital twins

A Digital Twin (DT) [19] can be seen as a complete software representation of an entity (object, process, or person) whose main components are physical space, digital or virtual space, and information processing that connects them bidirectionally (see Fig. 2). DT facilitates the convergence of physical and the virtual spaces. A DT must be able to simulate, monitor, regulate and control the state of the physical space and its processes [43]. It emphasizes and contextualizes the received data by creating real-time virtual representations of physical systems, i.e. high-fidelity models [43] that are multi-physical and multi-scale [8]. DT thus combine data from multiple sources in a single place and unifies and contextualize such data [40]. Large cross-domain applications could benefit from DT capabilities for accurately representing a large aggregation of objects and transforming them into services [19].

Minerva et al. [19] define the different properties that a DT must satisfy, some of which can be used to support certain data processing capabilities, as described below:

- Representativeness and Contextualization: virtual models of entities will mimic the status and features of the real-world entities that are relevant to the context of use. Such status and features will depend on the specific location and moment in time of the entities in the real world.
- Reflection: real-world entities will be timely and univocally represented using the values of the attributes, status and even behaviour of its virtual models.
- Composability: virtual models of entities can be grouped into a composed model according to the relations of the composition amongst the corresponding entities in the real world and whether grouping these virtual models offers advantages to satisfy the requirements of the use case.
- Entanglement: virtual models of entities must receive in real-time, or close to real-time, the information that represents the entities in the real world to make this information available to other applications and services. It should be mentioned that this entanglement should ideally be strong, i.e. the communication between entities and virtual models should be bidirectional and in real-time.
- Memorization: since DTs encompass real-world entities and their virtual models, meaningful past and present data about such entities, as well as the context of when and where such data originated, will be stored for their later analysis.
- Predictability: a virtual model of a real-world entity may be used to simulate its behaviour and interaction with other entities to determine the outcomes in a likely future or context.

DT's modelling capability resembles certain aspects discussed in Section 3, such as entity-based data fusion, feature-level data fusion or the multi-modelling approach, and thus can be exploited for fusing data to extract higher level information. Since the final purpose of data fusion is to obtain high-level information to obtain better conclusions, data fusion performed by DT enables the modelling and representation of high-fidelity physical entities to achieve this goal.

DT also pose certain challenges that should be considered. The most important, from the data fusion point of view, is the need to improve modelling accuracy in a standardized manner [45]. Moreover, data are generally not fully trustworthy, and the data required for modelling are not always available or not necessarily available at the right time [19], being necessary to generate synthetic data through simulation [46]. Another important challenge is related to the DT architecture and its components: the modularization design principle needs to be explored to improve modelling efficiency [47].

## 3. Related work

Data fusion is a multidisciplinary research area borrowing ideas from many diverse fields, such as signal processing, information theory, statistical estimation and inference, and artificial intelligence [22]. Many definitions for data fusion, also called *information fusion* or *data integration*, exist in the literature [4,22,13,23–25]. Data fusion can be defined as "the study of efficient methods for automatically or semi-automatically transforming information from different sources and different points in time into a representation that provides effective support for human or automated decision making" [23,24].

Data fusion extracts knowledge from raw data and improves data output quality [5]. It could also encompass the amalgamation of (i) original data to produce an output, and (ii) both original and processed data to construct the more useful outputs required for decision-making procedures and control-related activities. Data fusion can also be used to perform more complex feature-based and decision-based amalgamations of different types of input data to produce a numerical output, a feature output, or a higher-level decision [25]. This explains why some authors use the term *data fusion* when data are obtained directly from sensors without any processing and use the term *information fusion* when data are processed [15].

Data fusion offers meaningful advantages in handling heterogeneous data and information [15] to achieve the following goals: (i) improve the reliability (accuracy and completeness) of the data or information [15,5], (ii) reduce uncertainty, (iii) increase information quality [15,25] when information is obtained from multiple sources [15], and (iv) extracting higher level information [5]. In the following, the work related to data fusion is further analysed, focusing on classification frameworks, techniques and methods, data fusion evaluation and the main data fusion challenges are summarized.

### 3.1. Data fusion classification and models

Different surveys, such as [22,15], analyse and classify existing data

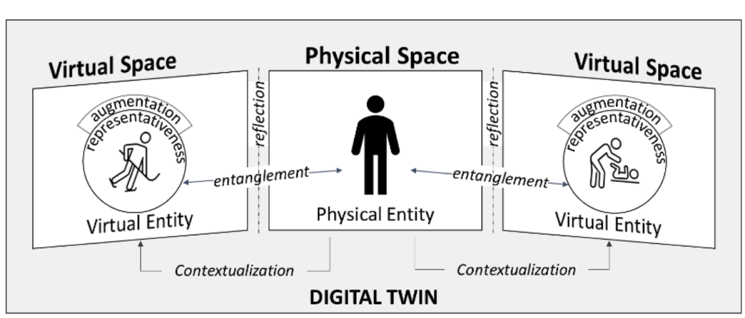



**Fig. 2.** Digital Twins: physical entity and virtual entities, and some common properties defined by Minerva et al. [19] (extracted from [44]).

fusion reference models and frameworks. Both surveys identify the JDL model [26] as one of the most widely used data fusion models that focuses on the abstraction level of the data manipulated rather than on their processing, although it is somewhat restrictive and especially tuned to military applications.

A recent literature review [27] analyses the existing data fusion models for multi-sensor fusion, i.e. when different channels are used to facilitate multi-modality and multi-location. This review considers three different categories, Data-level fusion, Feature-level fusion and Decision-level fusion, as depicted in Fig. 3. The first focuses on fusing information from different *homogeneous sources* to improve the quality of the output. When *heterogenous sources* are to be fused, Feature-level fusion or Decision level fusion are used. The former creates a higher dimensional feature vector from the different sources, i.e. then used for classification or pattern recognition. The latter fuses data from heterogeneous sensors to make a final decision for the input for the next steps in the system. A well-known framework for multi-sensor fusion was proposed presented by Kokar et al. [28], which was defined to support all types of multi-source fusion, including data fusion, feature fusion, decision fusion, and fusion of relational information with a measurable and verifiable performance.

Khaleghi et al. [22] highlight the fact that research on high-level fusion tasks and methodologies are attracting the attention of the community, as the requirements for low-level fusion are already satisfied by the existing proposals. The Entity Based Data Fusion (EBDF) process [10] is a proposal for high-level multi-sensor fusion that integrates information on the same real-world entity from different sources when high accuracy is required. As can be seen in Fig. 4 (left), EBDF entails two steps, entity resolution (ER), to determine whether two records are referencing the same entity or different entities, and data rationalization (DR) to extract and reconcile conflicting or incomplete information being prepared for creating the final *information product* related to an entity. An information product is a set of data or a piece of information that represents an entity. Regarding the first step, even using a highly parallel and high-speed processing system, the ER process could take a long time to execute when many data comparisons are needed, so that ER is usually performed on subsets of the source data called *blocks*. The process for creating these blocks is called *blocking*. The ER process only compares entity references within the same block to reduce the number of comparisons; the smaller the blocks the faster the ER process will execute. This blocking process is usually executed before the ER process and can be considered as another step. DR may be both the final step of the production of the information product and a precursor step for further processing. Healthcare is one of the domains in which this proposal is clearly an advantage in avoiding life-threatening situations, such as fusing information from different patients.

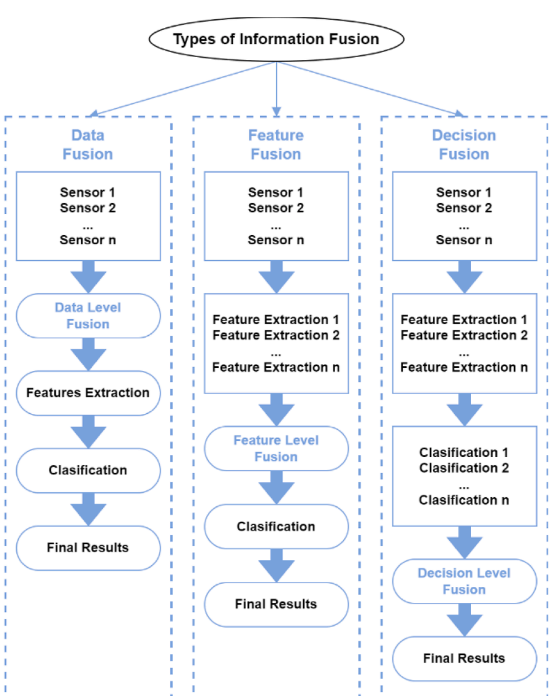



**Fig. 3.** Core categories of most common abstraction level-based (low-level) information fusion models (adapted from [22]).

EBDF applies data fusion techniques at different points of the data cycle to create the final information product that represents an entity. It also identifies errors that may arise from the data fusion process and describes alternatives for addressing them. It can be considered a fair and comprehensive data fusion framework since it entails i) a d*ata fusion process*, the EBDF itself, as well as ii) a *data quality management process* (DQMP) focused on data accuracy, which is the most difficult data quality dimension to achieve. Despite being a powerful proposal, it still has certain weaknesses that may hinder its use, the most important being (a) partial satisfaction of data fusion aspects and requirements, since EBDF only considers two fusion steps apart from the optional blocking, and (b) the assessment of a single quality criteria, accuracy, as part of (c) an evaluation process that is not sufficiently detailed.

The aforementioned frameworks and proposals focus on multi-sensor fusion. However, as indicated in [25], fusion may also be conducted by exploiting other sources such as forecasting or simulation, or even using other models that have different structures or inputs. The main reason behind these approaches is that no single model can perfectly satisfy all the demands of all the stages, phases and mechanisms of the use case being developed. It is therefore claimed in [25] that a *multi-model approach is the only way to develop a final product that comprehensively and accurately supports the information representation and meets the expected requirements, removing or mitigating the errors caused by a single-model approach*. Although there is a wide variety of data fusion models to build data fusion systems, general data fusion frameworks, functional models and methodologies must still be developed and/or enhanced [15].

### 3.2. Data fusion techniques and methods

According to Becerra et al. [15], once the architecture of a data fusion system has been designed, the appropriate data fusion techniques and methods to be used must be selected according to the task to be done and the system to be developed. Different publications, such as [5,15,25,27,10], identify the different data fusion techniques and methods that can be used. Abrahart and See [25] state that the most popular techniques for data fusion include low-level signal processing, traditional statistical methodologies, decision-making techniques and artificial intelligence technologies. Lau et al. [5] describe two groups of data fusion techniques, according to the different information enrichment obtained after data fusion. These groups are as follows:

- common data fusion techniques such as data association, state estimation, and decision fusion. These techniques are used to fuse lower-level information to generate identical level of information.
- techniques associated with data mining such as classification, prediction or regression, unsupervised Machine Learning, dimension reduction, statistical inference and analytics, and visualization. These techniques are used when simple input data from multiple sources are fused to generate higher level information enrichment.

Qiu et al. [27] identify similar techniques but the authors group them according to the abstraction level as Data-level fusion, *f*eature-level and decision-level fusion techniques. Qiu et al. [27] also state that different data fusion techniques are used for fusing features extracted from homogeneous and heterogeneous sensors, depending on the purpose of the fusion: (i) to reduce errors using methods based on probability and

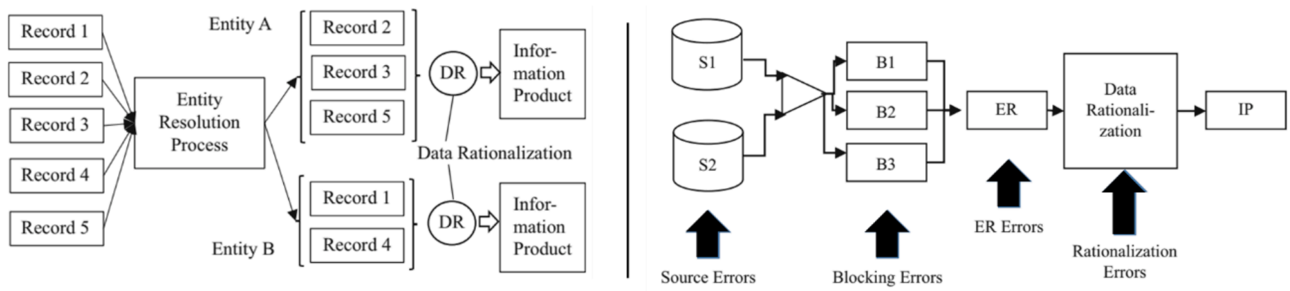



**Fig. 4.** (Left) Two steps of the Entity-Based Data Fusion (EBDF) process: entity resolution (ER) and data rationalization (DR). (Right) Points in the EBDF process where errors may happen (adapted from [10]). S: Source data; B: Block, a subset of source data used to accelerate the ER subprocess execution.

statistics;(ii) combine data to transform them into higher level data via machine learning algorithms; and (iii) solve space and time-dependant problems using automatic feature representation based on deep learning. Becerra et al. [15] state that data fusion techniques and methods can be grouped according to the level of the process they are applied to as: (i) sensor level, (ii) feature level, and (iii) score level. They also claim that these techniques and algorithms can be grouped according to the specific task to be performed, as (i) association, (ii) state estimation, and (iii) decision fusion. These techniques are used mainly in tracking processes.

Talbur et al. [10] consider that most data fusion systems currently use one or two types of the following matching strategies: (i) deterministic matching based on "if-then" logic with Boolean operators "and/or" to make their decisions; (ii) probabilistic matching based on a model implementing a scoring method; or (iii) matching based on machine learning. The earliest data fusion systems used Boolean rules because they are easy to construct, explain and maintain, e.g. alignment is fairly straightforward when using "if-then" style rules. However, the Boolean rule strategy operates at the attribute level of the data, which can be considered its major weakness.

As can be seen, there is a plethora of different data fusion alternatives, although it is still necessary to develop a holistic framework that guides the development of fusion systems. *Data fusion implementation should attempt to capture all the meaningful aspects of the input data to be fused and consider the uncertain relationship between this data and the expected result of the data fusion process* [25]. These aspects should be considered when selecting the techniques to adopt for every data fusion stage in the data fusion process.

### 3.3. Data fusion evaluation

Like any other software system, the assessment of data fusion systems, closely related to the Information Quality (IQ) assessment [22], is based on certain quality criteria that they should satisfy. These criteria are selected according to the application domain and measured using specific metrics [15]. Different classifications of IQ criteria have been defined, the best known being the ISO/IEC 25012 standard [21], which defines the quality criteria that may be used to assess and improve these systems. The need to properly identify and assess these IQ criteria has led to some general data fusion frameworks to integrate them as an integral part of their definition to enhance their outcomes [15].

Evaluating the performance of the data fusion along with the reliability is considered one the biggest problems for data fusion systems [15], so that IQ has been introduced in the field of information fusion systems. Unfortunately, IQ has not been widely explored in the data fusion process due to the complexity of its assessment and is one of the most complex stages in information processing. As there are no standard and uniform metrics or comprehensive evaluation methods for information fusion systems, developing an IQ assessment for data fusion systems is a new and highly complex task.

Despite the relevance of evaluation for data fusion systems, there are a limited number of proposals in this area. Some efforts have been made to evaluate the quality of the information generated by data fusion systems, such as [28,25,32]. However, most of these works simply identify certain criteria, metrics and measures without offering many details or precisely describing the tasks to be carried out, which may hinder their systematic use. Moreover, most evaluations are conducted considering information systems as black boxes, which turns the description of the quality assessment into a complex and difficult task.

Some efforts have been made to improve the definitions of frameworks and methodologies for evaluating the quality of the information generated by data fusion systems. For instance, a set of guidelines has been collected in [29], such as the use of standard test collections and results, the exploitation of standard evaluation metrics, comparison with other fusion algorithms, etc. It is claimed that these guidelines should be considered for defining these frameworks to avoid the usual drawbacks of existing strategies, and despite these efforts, the existing frameworks still unfortunately have the aforementioned limitations.

As the performance of a data fusion system depends mainly on two aspects (i) the quality of the input data, and (ii) the quality of the fusion method, its evaluation must also focus on these two aspects. Both must be jointly considered because a good IQ of the input data does not necessarily ensure the high fusion process IQ [15]. The quality of the data fusion methods is usually evaluated in terms of accuracy [30,31], data fusion performance [32,33], effectiveness [34,31], consistency [32], data fusion efficiency [34], and usefulness [31]. Accuracy is the most frequently evaluated quality attribute [15] and the most difficult to assess [6] because it can affect not only the source information but also the information fused. Different approaches, such as different statistical methods or techniques based on comparisons with different reference datasets have been exploited for its evaluation. It should be highlighted that accuracy is paramount in high-risk systems such as pervasive healthcare systems [5,10], which explains why it attracts the community's attention.

The EBDF proposal [10] is a framework that offers a Data Quality Management Process (DQMP) to reduce errors and also the risks associated with data fusion. DQMP considers the *verification of accuracy,* i) by the original source of information, which is often impractical because of the time and expense required, and ii) by comparing the information collected to a reference source known to be accurate, which may not exist or may not be ideal for the domain of interest. The paper claims that, due to the difficulties and problems related to verification, most data fusion processes normally rely on *validation*, which refers to the use of rules, usually Boolean, to check for outlier values or unexpected conditions in the source information. The failure of a validation rule indicates that the source information is inaccurate. Rules may test the quality of the values of individual fields for completeness, conformity to a required format, timeliness and other relevant data quality dimensions. Other rules may test the relationships between data items and, in relational models, to determine whether the relationships are present and correct. However, it should be noted that a source information passing the complete set of validation rules is not necessarily accurate, so that validation rules are usually considered as *soft* [10] because they impose less strict conditions than the original data fusion rules, i.e. a near match or partial match.

Some evaluation processes for the assessment of IQ guided by frameworks and methodologies, for instance the one defined in [32], rely on the use of evaluation software tools and testbeds [22,36]. For example, the Boeing Fusion Performance Analysis (FPA) tool [35] is a software that enables the computation of technical performance measures (TPM). It is typically executed manually to carry out a post-run analysis of the input data, provided as a set of files. Although it is claimed that FPA is platform-independent and can be used for any fusion system, it is actually configured and used to evaluate the data fusion of the Boeing tracking system. The multisensor-multitarget tracking testbed [36] is another tool for the evaluation of large-scale distributed fusion systems for the surveillance of moving objects that is capable of handling multiple, heterogeneous sensors in a hierarchical architecture. The testbed is a scenario generator that can generate simulated data for multiple sensors as well as a tracker framework that integrates different tracking algorithms. Once the tracking systems are connected to the testbed, this automatically generates the different scenarios and evaluates the accuracy, completeness, timeliness, ambiguity, and continuity in real-time mode. This tool offers an interface to human operators to establish certain manual configurations. The main disadvantages of these tools are that both rely to a considerable extent on human intervention and cannot be used to assess the data fusion quality of applications in other domains.

Several publications explicitly identify the different issues and challenges related to evaluating data fusion and how to properly measure an information systems' performance. For example, in [22] it is stated that there is no standard and well-established evaluation framework to assess the performance of data fusion algorithms. They also argue that data fusion performance evaluation is frequently done in simulated or unrealistic test environments substantially different from real-use cases and are frequently based on idealized assumption(s), which makes it difficult to predict how a proposal would perform in real-life applications. Some of the major, and usually ignored, problems of fusion evaluation identified in [22] are, (i) that existing proposals do not use a ground truth, even though many performance measures require this knowledge, (ii) performance has different, possibly conflicting, dimensions that are difficult to capture in one comprehensive and unified measure, (iii) performance measures might need to be adapted over time or according to the given context, further standardized measures of performance applicable to the practical evaluation of data fusion systems being necessary. Some other open issues regarding IQ monitoring and controlling are the following [15]: (i) the need for an ontology of IQ criteria, (ii) the definition a unified quality metric based on IQ criteria, (iii) the definition of proposals for compensating a low IQ and evaluating usability and IQ quality, (iv) the identification of the effect of subjectivity on IQ and dependencies on the context, (v) the quality assessment of the system changes, (vi) the adequate selection of quality criteria, and (vii) the traceability of IQ assessment throughout the process stages.

### 3.4. Data fusion issues and challenges

As Becerra et al. have stated [15], information systems have evolved and improved their efficiency to collect, process, store, analyse, and disseminate the enormous amount of heterogeneous data generated. Nevertheless, designing a unique and generalized engineering framework for these systems has become a very complex task because of the constantly emerging problems regarding the context, quantity and quality of data, information, and knowledge. Most of the unsolved issues and challenges in data fusion are related to the quality of the data or data sources, the data fusion process and evaluating the data fusion. The following data challenges are identified in [5]:

- Data quality. Data source quality directly determines the quality of the fusion output. The specific data quality aspects to improve are *data sensing coverage* and *data sensing longevity*. Insufficient data coverage generates an unrepresentative result and often implies that more sensors need to be installed to expand the sensing coverage. Data sensing longevity refers to long-term data collection, which depends on the capacity of the physical sensors to run independently without the need for external power sources.
- Data representation. A wide diversity of data sources frequently results in the incompatibility of data formats, especially when there is no standard.
- Data fusion techniques. Extracting knowledge frequently involves the use of data mining techniques to fuse different data sources. Low level data fusion techniques have been well explored but current research focuses on machine learning due to its ability to handle high-dimensional data.

As described in [22], most data fusion issues arise from the data to be fused as they may have outliers, spurious, conflicting and associated data. Other issues arise from the specific nature of the application's environment. It is also claimed that the input data to the fusion system may be imperfect, correlated, inconsistent and/or be in disparate forms. This work also emphasizes that inherent data imperfection is the most challenging problem of data fusion systems and suggest the following strategies to address it:

- exploit redundant data to alleviate effects such as imprecision and noise in the measurements and ambiguities and inconsistencies present in the environment.
- treat highly conflicting data carefully to avoid producing counter-intuitive results.

Scalability challenges are another issue related to data sources when exploiting wireless sensor networks. It must first be decided how processing should be conducted, since a centralized approach implies a large communication burden. While a decentralized approach alleviates this problem as each sensor processes the collected data locally, it also provides additional complexity for the management and development of distributed solutions. Wireless sensor networks may also cause potential collisions and transmissions of redundant data. As indicated in [22], many of these problems have been identified and investigated but no single data fusion approach has addressed all of them.

To sum up, a process for evaluating the quality of the information generated by data fusion systems should satisfy the following aspects as described in Table 1:

## 4. Data fabric and digital twins for an enhanced data fusion holistic framework

As mentioned in Section 3, a unique and holistic engineering framework is required for information fusion systems. The holistic framework should ideally encompass two main dimensions: (i) a data management process able to satisfy all the requirements of the stages and mechanisms of the pervasive computing system being developed, and (ii) a quality *evaluation* process of data fusion that considers the quality criteria and metrics selected for the system under development. In other words, the data management process should support a comprehensive and accurate representation of the information and offer a set of appropriate data fusion techniques which are selectable after designing the system architecture according to the tasks to be performed. The *quality* evaluation process should carefully describe the tasks to be done to facilitate its systematic use and be useful to detect and reduce errors and so also the risks associated with the data fusion stages, which was our aim in the present work. It should be noted that each dimension of this Enhanced X-DLC (EX-DLC) framework supports the characteristics identified in Section 3, especially those that required

**Table 1**
Evaluation aspects to be satisfied by a quality evaluating process that evaluates the quality of the information generated by data fusion systems.

| Identifier | Evaluation aspect |
|---|---|
| EA1 | Define quality in a manner that all stakeholders, and especially users, can understand. |
| EA2 | Offer enough details of the different activities and carefully describe the tasks required to allow its systematic use. |
| EA3 | Allow the identification of certain standardized information quality criteria, metrics and measures that should be selected depending on the application domains. |
| EA4 | Include accuracy assessment as mandatory, since this quality criterium is paramount in data fusion systems, especially in high-risk systems such as data fusion systems in the healthcare domain. and is also the most difficult quality attribute to evaluate. |
| EA5 | Cover the evaluation of both (i) the quality of the input data, and (ii) quality of the fusion method, since good input data information quality does not necessarily ensure good information quality of the fusion process. |
| EA6 | Support the evaluation using different verification possibilities (such as comparison with the original information source or with a reference source known to be accurate) and validation (e.g. Boolean rules, statistical methods, machine learning and AI algorithms) according to requirements and restrictions. |
| EA7 | Support data fusion evaluation automatically on runtime. |
| EA8 | Support data fusion evaluation as part of the actual system, not in a separate testing environment. |

the use of Digital Twins (DT). The DT properties defined by Minerva et al. [19] used by EX-DLC, i.e. *representativeness, contextualization, reflection, composability, entanglement, memorization*, and *predictability*, will also be emphasized in the following sections. The proposed holistic framework integrates and adapts several appropriate aspects, including some from other proposals, to respond to the issues identified. The differences between our proposal and others are summarized in Table 2 in terms of the stages of their underlying data management cycle.

### *4.1. Data management process based on data fabric and digital twins*

The goal of the process described here is to identify the features that need to be supported by a pervasive system to obtain data from the physical space, processing it and drawing conclusions for the virtual space to act over the physical space. Data fusion is required to conduct the data processing. The major data fusion objectives of this proposal are related to multi-source information processing, i.e. 1) to process the data related to all the attributes required for the fusion, 2) to increase data completeness, and 3) to extract higher-level information for making better high-level decisions. These decisions are usually related to entities that are generally users and other elements in the environment, so that fusing multi-sensor data to model and represent physical entities in a computing system can be considered paramount for data fusion. The need to represent physical entities also motivated the exploitation of Digital Twins.

In addition to the data management process of healthcare data fusion applications supported by the CloudDTH architecture [8](see Section 2), other frameworks can be used to design IoT-based systems, such as D-CPSS [50], which guides the design of the system architecture according to a data process to facilitate the integration of the large amounts of data to be processed by these systems. Both processes decide the stages to be conducted, since the data are generated until they are consumed or retired, including one or more data fusion stages. Many systems supporting these data processes are deployed on cloud computing platforms [8,51] and are also developed using the native services offered by the cloud platforms. Public cloud platforms, such as Google Cloud [52], AWS [53], and Microsoft Azure [54] offer profuse details of the data processes integrated in reference architectures for IoT-based systems that carry out some type of data fusion tasks at some point. The challenges related to efficient data management are known to be shared with other types of systems with similar characteristics, namely intelligent, context-aware, or adaptive systems [55]. For example, the Data Pipeline Model [37] incorporates Machine Learning techniques for decision-making. Other proposals for context aware systems add extra features to the process, e.g. the Context Toolkit [56] parallelizes certain stages of the process. MAPE-K [57], defined for self-adaptive systems, makes the data handled by a system available due to its shared knowledge base. Table 2 shows the data management stages supported by the analysed proposals.

**Table 2**
Comparative amongst stages of studied proposals, X-DLC and EX-DLC.

| *Proposals →* *Stages ↓* | CloudDTH Data Process | D-CPSS | Data Pipeline Model | Context Toolkit | MAPE-K | Google Cloud Data Lifecycle | Microsoft IoT Data Lifecycle | AWS Data Lifecycle Management | X-DLC | EX-DLC |
|---|---|---|---|---|---|---|---|---|---|---|
| Evaluation planning | | | | | | | | | | ✓ |
| Collection | ✓ | ✓ | ✓ | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ |
| Ingestion | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Raw data evaluation | | | | | | | | | | ✓ |
| Raw data storage | | ✓ | ✓ | | | ✓ | ✓ | ✓ | ✓ (optional) | ✓ |
| Pre-processing | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Pre-processed data evaluation | | | | | | | | | | ✓ |
| Pre-processed data storage | | | ✓ | | | | | | ✓ | ✓ |
| Modelling / representation / simulation | ✓ | ✓ | | ✓ | ✓ | | ✓ | | ✓ | ✓ |
| Modelled data evaluation | | | | | | | | | | ✓ |
| Model history | ✓ | | | ✓ | ✓ | | ✓ | | ✓ | ✓ |
| Analysis | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Inferred data evaluation | | | | ✓ | | | | | | ✓ |
| Inferences history | ✓ | | | ✓ | ✓ | | ✓ | ✓ | ✓ | ✓ |
| Visualization / actions (planning and execution) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Archive or retire | | | | | | | | ✓ | ✓ (optional) | ✓ (optional) |

A data process called *X-DLC,* based on the analysis of the stages of these proposals was defined in [17] inspired by the Data Fabric approach. As can be seen in Table 2, X-DLC includes most of the common stages, i.e. collection, ingestion, pre-processing, analysis, and visualization and/or actions, as well as others not quite so common but also identified by some of the data processes analysed. All the X-DLC stages were defined to be highly cohesive and offer a higher degree of Separation of Concerns than other proposals facilitating their traceability to the components in the system architecture. However, the X-DLC stages are not fully customized to a data fusion process and their data processing tasks (especially those for data fusion) are not described in detail. These problems led us to define Enhanced X-DLC (EX-DLC), which integrates features from other previously proposed data fusion models, including the well-known EBDF process and Kokar's model (see Section 3).

Data management stages supported by EX-DLC are also identified in Table 2. As EX-DLC must be traced to the architecture of the system to be developed, Fig. 5 shows these stages as system components and how they run through time. Executing the EX-DLC stages, running from left to right, does not require human intervention, as required in the literature on data fusion. The stages aligned vertically in Fig. 5 can be run in parallel to speed up the process, e.g. the analysis of the received measured values that have been fused and modelled along with the already stored historical fused data (*Analysis*) can be run in parallel with the storage of the values received in real-time (*Model History*). Fig. 5 also shows the stages in charge of carrying out certain data fusion tasks as well as the DT properties exploited in each stage.

The transmission process, included in the Collection stage, may be defined to support data processing for better data security, although none of the data fusion proposals or ours explicitly addresses data processing in this stage. As security is not the main focus of our work, the transmission process data process is not described in the following sections. Any errors related to the physical system or sensor malfunctions could affect the quality of the collected data and would also require data fusion support. However, the data fusion in the physical system is outside the scope of this work, so that few details will be provided on this issue. Although the case study described in Section 5 to illustrate the use of the EX-DLC is related to the healthcare domain, EX-DLC can be used in other domains since its definition is based on generic proposals.

The EX-DLC stages described below also identify the DT properties exploited and the data fusion aspects considered. Frequent errors that can arise during data fusion are also identified so that they can be properly addressed when they are detected during the evaluation.

#### 4.1.1. Collection

In this stage, the data related to properties of entities relevant to the system are obtained by sensor networks in the physical space. Multiple sensors and sources can be used to measure the same properties of a particular entity that may be a thing, person, place or process. The data collected in this stage are transmitted to the computing system that manages the virtual space (cyber-system), in which most of the data fusion processing occurs. It should be highlighted that the security of transmitted data should be guaranteed, so that a type of data processing such as encryption can be used [56,58]. According to [56], another appropriate data transformation or data fusion system can also be implemented before the transmission, should it be needed by the system under development, e.g. to detect physical errors or sensor malfunction and to correct the resulting erroneous information. Data fusion tasks carried out at this stage are outside the scope of this work, since the focus is on the virtual system and this subject will be addressed in future work.

Certain errors may occur [10] in relation to the source information. Data quality defects may be in either (i) inconsistent formatting, (ii) erroneous information difficult to detect and correct, and (iii) challenges resulting from the use of semi-structured and unstructured sources, such as social media. These errors can be eliminated or reduced during pre-processing stage (see Section 4.1.4).

#### 4.1.2. Ingestion

The cyber-system receives the entities' data collected through a component that acts as a gateway known as ingestion that routes messages from the devices in the physical space to the components implemented in the next stages and can also be used to filter and discard messages that include values outside the predefined valid ranges supported by the sensors. This prevents the cyber-system from receiving and processing erroneous data, e.g. due to sensor malfunctions. However, since this aspect is closely related to the physical system, it is outside the scope of the present study.

Ingestion is partially supported by the entanglement DT property, as it is related to the communication between the physical and virtual spaces and the reception of data in real-time. This property will be further described in the context of the *Modelling/Representation/Simulation* stage.

Ingestion in EX-DLC is based on the blocking strategy defined by the EBDF data fusion process [10] to facilitate the management of data belonging to the different entities of the system under development. When different types of entities are modelled, a different block is created for each type, after which filtering-based routing is conducted to determine the appropriate block in which to allocate the data received

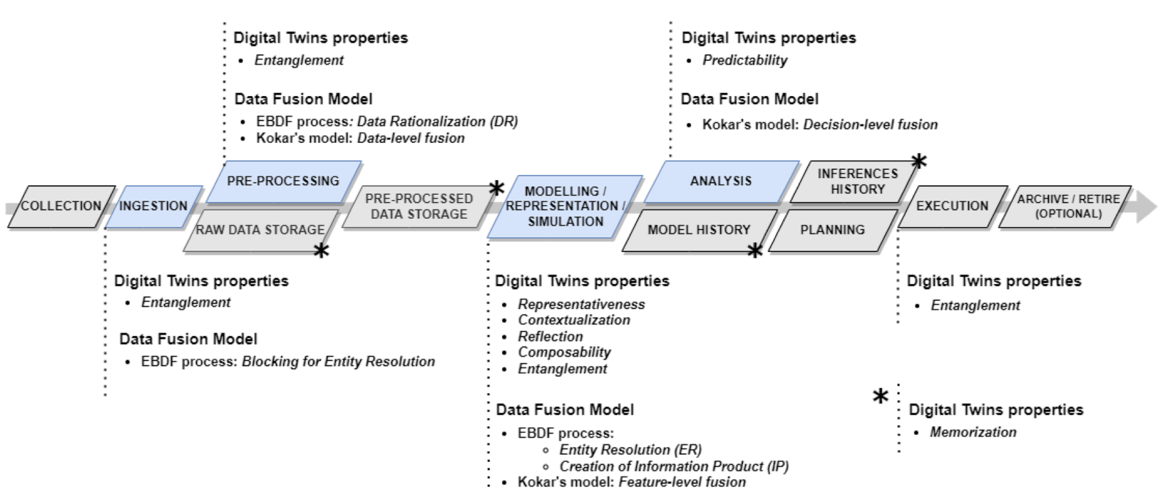



**Fig. 5.** EX-DLC process. Stages exploiting the memorization DT property that do not perform data fusion are identified by *.

according to their entity type. Apart from filtering, normally based on Boolean rules, other low-level or sensor level data fusion techniques such as data association, etc. can be used for data fusion in this stage implementing the blocking strategy.

The main errors that may be introduced in this stage [10] include placing various records with equivalent references in different blocks. This means that their references cannot be compared by data fusion, since it can only compare references in the same block, so that any records with equivalent references would not be linked and clustered together. Creating different blocks for the different kinds of entities helps to minimize this type of errors, as stated in Section 3.1.

#### 4.1.3. Raw data storage

The raw data received are temporarily stored in this stage. If a blocking strategy has been implemented as part of the ingestion, the data are stored in different blocks. Storage can be useful, as stated in [56], for traceability and detection problems, e.g. to detect transmission or ingestion problems. This stage is partially supported by the memorization DT property, which refers to the storage of meaningful past data used to create virtual models of physical entities and its generation context, as described in Section 2.2.

#### 4.1.4. Pre-processing

The data ingested into the cyber-system may be inconsistent even if they are related to the same entity. The purpose of the pre-processing stage is to reduce errors in the data received. In this stage, processes such as cleaning or transformation can be used to deal with data received in an unsuitable format in order to extract and reconcile conflicting or incomplete information, according to the application's needs. These data transformation processes are also considered as data fusion. This stage adopts aspects from the Data Rationalization (DR) stage of the EBDF data fusion process and from Kokar's model data level fusion. Low-level or sensor level data fusion techniques, such as denoising or feature extraction processes, Boolean rules, etc., are applied to the data received to obtain missing data or transform them into a suitable format. It should be highlighted that several data pre-processing stages can be carried out in sequence, each one followed by a data storage stage, according to the data fusion requirements of the system under development.

The main errors that may be introduced in this stage [10] are as follows:

- Errors in conflict resolution when two or more sources report different values for the same attribute.
- Errors in value harmonization, i.e. errors in selecting the right value for an attribute from a set of values with the same meaning but reported in different ways (e.g. by different coding schemes).

These errors can be reduced by adding appropriate sensor and measurement meta-data to the data received, as recommended in [56], which can be used to support the pre-processing tasks, e.g. sensor precision or accuracy meta-data can be considered in the first case, and the measurement unit as long with the value in the second case.

#### 4.1.5. Pre-processed data storage

The pre-processing stage's data output is temporarily stored and this stage is partially supported by the memorization DT property, which, as described in Section 2.2, refers to the storage of meaningful past data from physical entities and its generation context.

#### 4.1.6. Modelling, representation, and simulation of data

The purpose of this stage is to combine data related to an entity to obtain high-level data that represents this entity. The values of the digital model that represents or simulates the state of the physical entity, i.e. its digital twin, are updated using the data received. This is also considered a type of data fusion. Amalgamating models can be used to more completely represent the information. In EX-DLC, the modelling of entities is based on the integration of the Entity Resolution (ER) and creation of Information Product (IP) stages of the EBDF data fusion process and on the Feature level DF stage of Kokar's model. In order to combine high-level data representing an entity as a DT, feature level data fusion techniques, such as association, state estimation, simulation processes, Boolean rules, etc. are applied to the pre-processed data result of the previous stage. The challenges related to the contextualization, representation, and modelling of data is supported by the Representativeness, Contextualization, Reflection, Composability, and Entanglement DT properties detailed in Section 2.2.

The importance of the data fusion performed in this stage goes beyond the representation itself. Data from the DT will be used as the input to further analysis stages to generate high-level decisions. For example, data representing a specific person, such as body temperature and heart rate, can be analysed and used to decide whether this person could be infected by the COVID-19 virus. DT will fusion and model the information received from the previous stage by default, even if it is erroneous. Data fusion techniques, such as Boolean rules, can be used as part of the DT logic to discard or correct out-of-range values. As described below, data management and data fusion evaluation processes should be responsible for controlling and ensuring the quality of the information at different points, including the stages prior to modelling.

Of the different errors that can happen during this stage [10], the most frequent is the generation of many different records to model and describe the characteristics of the same entity. Errors on deciding whether the references of two data records should link to the same entity can also occur and reduce the accuracy of the data fusion process.

#### 4.1.7. Model history

Each update of the values of an entity's virtual model is stored in this stage for use in subsequent stages. This stage is partially supported by the memorization DT property (see Section 2.2). The data stored in this stage are used as an input for the *Analysis* stage.

#### 4.1.8. Analysis

The analysis stage analyses the digital model and the historical data from the previous stages and infers new information with a higher level of abstraction to make decisions on the entities in the physical world. Obtaining this high-level information is considered a data fusion task. This stage is based on the Decision level DF stage of Kokar's model, since a high-level decision is obtained from a set of hypotheses using the information extracted and modelled in the *Modelling/Representation/Simulation* stage. The high-level decisions are usually involved in achieving the application goals. To obtain a unique high-level decision, decision level data fusion techniques, such as statistical inference and analytics, complex inference methods based on artificial intelligence (AI) techniques like Machine Learning, Boolean rules, etc., are applied using modelled and/or historical data. The EX-DLC Analysis stage is directly supported by the Predictability DT property (see Section 2.2).

It should be noted that several unique high-level decisions can be made in this stage, according to the application goals. For example, data representing a specific person, such as body temperature and heart rate, can be analysed and used to infer whether that person could be infected by the COVID-19 virus. Similarly and simultaneously, data representing a specific facility, such as temperature and humidity, can be analysed and used to decide whether the air quality of that facility is acceptable.

Although not explicitly stated in [10], errors can also be introduced in this stage that jeopardize the accuracy of the inferences results.

#### 4.1.9. Inferences history

This stage is responsible for the storage of the inferences as historical records, exploiting the memorization DT property, which may be used in the *Analysis* stage. The DT property refers to the storage of meaningful past data of physical entities and its generation context, as described in Section 2.2.

#### 4.1.10. *Planning*

This stage identifies the actions that should be carried out according to the results of the *Analysis* stage. These actions are provided to the following stage for its execution. For instance, in the case study presented in Section 5, if it has been inferred that the distance between two people is less than 3 metres during the *Analysis* stage, then the action would be to warn these people about their proximity to each other. This information would then be forwarded to the next stage, along with the message recommending those involved to use a face masque to prevent the spread of COVID-19.

#### 4.1.11. *Execution*

The set of actions to be carried out, arranged in the *Planning* stage, are received and executed in this stage. The execution of certain actions may affect the physical environment according to the application requirements. In these cases, the execution is delegated to the appropriate actuators in the physical environment. In this proposal, this is achieved by taking advantage of the (near-)real-time bidirectional data link provided by DT. This stage is thus partially supported by the Digital Twins' property known as entanglement, related to bidirectional communication between the physical and virtual spaces (see Section 2.2).

#### 4.1.12. *Archive/retire (optional)*

This stage is responsible for storing in a different setting or discarding, as appropriate, the data stored in other stages. This is important not only for the system performance, but also for optimizing the system costs, especially in cloud-based systems. It is also optional, as the results of the data fusion carried out as part of data management do not depend on its results.

### 4.2. *Data fusion evaluation process based on international standards*

It is important to evaluate the information quality (IQ) of data fusion in analysing the performance of a data fusion system. Some proposals, such as the EBDF model, from which some aspects are incorporated in this proposal, include a data quality management process (DQMP). EBDF DQMP is focused on data accuracy, which is the most difficult data quality dimension of those to be addressed. However, EBDF has some flaws regarding this, so that our aim was to develop a comprehensive data fusion evaluation process based on palliating the DQMP's flaws and satisfying the requirements given in Table 1.

DQMP [10] outlines a process for ensuring and improving the data quality of data fusion systems that perform entity-based data fusion. It focuses on (i) evaluating a single quality criterium, accuracy, and even though most of the examples refer to applications in the healthcare domain, the applicability of the proposal was not shown by a use case. Furthermore, the (ii) quality management process is not sufficiently detailed which hinders its use in a systematic manner. To complement the DQMP and obtain a more detailed and standardized process, the international standard for Systems and software Quality Requirements and Evaluation (SQuaRE) ISO/IEC 25040 [20] was used to define this proposal due to its similarities with the DQMP process. This standard provides a detailed process description for evaluating software product quality and specifies the requirements for its application. This standard facilitates both the definition of the steps in the evaluation and identifies the information quality criteria and metrics that should be selected for different applications. Table 3 summarises the differences between the three quality processes based on the evaluation aspects considered as the ideal characteristics of a data fusion evaluation process in Table 1. It can be seen that the data fusion evaluation proposed as part of EX-DLC is the only one that satisfies all these aspects.

DQMP defines four components related to planning, control, assurance and improvement of data quality, for which the proposal vaguely enumerates some tasks to be carried out. These components and its tasks are detailed in Table 4. Most of the tasks resemble the tasks defined by ISO/IEC 25040 that are also given in Table 4 along with the equivalent tasks in both processes. As can be seen, the (i) Data Quality Planning component in the DQMP is equivalent to two tasks in ISO/IEC 25040, i.e. Establish the evaluation requirements and Specify the evaluation. The standard includes other tasks for the Design of the evaluation that has no equivalent in DQMP. The Execute evaluation activity of the standard corresponds with the components (ii) Data Quality Control and (iii) Data Quality Assurance in DQMP. Finally, the tasks defined for the activity Conclude evaluation of the standard have a similar goal to (iv) Data Quality Improvement of DQMP. Few tasks of one process have no clear equivalent to any task in the other process. The above indicates that both processes can be complementary due to their similarities, so that our proposal took the process defined by the standard as the base, since it is better documented than DQMP, while additional DQMP tasks are also considered.

**Table 3**
Summary of differences between the quality processes based on aspects specified in Table 1.

| Evaluation aspect identifier | Quality process DQMP | ISO | Evaluation process for EX-DLC |
|---|---|---|---|
| EA1 Stakeholders understanding of Quality | | ✓ | ✓ |
| EA2 Systematic use | | ✓ | ✓ |
| EA3 Standardized information | | ✓ | ✓ |
| EA4 Assessment of accuracy | ✓ | | ✓ |
| EA5 Quality evaluation of input data and fusion method | ✓ | ✓ | ✓ |
| EA6 Evaluation using verification and validation | ✓ | ✓ | ✓ |
| EA7 Automatic Evaluation | | | ✓ |
| EA8 Evaluation in a real setting | | | ✓ |

Based on the integration of the ISO/IEC 25040 and the DQMP processes, the tasks to be carried out for each activity are detailed below in greater detail than the standard to address the *EA2* evaluation aspect (see Table 1). The first three activities defined by the ISO/IEC 25040 standard (Establish the evaluation requirements, Specify the evaluation, and Design the evaluation) refers to the planning activities common to both. We therefore consider these activities as part of a general planning activity labelled Plan the evaluation as depicted in Table 4. It should be noted that the redefined process will guide the evaluation of data fusion systems and address the other requirements and challenges identified in Table 1.

#### 4.2.1. *Plan the evaluation*

The sub-activities and tasks of this activity are detailed as follows.

*4.2.1.1. Establish the evaluation requirements.* The first activity includes the following tasks:

- 1a. Establish the purpose of the evaluation. Document the reason(s) to evaluate the quality of the data fusion system. The general reasons to evaluate data fusion systems are discussed in Section 3, for example "measurement of the performance of the data fusion processes performed by the developed system".
- 1b. Obtain the software product quality requirements by interviewing the system's stakeholders. Other requirements may also be elicited from the bibliography of the application domain. These requirements must be specified by a quality model such as the ISO/IEC 25012 [21] standard, which was previously adopted for the evaluation of data fusion systems and consists of a set of data characteristics such as *accuracy, completeness, consistency* or *credibility*, amongst others. Since data fusion aims to ensure the *accuracy* and *completeness* of data and considering that *accuracy* is paramount and one of the most difficult quality attributes to assess, these two quality characteristics must always be evaluated. This facilitates addressing evaluation aspects *EA3* and *EA4* specified in Table 1. According to

**Table 4**
Equivalent tasks and activities in the EBDF Data Quality Management Process (DQMP, the ISO/IEC 25040 evaluation process, and the new data fusion evaluation process (selected task names include an identifier).

| DQMP components [59] | Tasks | | ISO/IEC 25040 evaluation process activities [20] | EX-DLC Data fusion evaluation process |
|---|---|---|---|---|
| Data quality planning | – | 1a. Establish the purpose of the evaluation | **Establish the evaluation requirements** | **Plan the evaluation** |
| | Develop and manage quality requirements | 1b. Obtain the software product quality requirements | | |
| | 1c. Identify the nature of the defects in final product that create risks | – | | |
| | – | 1d. Identify product parts to be included in the evaluation | | |
| | Develop and manage quality standards<br>Determine acceptable levels for defects rates | 1e. Define the stringency of the evaluation | | |
| | – | 2a. Select quality measures | **Specify the evaluation** | |
| | Develop and manage quality policies | 2b. Define decision criteria for quality measures | | |
| | | 2c. Define decision criteria for evaluation | | |
| – | – | 3a. Plan evaluation activities | **Design the evaluation** | |
| Data quality control | Product inspection by the established techniques of statistical process control | 4a. Make measurements | **Execute the evaluation** | **Execute the evaluation** |
| Data quality assurance | Ensure the component parts of the product fall within expected tolerances | 4b. Apply decision criteria for quality measures | | |
| | | 4c. Apply decision criteria for evaluation | | |
| Data quality improvement | Error reporting and collection | 5a. Review the evaluation results | **Conclude the evaluation** | **Conclude the evaluation** |
| | | 5b. Create the evaluation report | | |
| | Root cause analysis<br>Implement process improvements | 5c. Review quality evaluation and provide feedback to the organisation | | |
| | – | 5d. Perform disposition of evaluation data | | |

ISO/IEC 25012, *Accuracy* is defined as "the degree to which data has attributes that correctly represent the true value of the intended attribute of a concept or event in a specific context of use". It has two main aspects, *Syntactic Accuracy* and *Semantic Accuracy*, defined as the closeness of the data values to a set of values defined in a domain considered syntactically or semantically correct, respectively. *Completeness* represents the degree to which data associated with an entity have values for all the expected attributes and related entity instances in a specific context of use. In other words, it decides whether all the properties have values or if some are empty or null. The definitions of the information quality and its characteristics in the ISO/IEC 25012 can be used to address the evaluation aspect *EA1* (see Table 1).

- 1c. Identify the nature of the defects in the final product that create risks (from DQMP). In general, defects can affect (i) the input data and every (ii) fusion method executed as part of the system data management process (see Section 3.4). The data management process specified in Section 4.1 identifies the errors that can happen in each data fusion stage, i.e. *Ingestion, Pre-processing, Modelling/Representation/Simulation*; and *Analysis* as well as those in the *Collection* stage. Any other errors that can affect the operation of the system under study must also be identified.
- 1d. Identify product parts to be included in the evaluation. The components of the data fusion system to be evaluated must be identified by using the results of the previous task. Fig. 6 shows when the evaluation must be carried out for the EX-DLC process, using Boolean rules, after every data fusion stage (see Section 4.1). In other words, the data fusion evaluation will be carried out after the Ingestion stage to assess the quality of (i) the raw data received and of the (ii) filtering method used for blocking; after each Pre-processing stage, to assess the quality of the different pre-processing methods; after the Modelling/Representation/Simulation stage, to assess the quality of the data fusion methods used to model entities; and after the Analysis stage, to assess the quality of the inferences. This helps to address the *EA5* evaluation aspect given in Table 1.
- 1e. Define the stringency of the evaluation. The goal is to provide the appropriate security to the data fusion system quality for its intended use and the purpose of the evaluation. This includes the expected evaluation levels, the evaluation techniques to be applied and the evaluation results to be achieved. The expected evaluation levels and results are defined according to the guidelines in ISO/IEC 25012. At least two acceptance levels should be defined for the evaluation results (see Table 7): *unacceptable* and *acceptable. Acceptable* is the minimum satisfactory level. The minimum quality acceptance levels for *accuracy* and *completeness* must be defined. The results for both characteristics must be acceptable to consider the evaluation acceptable. ISO/IEC 25012 specifies that the following stringency

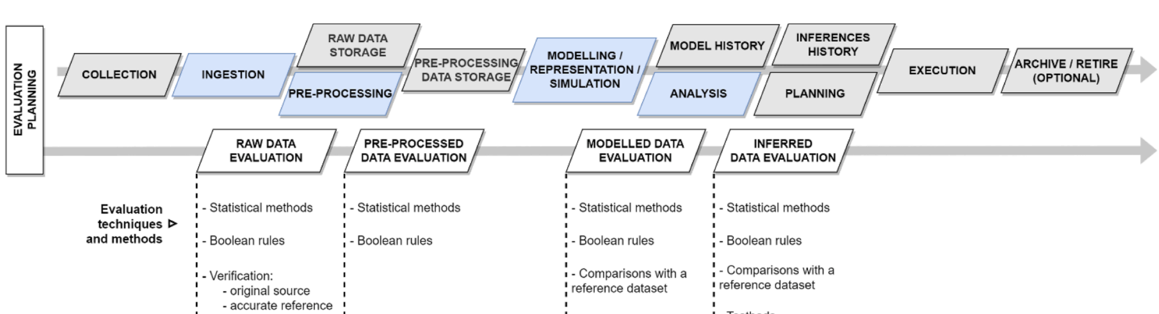



**Fig. 6.** Overview of the EX-DLC holistic data fusion framework. Evaluation activities (white background) are integrated with the EX-DLC data management process when data fusion should be evaluated. The different data fusion evaluation methods and techniques that can be used at each stage are also identified.

aspects must be used for the characteristics evaluated: type (inherent or system-dependant), previous documentation/specification required, measurement method, variables, formula, and scale. An example is given in Table 7.

*4.2.1.2. Specify the evaluation.* This activity specifies the modules and quality evaluation criteria and includes the following tasks:

- 2a. Select the quality measures. Quality measures should be selected for every software quality evaluation requirement. The procedures should measure every software quality characteristic (or sub-characteristic) with sufficient accuracy to allow the criteria to be set and comparisons to be made. ISO/IEC 25024 [61] defines data quality metrics for quantitatively measuring the characteristics defined in ISO/IEC 25012. The metrics will thus be selected following this standard.
- 2b. Define decision criteria for quality measures. Decision criteria are numerical thresholds or targets used to describe the level of confidence of each result. A decision criterion should be defined for individual metrics and can be set using benchmarks, historical data or other techniques. Since some works, such as [60], set the acceptable threshold at 75 % and since it is mandatory to evaluate *accuracy* and *completeness*, it is reasonable to establish that only results equal or above a threshold of 80 % will be considered as an acceptable measurement. Depending on the relevance of the attribute to measure, the value of its particular threshold could be higher.
- 2c. Define decision criteria for evaluation. This task prepares a procedure for summarizing different criteria for the quality characteristics and its output should be used as input for the software product quality assessment. Evaluation of the quality characteristics selected, such as *accuracy* and *completeness* and others, will be considered acceptable if the results for all the aspects of a particular product to evaluate are acceptable, i.e. if the EX-DLC stages of data fusion obtain a result equal or above the threshold defined in the previous task. The overall evaluation of the system can be summarized from the system's particular requirements and application domain.

*4.2.1.3. Design the evaluation.* This activity finally specifies the evaluation plan.

- 3a. Plan evaluation activities. All the previously identified evaluation activities are scheduled as part of the evaluation plan, which should include the purpose of the evaluation, standards, the available software and hardware resources, the people involved (if applicable) as well as the evaluation methods (verification, validation, etc.) and tools as follows:
- Evaluation techniques and methods must be selected according to the application, from the plethora of different possibilities shown in Fig. 6, and the stage of the process to evaluate. This addresses the evaluation aspect *EA6* identified in Table 1.
- Tools should ideally be software tools to enable an automated evaluation in run-time and minimizing human intervention. They should be integrated with the system's real data as far as possible to address evaluation aspects *EA7* and *EA8,* detailed in Table 1.

As the data fusion evaluation tools support is limited, it is recommended to configure or develop the type of evaluation components integrated in the system architecture, e.g. as part of an evaluation subsystem. This is especially appropriate for highly demanding (high-risk) data fusion systems, e.g. data fusion applications in the healthcare domain. The development of the data fusion evaluation subsystem should be carried out at this point before continuing with the remaining data quality evaluation framework activities and considering the planning specified in the previous tasks.

Based on the aspects defined in tasks 1c and 1d, Fig. 6 shows how the evaluation process is integrated with the data management process, the stages of the evaluation process being identified by a white background. The first, Evaluation planning, is related to all the activities and tasks defined in Section 4.2.1. The other stages make up the data fusion evaluation subsystem. Each stage must be developed as a component that performs the data fusion evaluation processes included in task 1d, according to what has been defined in task 2a. The components must implement some of the methods and techniques summarized in Fig. 6 appropriate for the stage it is related to and the aims of the data fusion. These data fusion evaluation components must be executed automatically immediately after the execution of their evaluated data fusion component. Fig. 6 shows how both the data management process and the data fusion evaluation process can be integrated to form the EX-DLC holistic data fusion framework proposed in this work.

*4.2.2. Execute the evaluation*

This activity consists in executing the evaluation and entails the following tasks:

- 4a. Make measurements. The selected quality metrics are applied to the identified software product parts or components, according to the *Evaluation Plan*. As stated in the previous activity, every method selected to evaluate the quality of the data fusion stages of the system is executed in run-time by a software component that is part of the system. Measurement results can be recorded in the system logs, stored in a system database, or notified by any notification or messaging mechanism.
- 4b. Apply the decision criteria for the quality measures. The decision criteria are applied to the measured values. The result may be given as the assertion to which every measurement converges, as defined in 2b. This task is conducted either as part of the operation of the evaluation software components or manually.
- 4c. Apply the decision criteria for evaluation. The decision criteria are summarized for each characteristic. The result of the evaluation is given as the assertion to which the software product converges on quality requirements, as defined in 2c. This is carried out either by the evaluation software components or manually if no evaluation system has been developed. The set of decision criteria is summarised for all the sub-characteristics and characteristics as evidence of the level of the quality requirements met by the data fusion system and each of their data fusion stages.

*4.2.3. Conclude the evaluation*

The final evaluation activity includes the tasks for reviewing the results, creating the final report, and providing feedback, as follows:

- 5a. Review the evaluation results. The evaluator/s and the requester shall carry out a joint review of the evaluation results.
- 5b. Create the evaluation report. This report should include the requirements of the evaluation, the results of the measures and analyses performed, any limitations or constraints, the evaluators, and their qualifications, etc.
- 5c. Review quality evaluation and provide feedback to the organisation. This involves evaluating the results and validating the evaluation process, along with the actions applied. The feedback given by the evaluator should be used to improve the evaluation and the data fusion processes.
- 5d. Perform disposition of evaluation data. If needed, all the evaluation data shall be disposed (returned, archived, or destroyed) as appropriate.

## 5. Case study

This section describes a case study in which our data fusion holistic proposal was applied to address, amongst others, the issue regarding the lack of real system use cases. The first dimension of the framework was used to guide the design and development of the prototype of a smart and pervasive healthcare data fusion system for COVID-19 prevention in nursing homes. After this, the data fusion evaluation of the prototype was designed, following the second dimension of the framework and the components of an evaluation subsystem were integrated into the prototype. The holistic framework was applied according to the following:

1 Data management process based on data fabric and digital twins (DT).
  a Design of the system architecture and its components based on EX-DLC considering that certain stages perform data fusion tasks and that DT properties aspects support some of the stages, especially modelling/representation/simulation (see Fig. 5).
  b For every component of the system architecture that should perform data fusion tasks, select the most appropriate data fusion methods or techniques from the different possibilities, according to the requirements and the corresponding EX-DLC data fusion stage (see Fig. 6).
  c Data fusion evaluation process based on international standards (see Table 4).
2 Plan the evaluation specifying the evaluation requirements and details, and the design of the evaluation subsystem based on (i) the EX-DLC evaluation steps and (ii) their data fusion evaluation methods and techniques (see Fig. 6).
  a Execute the evaluation automatically as part of the system operation.
  b Conclude the evaluation.

A preliminary version of the prototype was described in [61]. This paper focuses on the data fusion carried out by the data management process and its evaluation, even though a smart and pervasive healthcare environment could become extremely complex, the current system is offered as a simple prototype for the sake of simplicity and to facilitate its applicability. We provide a summary of the prototype's main characteristics in Section 5.1, its architecture designed according to EX-DLC and the DT properties that support the system, including the new data fusion evaluation subsystem (see Section 5.2), and the results of the data fusion quality evaluation (Section 5.3).

### 5.2. System description

The aim of the current prototype of a pervasive healthcare system is the proactive prevention of the spread of COVID-19 in nursing homes, considering that these centres have been seriously affected by this pandemic. For this, the design was based on the well-known prevention measures laid down by medical authorities worldwide, i.e. social distance, face masks, open spaces, unobstructed airflow, air quality, etc.

The smart pervasive healthcare system prototype was developed for the nursing home "Las Hazas" in Hellín [62], Albacete, Spain. This nursing home can accommodate 200 users and has numerous common areas distributed over three floors. The maximum number of workers in a single shift is 50. To prevent the spread of COVID-19 in the nursing home, the prototype supports the functionalities given in Table 5. It also illustrates the data gathered and used to support each one.

**Table 5**
System functionality and data used data.

| Functionality | Data used |
|---|---|
| **Monitoring the location and physiological attributes of system users** | Heart rate, body temperature and location (longitude and latitude) |
| **Detection of close contacts between users** | Location (longitude and latitude) |
| **Notification as a reminder of the recommendation for proper use of face masks** | Location (longitude and latitude) |
| **Inference and notification of infections** | Heart rate, body temperature |
| **Measurement and analysis of the air quality and notification of alerts for low air quality and appropriate actions** | Concentration of $CO_2$, ambient temperature, and relative humidity |

The inmates and staff wear smart bands for measuring their heart rate, body temperature and location (longitude and latitude). The staff take frequent readings of the inmates' physiological signals by medical devices connected to the elderly's mobile devices. Mobile devices transmit the data for individual users to the cyber-subsystem, which carries out the data fusion required following the processes defined in the proposal. In addition, the sensors installed in the common areas of the nursing home measure the $CO_2$ concentration, ambient temperature and relative humidity. The different facilities have a dedicated device that receives the facility sensor signals and transmits them to the cyber-subsystem. A maintenance technician periodically measures the facility's properties using more accurate sensors connected to the facility's dedicated device. All users can see their physiological or location data in real time from an application installed on their smartphone, that is also used to provide notifications. The air quality data device in each room includes a display with these data in real time. Other screens installed at different points in the residence simulate a map giving the state of the facility's air quality in real time. The system administrators have access to the data stored during the system's execution. All the values are shown associated with the attribute and the measurement unit if applicable for easy interpretation.

### 5.3. System architecture and deployment

This section describes the proposed holistic EX-DLC framework was used to design and develop a system that supports both the EX-DLC data management process and the data fusion quality evaluation process. The cloud platform chosen for the deployment of the prototype was Microsoft Azure [54], due to its suitability for supporting the development of IoT-based systems. Fig. 7 shows the system architecture, which uses different Azure services as components to support the different EX-DLC stages. The Azure services used are classified into different types based on their capabilities, as can be seen in Fig. 7. *Azure Functions* (*Store raw data, Pre-process user data,* etc.) follows the serverless approach to develop services that execute the core logic and were used to support different stages of the data fabric architecture, especially to implement the Boolean rules used in the data fusion stages. The *Event Hubs* service (*Hub user, Hub distance*, etc.) was also used to support different stages enabling the communication between the different services by acting as an event broker. The *Application Insights* service monitored the operation of the different services. Details of these services can be found in the Azure documentation. The areas of the diagram are coloured according to the EX-DLC stage that supports illustrating the data and the components' execution flow. The stages and components of the automatic quality evaluation subsystem are also shown in Fig. 7 (white areas). The architecture and deployment of both subsystems are detailed in the following sections.

#### 5.3.1. Data management subsystem

The architecture of this subsystem was designed as a data fabric architecture that supports the EX-DLC data management process. The components that support the optional stage of archive/retire (in grey) are excluded from this prototype. The most suitable Azure native services were selected for the different stages according to the stage requirements and the capabilities offered by these services. Their costs were also considered, plus the credit limit of the Azure subscription. As can be seen in Fig. 7, the developed Data Management Subsystem is composed of two main subsystems as follows:

- The physical and social subsystem is that of the nursing home's real environment augmented by different devices, sensors and actuators for collecting data from multiple sources and unobtrusively reacting to the needs of users and facilities. The devices, sensors and actuators are related to a particular entity, so that this subsystem supports the

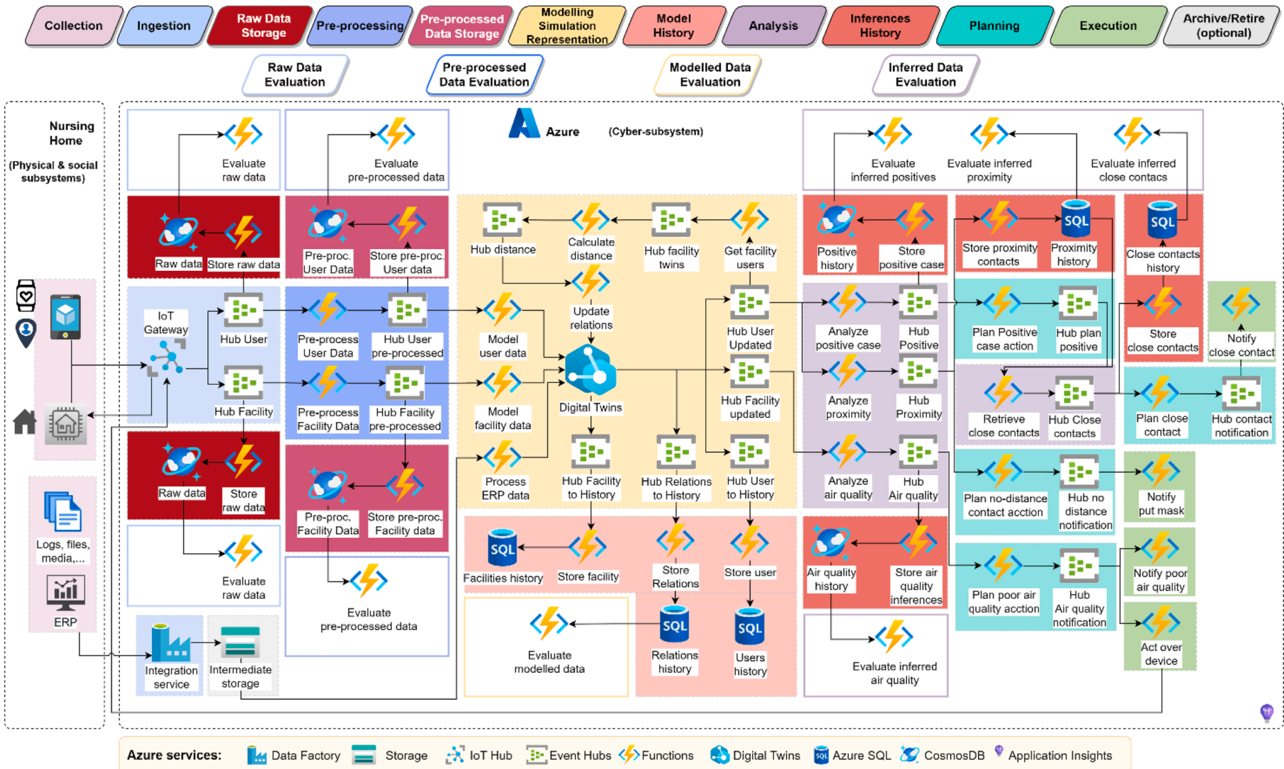



**Fig. 7.** Architecture components of the prototype implemented on Microsoft Azure and the corresponding stages in EX-DLC, including additional evaluation stages.

first stage, i.e. *data* collection (see Section 4.1.1) from different sensors and devices and also the execution stage (see Section 4.1.11) if required. This subsystem was developed to fuse sensor data before being transmitted by a multi-source approach. For this, the different sensor data of an attribute are fused in the proxy device of the entity it belongs to, e.g. smartphones or edge device, depending on whether the type of entity is a user or a thing. These fused data are then sent to the cyber-subsystem by the proxy devices. This type of entity-based data fusion was implemented to ease the blocking strategy defined for the next stages in the cyber-subsystem.

- The cyber-subsystem is the computing system that performs most of the data processing. Its main components support the data fusion processes, including a modelling stage supported by DT. This subsystem supports all the EX-DLC stages except the collection and execution stages. It was decided to employ Boolean rules for all the EX-DLC data fusion stages because of their simplicity and because all the data fusion operations required can be performed at the attribute level.

*Ingestion* is the first stage of the cyber-subsystem (see Section 4.1.2). For its development, the *IoT Hub* service (*IoT gateway*) was used as a gateway to the cyber-subsystem to facilitate bidirectional communication with the physical subsystem entities, receiving the data from these and executing actions on the devices. This service also facilitates the use of the Boolean rules exploited to support the filtering capability necessary for the blocking strategy, i.e. different blocks are established for different entity types. This blocking enables determining the type of entity, *user* or *facility* of the data received, so that data of the two types of entities in this system are transmitted through different hubs, i.e. Hub user and Hub facility. After Ingestion, the *CosmosDB* service, a NoSQL database, is used to store the raw data received in the established blocks, based on their entity type (User raw data, Facility raw data) as part of the Raw Data Storage stage (see Section 4.1.3)

After the raw data storage, a Pre-processing stage (see Section 4.1.4) is performed using different *Azure Functions*. Its goal is to increase the quality of the data that will be fused to update the models of the entities of the physical and social space. The attributes of an entity with multiple values are processed to generate a single value. The Pre-process User and Facility Data functions obtain this value from the sensor with the best accuracy, resolution and priority. These single values are then stored as part of the Pre-processed Data Storage stage (see Section 4.1.5) by means of the corresponding Store pre-processed User and Facility Data functions. They are also transmitted through the corresponding User and Facility pre-processed Hubs.

After the pre-processing, as part of the *Modelling/Representation/Simulation* stage (see Section 4.1.6), the *Azure Digital Twins* service (Fig. 7, in yellow) is used to address the data contextualization problem associated with the data fabric. It also supports data fusion since entity data are managed by Azure Digital Twins instead of storing the data received in an unstructured way through data lakes. The Azure Digital Twins service receives the entities' data collected by sensors in real time. This service is also used to fuse and update the virtual models that represent these entities as well as their different relations and interactions at a particular time. The Azure Digital Twins service is thus used to represent the physical world in the virtual world and connecting them to each other. This also facilitates that further analysis processes can make better decisions regarding the actions to be carried out to satisfy the users and environmental needs using the fused information. DT's bidirectional communication capability is achieved in combination with the IoT Hub service.

Fig. 7 shows that the *Modelling/Representation/Simulation* stage implementation encompasses the *Digital Twins* service, *Event Hubs* services as well as the following *Azure Functions*:

- *Model user data* and *Model facility data* are responsible for creating, updating and deleting the different DT' models of users and facilities, respectively, to represent the data received in real-time from those entities.
- Get facility users is executed every time a user DT is updated and obtains all the users that share the facility at that time.

- Calculate distance processes the list of users from the previous function and calculates the distance between the DT of the users by their location (longitude and latitude).
- Update relations creates, updates and deletes relations between the DT of a facility and the user entities obtained in the previous function, depending on the distance between them. After this execution, the system model reflects the relation of proximity between all the DTs of the users affected by the last update.

These functions, which are the services that perform the data fusion, implement the appropriate Boolean rules for their goal.

The *Digital Twins* service also offers a tool for visualizing the entities' DT in real-time (see Fig. 8). This tool creates a DT graph whose relationships show the users (UserXXXX) in a certain room (RoomYY) and those related to other users at a specific time. By clicking on each node of the graph, it is possible to access to the real-time values received from the selected DT. This graph clearly illustrates the ability of DT to contextualize data.

The relational *Azure SQL* and *CosmosDB* databases *Users history, Facilities history* and *Relationships history* are used for storing historical information of entities and their relations supporting the *Model History* stage (see Section 4.1.7).

The DT service also offers a tool known as *3D Scenes for Azure Digital Twins* to visualize the DTs within a 3D environment that represents the real space and then check their properties, facilitating the multi-scale and multi-physics modelling characteristic of DTs (see Section 2.2). Using this tool, a 3D interface was developed to improve user experience regarding other types of information visualization strategies. This interface shows in real-time the status of the air quality in any room by a colour scale (see Fig. 9). The interface also has a widget that shows the air quality parameters. If the air quality is not adequate, an alert, represented as an icon, is shown in the interface. The information shown in Fig. 9 can be seen as fused data related to all the nursing home facilities. It should be noted that data fused, modelled and presented in this way could be useful to nursing home staff, since they show the facilities that require ventilation or even evacuation. It can also be used by the elderly to indicate the facilities to avoid COVID-19 infections.

The data fused in the modelling stage are used during the Analysis stage (see Section 4.1.8) to satisfy the requirements and achieve the goals of the data management system. This stage is supported by four different *Azure Functions* (each one related to an inference) that are currently implemented as Boolean rules:

- Analyse proximity determines whether the distance between different users is less than 3 metres to send them a reminder of the recommendation of using a face masque.
- Analyse COVID-19 positive determines that a user is infected if the values of their body temperature and heart rate are above the thresholds laid down by the health authorities. The algorithm used is based on the evidence that for febrile cases of the disease, the heart rate increases 15 beats per minute for each degree Celsius that body temperature increases [63].
- Retrieve close contacts obtains a list of users that have been in contact with a user infected for at least 15 min in the last 5 days.
- Analyse air quality infers poor air quality of a facility if some of its $CO_2$, temperature and humidity attributes are out of the recommended range for nursing homes by the health authorities.

The results of the inferences are stored in the *Positive history, Poor air quality history*, and *Close contacts history* databases as part of the *Inferences History* stage (see Section 4.1.9).

The Planning stage (see Section 4.1.10) is run after the analysis has been conducted. For every situation to be managed, an Azure function was developed to plan the actions that should be taken according to the inferred results, i.e. Plan close contact, *Plan no-distance contact action*, etc. These actions are later run as part of the Execution stage (see Section 4.1.11) using the corresponding Azure Functions, i.e. Notify close contact, Notify put on masque, etc. Some of these actions simply send notifications or commands to the devices that act as the proxies of the entities, using the bidirectional communication capability offered by the *IoT Hub* service.

It should be highlighted that the IoT Hub service records the different devices associated with the different users and facilities modelled by means of the DTs service and, thanks to the bidirectional communication link, physical entities and virtual entities can be synchronized almost in real time. The fast DT synchronization characteristic is paramount for COVID-19 prevention, i.e. the system's main aim. Adopting other less complex approaches to store, query, show and notify information without support for real-time communications would not therefore be appropriate in this and similar cases.

### 5.3.2. Data fusion quality evaluation subsystem

As depicted in Fig. 7, the components of the evaluation subsystem that carry out the evaluation of the data fusion stages were also implemented in *Azure Functions*. Evaluate raw data (for every entity type) evaluates the ingestion filter-based blocking quality. Evaluate preprocessed data (for every entity type) evaluates the quality of the preprocessing technique applied to the raw data, i.e. the selection of the best attribute value. Evaluate modelled data evaluates the quality of the entities' relations created as part of the modelling. Finally, evaluate inferred positives, inferred proximity, etc. evaluate the quality of the corresponding analysis. All these *Azure Functions* services execute the Boolean rules defined in Table 6. In all cases, the data fusion evaluation component is executed automatically and immediately after the execution of their evaluated data fusion component, once the data fusion stage results have been stored.

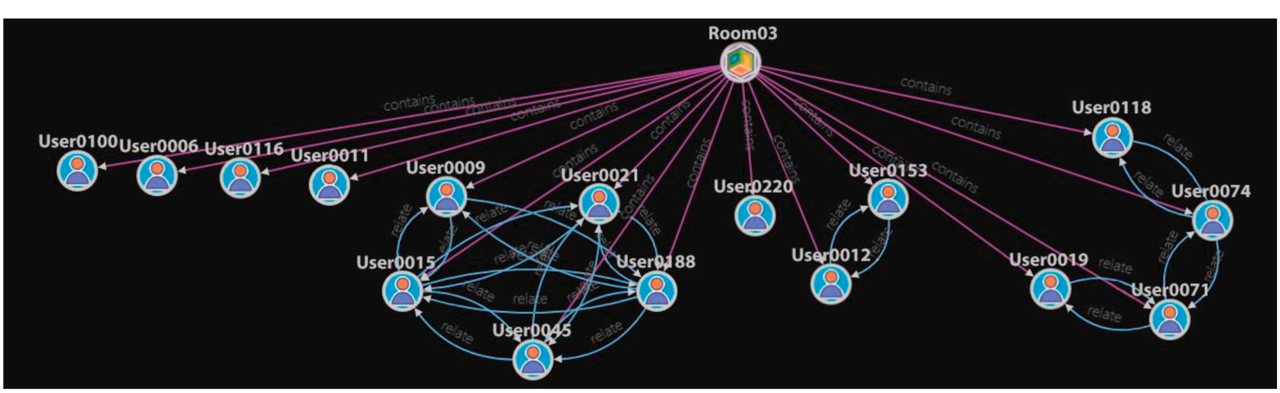



**Fig. 8.** Graph of DTs and their representation at a particular time.

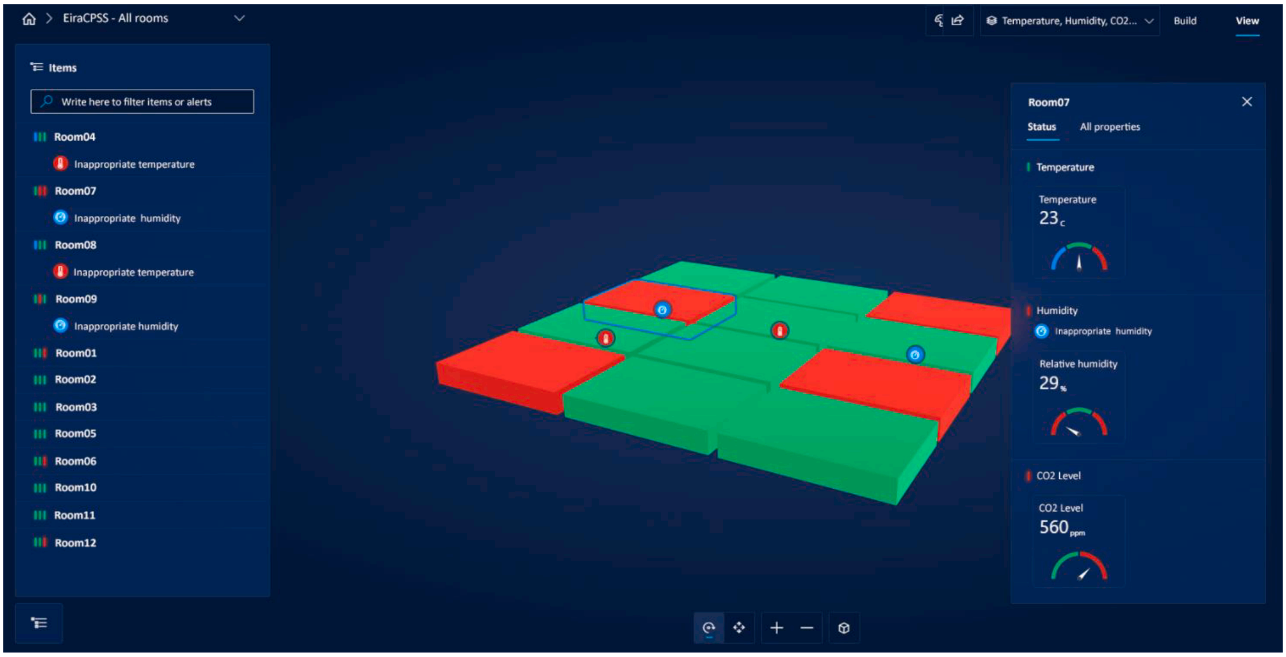



**Fig. 9.** Qualitative 3D interface representing the DTs depicting the nursing home facilities.

### 5.4. *Case study data fusion evaluation*

As mentioned, the system supports well-known COVID-19 prevention measures that have been considered valid. This is why we consider that the system can help to prevent infections. Bearing that in mind and since our goal was not to evaluate the prevention system, but to show how the data fusion evaluation process can be applied in a real system, this Section does not describe an evaluation of the prototype but focuses on showing the application of the EX-DLC evaluation process for evaluating the data fusion carried out by the prototype, i.e. by the subsystem designed using the first EX-DLC dimensions. The data fusion carried out by the system described in Section 5.2 was thus evaluated following the evaluation process proposed here and defined in Section 4.2 to show the proposals' applicability. The following sections describe how the activities of the data fusion evaluation process was conducted.

#### 5.4.1. *Plan the evaluation*

The work carried out in the context of the three sub-activities of the *Plan the Evaluation* activity is summarized in the following.

*5.4.1.1. Establish the evaluation requirements.* The evaluation requirements are detailed in the context of the different tasks involved in this activity.

- 1a. Determine the purpose of the evaluation. The purpose of the evaluation is the measurement of the degree of precision of the data fusion processes performed by the developed system.
- 1b. Obtain the software product quality requirements. Since the data fusion system to be evaluated is a prototype and the purpose of the work is to show the applicability of the framework proposed, only the mandatory quality characteristics, accuracy and completeness, are considered as quality requirements of the system.
- 1c. Identify nature of the defects in final product that create risks. Based on the data management process proposed in Section 4.1, we defined the four stages in which errors can be introduced: Ingestion, Pre-processing, Modelling/Representation/Simulation and Analysis. However, errors could also happen during the collection stage.
- 1d Identify product parts to be included in the evaluation. Based on the data management process proposed in Section 4.1 and on the results of the previous task indicating the points at which errors may occur, we defined four points to include in the evaluation: the data management process stages of Ingestion, Pre-processing, Modelling/Representation/Simulation and Analysis, since they are responsible for performing data fusion tasks.
- 1e. Defining the stringency of the evaluation. Two acceptance levels were established for the evaluation results: unacceptable and acceptable.

*5.4.1.2. Specify the evaluation.* The evaluation is specified in the context of the different tasks included in this activity.

- *2a. Selecting the quality measures* to use in the evaluation. As indicated in Section 4.2.1, the metrics were selected from the standard ISO/IEC 25024. Since no additional quality requirements and characteristics were considered other than *accuracy* and *completeness*, the metrics *semantic accuracy* of data and *syntactic accuracy* for *accuracy,* and the metric *attribute completeness* for *completeness* were selected (see Table 7).

The real-world entities identified in the context of the use case described in Section 5 are the users (elderly and caregivers) and nursing home facilities. The selected metrics apply to the attributes of the user and the facility. After the Ingestion stage, it should be determined whether the different entities' data have been redirected, using filtering, to the right block, according to the entity type (*user* or *facility*). The attributes to evaluate after the Pre-processing stage for the system described in Section 5 are $CO_2$ *level, humidity*, and *temperature* for the facilities, and *heart rate, body temperature*, and *location coordinates* for the user. After the Modelling/Representation/Simulation stage, the characteristics of the *user relationship* attribute are evaluated. When the inferences have been made in the Analysis stage, the user attributes of *proximity, positive in COVID-19* and *close contact* are evaluated. In the case of facilities, the *air deficiency* attribute is also evaluated in this last stage.

To measure the *accuracy*, it is necessary to establish the semantic and syntactic rules for each attribute. For the semantic rules, the working ranges provided by the manufacturers of the sensors were used. The location attribute is composed of longitude and latitude, Sensor

**Table 6**
Semantic and syntactic accuracy and completeness validation rules.

| Data fusion stage | Characteristic | Entity | Attribute | Rules to be applied |
|---|---|---|---|---|
| Ingestion | Accuracy (Semantic) | Facility | Device name | Contains "Facility" |
| | | User | Device name | Contains "User" |
| | Accuracy (Syntactic) | Facility | Entity type | Data set is of type Facility |
| | | User | Entity type | Data set is of type User |
| | Completeness | Facility | Device name | Value not null |
| | | User | Device name | Value not null |
| Pre-processing | Accuracy (Semantic) | Facility | $CO_2$ level | Value between 0 and 1200 |
| | | | Humidity | Value between 20 and 95 |
| | | | Temperature | Value between −30 and 50 |
| | | User | Heart rate | Value higher than 0 |
| | | | Temperature | Value between −30 and 50 |
| | | | Location | Longitude value between −90 and 90 and Latitude value between −180 and 180 |
| | Accuracy (Syntactic) | Facility | $CO_2$ level | Integer |
| | | | Humidity | Integer |
| | | | Temperature | Integer |
| | | User | Heart rate | Integer |
| | | | Temperature | Decimal |
| | | | Location | Decimal tuple |
| | Completeness | Facility | $CO_2$ level, humidity, temperature | Values not null |
| | | User | Temperature, heart rate | Values not null |
| Modelling | Accuracy (Semantic) | User | Relationship | (IsRelated is true and Distance value between 0 and 3.00) or (IsRelated is false and Distance value not between 0 and 3.00) |
| | Accuracy (Syntactic) | | Relationship | Tuple of Boolean and decimal |
| | Completeness | | Relationship | Distance not null |
| Analysis | Accuracy (Semantic) | Facility | Air deficiency | (Parameter is "Temperature" and Value >= 25 and Reason is "High") or (Parameter is "Temperature" and Value <= 23 and Reason is "Low") or (Parameter is "Humidity" and Value >= 70 and Reason is "High") or (Parameter is "Humidity" and Value <= 30 and Reason is "Low") or (Parameter is "CO2Level" and Value >= 500 and Reason is "High") |
| | | User | COVID-19 Positive | (IsPositive is true and Temperature >= 37.5 and HeartRate >= 90) or (IsPositive is false and (Temperature < 37.5 or HeartRate < 90)) |
| | | | Proximity | (State is "Far" and relation was deleted) or (State is "Far" and Distance > 3) or (State is "Near" and Distance <= 3) |
| | | | Close contact | (IsCloseContact is true and Duration of contact >= 15′ and MinDistance <= 2) or (IsCloseContact is false and ((Duration of contact < 15′ or MinDistance > 2)) |
| | Accuracy (Syntactic) | Facility | Air deficiency | Value is double and Reason is string |
| | | User | COVID-19 Positive | IsPositive is Boolean |
| | | | Proximity | State is string and Distance is Double |
| | | | Close contact | Duration is TimeSpan |
| | Completeness | Facility | Air deficiency | Value not null |
| | | User | COVID-19 Positive | IsPositive not null |
| | | | Proximity | Distance not null |
| | | | Close contact | Duration, sourceId and TargetId not null |

precision is used for each coordinate. Inferred values such as *air deficiency, positives in COVID-19*, and *close contacts* are considered Boolean values. *Proximity* between users is made up of an attribute composed of a relation between users and the distance in meters. Syntactic rules consider the expected data type. Table 6 shows these criteria in detail.

- *2b. Defining the decision criteria for quality measures*. Apart from the default threshold of 80 % to consider a measurement as acceptable established in Section 4.2.1, the acceptance level was raised to 90 % for the attributes of *positive in COVID-19* or *close contacts,* given their importance. Table 7 summarizes the acceptance level values for the selected metrics for the quality characteristics and attributes, along with the specified measurement method. It also includes the stage in which the different entities' attributes are fused.

- *2c. Define the decision criteria for evaluation*. As mentioned in Section 4.2.1, every characteristic of every EX-DLC stage that performs data fusion is considered acceptably evaluated if its evaluation result is equal or above the threshold defined in the previous task. For the case study, the global evaluation of the system was not summarized in a pre-established manner, since we considered that the different data fusion components operated independently. Although the inputs of some of the components may depend on the outputs of the predecessors, good data fusion quality in one does not guarantee good data fusion quality in the others. Only the basic quality characteristics of *accuracy* and *completeness* were evaluated.

*5.4.1.3. Design the evaluation*

As shown in Table 7, several Boolean rules were chosen to evaluate the different quality characteristics selected according to the different entity's attributes fused in the developed system. Boolean rules are one of the data fusion evaluation techniques described in Section 3.2, and are easy to specify, understand, and implement. Since the fusion stages implemented in the developed system are based on Boolean rules, using them to validate the data fusion stages is the most logical and straightforward approach. However, as pointed out in Section 3.2, the Boolean rules for validation are 'soft' with respect to the original data fusion rules, i.e. they impose less strict conditions and only evaluate a near or partial match.

The Boolean rules for validation have been implemented in the data fusion evaluation components included in Fig. 6. Overview of the EX-DLC holistic data fusion framework. Evaluation activities (white background) are integrated with the EX-DLC data management process when data fusion should be evaluated. The different data fusion evaluation

**Table 7**
Acceptance levels for entity's attributes and selected metrics for each quality characteristic.

| Characteristic | Metric/s | Measurement method | Attribute | | Stage(s) | Acceptance level |
|---|---|---|---|---|---|---|
| Accuracy | Semantic accuracy of data And Syntactic accuracy of data | X: Ratio of attribute registries that fits semantic/syntactic rules $X = A/B$ $A =$ number of attribute registries that fits semantic/syntactic rules $B =$ Total of registries | Facility | $CO_2$ level | Pre-processing | $X>=0.8$ |
| | | | | Temperature | Pre-processing | |
| | | | | Humidity | Pre-processing | |
| | | | | Air deficiency | Analysis | |
| | | | User | Heart rate | Pre-processing | |
| | | | | Body temperature | Pre-processing | |
| | | | | Location | Pre-processing | |
| | | | | Relationship | Modelling | $X>=0.9$ |
| | | | | COVID-19 positive | Analysis | |
| | | | | Proximity | Analysis | |
| | | | | Close contact | Analysis | |
| Completeness | Attribute Completeness | X: Ratio of required attribute registries that are non-null $X = A/B$ $A=$ number of required attribute registries that are non-null $B =$ Total of registries | Facility | $CO_2$ level | Pre-processing | $X>=0.8$ |
| | | | | Temperature | Pre-processing | |
| | | | | Humidity | Pre-processing | |
| | | | | Air deficiency | Analysis | |
| | | | User | Heart rate | Pre-processing | |
| | | | | Body temperature | Pre-processing | |
| | | | | Location | Pre-processing | |
| | | | | Relationship | Modelling | |
| | | | | COVID-19 positive | Analysis | |
| | | | | Proximity | Analysis | |
| | | | | Close contact | Analysis | |

methods and techniques that can be used at each stage are also identified.. Following the guidelines described in Section 4.2.1, these evaluation components are executed automatically in run-time immediately after their evaluated data fusion component. The results of the evaluation of the attributes range between 0 and 1. After the execution, the evaluation of numerical results is interpreted and summarized to determine whether or not they are acceptable, using the guide specified in Table 7, also whether the data fusion evaluation has been satisfactory according to what was defined in tasks *2b,* and *2c* and *1e* (also in Section 4.2.1), respectively. The evaluation report is provided in the following section.

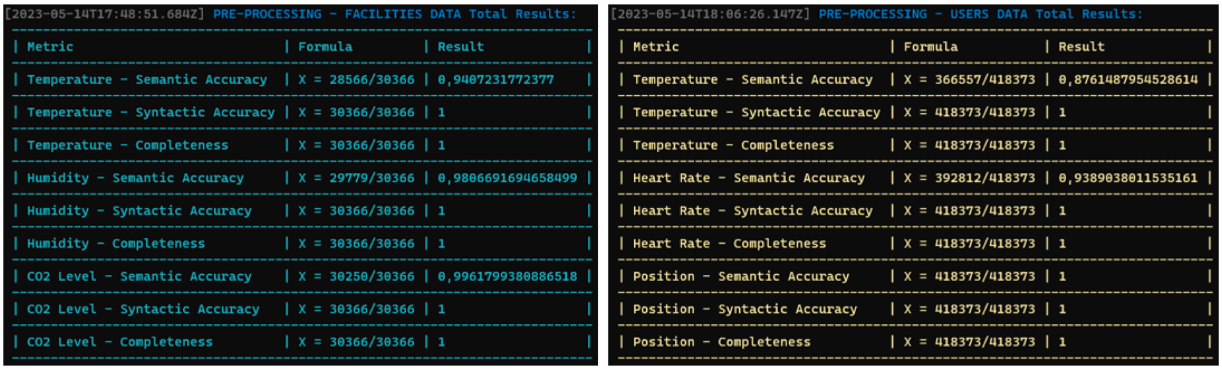
### 5.4.2. *Evaluation execution*

The evaluation was conducted by carrying out load tests that followed the guidelines given by Microsoft [64]. We also considered the use limits of the Azure services deployed, their cost, and the credit available in the Azure subscription in which the prototype is currently deployed. A total of 250 users were simulated: 200 being the maximum number of nursing home residents, plus 50 employees. The test lasted for 9 h, the period of the first daily shift in the nursing home, including the playful activities period. The different tasks in the evaluation execution activity are detailed in the following.

- 4a. Make measurements. After starting the execution, the data fusion system is fed with pseudo-random data from the entities' attributes collected by the different system sensors. The collection emulator is capable of generating invalid data (e.g. outliers) for certain attributes within a configurable random percentage range, which was between 0 and 10 % for this evaluation.

Each time the components associated with the data fusion stages of Ingestion, Pe-processing, Modelling/Representation/Simulation and Analysis are executed, the related evaluation components (see Figs. 6 and 7) are executed after storing the data fusion results in the corresponding database. The measurement method based on the formula specified in Table 7 is applied to the output of every characteristic, i.e. the data fusion results of every data fusion component. The numerical results of the data fusion evaluation performed by every component are currently provided as system logs. For example, Fig. 10 shows the results of the evaluation of all the metrics after the pre-processing stage. The 'Formula' column shows the operation conducted that divides the number of data sets that passed the evaluation according to the corresponding Boolean rule by the total number of data sets evaluated for individual metrics. The result of this operation is shown in the 'Result' column.

- 4b. Apply the decision criteria for quality measures. As can be seen from the images with the evaluation results included in the previous task, the results are 1 or near 1 in most cases, but always higher than the acceptance thresholds defined in Table 7. The corresponding measurements were interpreted as acceptable if the acceptance level threshold is achieved or surpassed, or as unacceptable in the opposite case. This was executed manually and the interpretation was specified as Measurement result in Table 8 in Section 5.3.20.
- 4c. Apply the decision criteria for evaluation. The summary of the decision criteria was carried out by grouping the different quality characteristic results per characteristic and data fusion stage. The corresponding characteristic results were interpreted as acceptable if the acceptance of all the sub-characteristics was interpreted as acceptable, or as unacceptable in the opposite case by a manual



[2023-05-14T17:48:51.684Z] PRE-PROCESSING - FACILITIES DATA Total Results:

| Metric | Formula | Result |
|---|---|---|
| Temperature - Semantic Accuracy | X = 28566/30366 | 0,9407231772377 |
| Temperature - Syntactic Accuracy | X = 30366/30366 | 1 |
| Temperature - Completeness | X = 30366/30366 | 1 |
| Humidity - Semantic Accuracy | X = 29779/30366 | 0,9806691694658499 |
| Humidity - Syntactic Accuracy | X = 30366/30366 | 1 |
| Humidity - Completeness | X = 30366/30366 | 1 |
| CO2 Level - Semantic Accuracy | X = 30250/30366 | 0,9961799380886518 |
| CO2 Level - Syntactic Accuracy | X = 30366/30366 | 1 |
| CO2 Level - Completeness | X = 30366/30366 | 1 |

[2023-05-14T18:06:26.147Z] PRE-PROCESSING - USERS DATA Total Results:

| Metric | Formula | Result |
|---|---|---|
| Temperature - Semantic Accuracy | X = 366557/418373 | 0,8761487954528614 |
| Temperature - Syntactic Accuracy | X = 418373/418373 | 1 |
| Temperature - Completeness | X = 418373/418373 | 1 |
| Heart Rate - Semantic Accuracy | X = 392812/418373 | 0,9389038011535161 |
| Heart Rate - Syntactic Accuracy | X = 418373/418373 | 1 |
| Heart Rate - Completeness | X = 418373/418373 | 1 |
| Position - Semantic Accuracy | X = 418373/418373 | 1 |
| Position - Syntactic Accuracy | X = 418373/418373 | 1 |
| Position - Completeness | X = 418373/418373 | 1 |

**Fig. 10.** Data fusion evaluation numerical results for the *Pre-processing* stage based on Table 7.

**Table 8**
Summary of evaluation results per measurement and data fusion stage quality characteristic.

| Data fusion stage | Characteristic | Entity | Attribute | Measurement numeric result | Measurement result | Characteristic result |
|---|---|---|---|---|---|---|
| Ingestion | Accuracy (Semantic) | Facility | Device name | $X = 34{,}945/34{,}945 = 1$ | Acceptable | Acceptable |
| | | User | Device name | $X = 487{,}005/487{,}105 = 0{,}9998$ | Acceptable | |
| | Accuracy (Syntactic) | Facility | Entity type | $X = 34{,}945/34{,}945 = 1$ | Acceptable | |
| | | User | Entity type | $X = 487{,}105/487{,}105= 1$ | Acceptable | |
| | Completeness | Facility | Device name | $X = 34{,}945/34{,}945 = 1$ | Acceptable | Acceptable |
| | | User | Device name | $X = 487{,}105/487{,}105 = 1$ | Acceptable | |
| Pre-processing | Accuracy (Semantic) | Facility | $CO_2$ level | $X = 28{,}543/30{,}242 = 0{,}9407$ | Acceptable | Acceptable |
| | | | Humidity | $X = 29{,}779/30{,}366 = 0{,}9806$ | Acceptable | |
| | | | Temperature | $X = 28{,}566/30{,}366 = 0{,}9407$ | Acceptable | |
| | | User | Heart rate | $X = 392{,}812/418{,}373 = 0{,}9389$ | Acceptable | |
| | | | Temperature | $X = 366{,}557/418{,}373 = 0{,}8761$ | Acceptable | |
| | | | Location | $X = 418{,}373/418{,}373 = 1$ | Acceptable | |
| | Accuracy (Syntactic) | Facility | $CO_2$ level | $X = 30{,}250/30{,}366 = 0{,}9961$ | Acceptable | |
| | | | Humidity | $X = 30{,}366/30{,}366 = 1$ | Acceptable | |
| | | | Temperature | $X = 30{,}366/30{,}366 = 1$ | Acceptable | |
| | | User | Heart rate | $X = 418{,}373/418{,}373 = 1$ | Acceptable | |
| | | | Temperature | $X = 418{,}373/418{,}373 = 1$ | Acceptable | |
| | | | Location | $X = 418{,}373/418{,}373 = 1$ | Acceptable | |
| | Completeness | Facility | $CO_2$ level, humidity, temperature | $X = 30{,}366/30{,}366 = 1$ | Acceptable | Acceptable |
| | | User | Temperature, heart rate, location | $X = 418{,}373/418{,}373= 1$ | Acceptable | |
| Modelling | Accuracy (Semantic) | User | Relation | $X = 718{,}303/745{,}692= 0{,}9632$ | Acceptable | Acceptable |
| | Accuracy (Syntactic) | User | Relation | $X = 745{,}692/745{,}692 = 1$ | Acceptable | |
| | Completeness | User | Relation | $X = 745{,}692/745{,}692 = 1$ | Acceptable | Acceptable |
| Analysis | Accuracy (Semantic) | Facility | Air deficiency | $X = 34{,}793/35{,}162 = 0{,}9895$ | Acceptable | Acceptable |
| | | User | COVID-19 Positive | $X = 309{,}065/309{,}066 = 0{,}9999$ | Acceptable | |
| | | | Proximity | $X = 120{,}234/120{,}234 = 1$ | Acceptable | |
| | | | Close contact | $X = 27{,}003/27{,}003 = 1$ | Acceptable | |
| | Accuracy (Syntactic) | Facility | Air deficiency | $X = 35{,}162/35{,}162= 1$ | Acceptable | |
| | | User | COVID-19 Positive | $X = 309{,}066/309{,}066 = 1$ | Acceptable | |
| | | | Proximity | $X = 120{,}234/120{,}234 = 1$ | Acceptable | |
| | | | Close contact | $X = 27{,}003/27{,}003 = 1$ | Acceptable | |
| | Completeness | Facility | Air deficiency | $X = 35{,}162/35{,}162 = 1$ | Acceptable | Acceptable |
| | | User | COVID-19 Positive | $X = 309{,}066/309{,}066 = 1$ | Acceptable | |
| | | | Proximity | $X = 120{,}234/120{,}234 = 1$ | Acceptable | |
| | | | Close contact | $X = 27{,}003/27{,}003 = 1$ | Acceptable | |

process. The interpretation was specified as Characteristic result in Table 8 in Section 5.3.20.

*5.4.2.1. Evaluation results and conclusions.* The evaluation results and conclusions are given according to the different tasks involved in this activity:

- 5a. Review the evaluation results. The evaluation results were reviewed and discussed by all the authors.
- 5b. Create evaluation report. The entire Section 5.3.2 can be seen as the evaluation report. Table 8 constitutes a summary of the evaluation results per measurement and data fusion stage quality characteristic. As can be seen, the evaluation of the quality characteristics, *accuracy* and *completeness*, is *acceptable* for each data fusion stage performed by the prototype. From this it can be concluded that the evaluation of the different data fusion components of the prototype architecture was satisfactory, according to the criteria defined. The overall evaluation of the system of this prototype was not summarized according to a pre-established system as we considered that the different data fusion components operate independently although connected by inputs and outputs, and that the correct data fusion quality of one did not ensure good data fusion quality in the others.
- 5c. Review quality evaluation and provide feedback to the organisation.

From the satisfactory evaluation results, it can be concluded that the proposal facilitates the design and development of data fusion systems and helps to achieve the system's quality requirements. Although the overall evaluation of the data fusion performed by the proposed system seems satisfactory, the evaluation was performed in a period of only nine hours to stay within the available Azure subscription credit and using simulated data. Furthermore, only the basic *accuracy* and *completeness* quality characteristics were evaluated. It can thus be considered that a more complete evaluation, including more quality characteristics in a longer period, etc. should be carried out to determine with greater certainty whether the entire data fusion system can be considered satisfactory.

- 5d Performed disposition of evaluation data. The results of this evaluation can be made available and may be used as benchmark data for future evaluations, especially if new requirements are required.

## 6. Conclusions and future work

Society currently aims to maximize the benefits of developing novel solutions in diverse fields such as healthcare to monitor and prevent diseases, etc. Due to recent technological advances, certain computing paradigms such as pervasive computing can offer enhanced personal support beyond the conventional support offered by desktop computers. The fusion of data collected by multiple sensors installed in the environment plays an important role in this pervasiveness. These environments are also populated with actuators that can react unobtrusively to the users and environment's needs.

Several issues make data fusion a challenging task, most of which are related to data or data source quality, the data fusion process and the evaluation of the data fusion. Of the different data fusion quality aspects, accuracy is the most difficult to address. The present work proposes the EX-DLC holistic framework to improve data fusion in pervasive systems by addressing the issues identified. It can be used to design the system architecture, the data fusion approach and the data fusion evaluation as part of the system, encompassing two dimensions:

- a process for guiding the design of the system architecture focusing on the data management based on the process defined in [17]. It integrates aspects of Data Fabric and Digital Twins to address the relevant challenge of information representation of the different entities of the physical space in the virtual space. This process also includes aspects and techniques from different data fusion models. We also analysed the way in which some of the properties associated with DT are exploited by the data management process.
- a process for the evaluation of data fusion systems based on international standards to ensure the quality of the data fusion tasks performed by the system. It also offers guidelines for designing the architecture of an evaluation subsystem that performs the evaluation automatically in runtime as part of the system.

A system designed to prevent the spread of COVID in nursing homes was also developed using the proposal. The system monitors and, if necessary, controls, the activity, some physiological constants of the users and the staff and the air quality in the building. The developed system was configured to be deployed in a real Spanish nursing home and used DT to model the nursing home users, staff and facilities. A 3D interface was included in the system to show the state of the DTs that modelled the facilities in the virtual environment. The satisfactory evaluation results of the data fusion stages indicate state that the proposal facilitates the design and development of data fusion systems and helps to achieve the system' quality requirements.

The proposal here presented exploits DT as one of its main foundations, although it should be mentioned that some authors are against their use because of the high cost of their development. For instance, Barricelli et al. [48] state that the creation and application of a DT can be costly because the maintenance of the physical entity itself is quite expensive. Alternatively, a digital representation could be developed using fewer complex technologies such as a database, a set of equations or even a spreadsheet. The key added value that DT supports is the *entanglement* property. Its data link, ideally two-way, is what differentiates DT from similar concepts. As the Digital Twin Consortium points out [49], this link makes it possible for users to know the state of the entity by querying data, and, for actions communicated through the DT, to take effect in its physical counterpart, so that the physical entities and virtual entities are synchronized at a specified frequency, ideally in near real time and with high fidelity.

During the development of the proposal and the system, different lines of future work were identified. One of these is to carry out a more detailed study of architectural proposals to improve the process based on Data Fabric architectures as well as its validation, developing different more complex case studies than the one presented. Regarding the data fusion, it would also be interesting to define the tasks performed as part of the Collection stage in a more detailed manner considering aspects as scalability, security, or sensors malfunction. It would be interesting to integrate an additional pre-processing stage for the generation of data when incomplete data are received from the Collection stage.

Although the overall evaluation of the data fusion performed by the prototype was satisfactory, a more complete evaluation should be carried out to determine whether the evaluation of the entire data fusion system can be considered satisfactory in greater detail. This evaluation could measure more quality characteristics, be performed during a larger period of time, use real data, etc. The Boolean rules could also be replaced by other data fusion techniques as well as more complex evaluation techniques such as those based on AI technologies. A ground truth or benchmark data, such as those already stored in the database of the system developed, could be integrated into the evaluation system to support the verification of the data fusion conducted using AI technologies. We would also like to explore including context in the data fusion evaluation. Context is defined in [4] as metadata that contributes to the situation assessment of data fusion systems and provides important information. Including context would improve the information quality of the data fusion process and provide end-users with a better assessment of the situation to make better decisions. Some recent studies [15] are currently following this line of research.

Bearing in mind that the application domain and goals influence the data fusion requirements, we plan to explore the system modelling also considering the Domain-Driven-Design-based approach for architecting Digital Twins proposed in [44]. It is also planned to add new functionalities to the prototype and deploy it on other cloud platforms.

## Authors statement

All persons who meet authorship criteria are listed as authors, and all authors certify that they have participated sufficiently in the work to take public responsibility for the content, including participation in the concept, design, analysis, writing, or revision of the manuscript. Furthermore, each author certifies that this material or similar material has not been and will not be submitted to or published in any other publication.

## CRediT authorship contribution statement

**Aurora Macías:** Conceptualization, Methodology, Validation, Investigation, Writing – original draft. **David Muñoz:** Conceptualization, Validation, Software, Writing – original draft. **Elena Navarro:** Supervision, Conceptualization, Methodology, Writing – review & editing, Project administration, Funding acquisition. **Pascual González:** Supervision, Conceptualization, Methodology, Writing – review & editing.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

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## Bibliography

[1] A. Macías, E. Navarro, Paradigms for the conceptualization of Cyber-Physical-Social-Thinking hyperspace: a thematic synthesis, J. Ambient Intell. Smart Environ. 14 (4) (2022) 285–316, https://doi.org/10.3233/AIS-210492.
[2] M. Weiser, The computer for the 21st Century, IEEE Pervasive Comput. 1 (2002) 19–25, https://doi.org/10.1109/MPRV.2002.993141.
[3] M. Satyanarayanan, Pervasive computing: vision and challenges, IEEE Personal. Commun. 8 (2001) 10–17, https://doi.org/10.1109/98.943998.
[4] N. Streitz, A. Kameas, I. Mavrommati, The Disappearing Computer: Interaction Design, System Infrastructures and Applications for Smart Environments, Lecture Notes in Computer Science, Springer-Verlag, Berlin, Heidelberg, 2007.
[5] B.P.L. Lau, S.H. Marakkalage, Y. Zhou, N.U. Hassan, C. Yuen, M. Zhang, U.-X. Tan, A survey of data fusion in smart city applications, Inf. Fusion 52 (2019) 357–374, https://doi.org/10.1016/j.inffus.2019.05.004.
[6] R.L. Ackoff, From data to wisdom, J. Appl. Syst. Anal. 16 (1989) 3–9.
[7] M. Chen, D. Ebert, H. Hagen, R.S. Laramee, R. van Liere, K.-L. Ma, W. Ribarsky, G. Scheuermann, D. Silver, Data, Information, and Knowledge in Visualization, IEEE Comput. Graph. Appl. 29 (2009) 12–19, https://doi.org/10.1109/MCG.2009.6.
[8] Y. Liu, L. Zhang, Y. Yang, L. Zhou, L. Ren, F. Wang, R. Liu, Z. Pang, M.J. Deen, A Novel cloud-based framework for the elderly healthcare services using digital twin, IEEE Access 7 (2019) 49088–49101, https://doi.org/10.1109/ACCESS.2019.2909828.
[9] L.J. Basile, N. Carbonara, R. Pellegrino, U. Panniello, Business intelligence in the healthcare industry: the utilization of a data-driven approach to support clinical decision making, Technovation. (2022), 102482, https://doi.org/10.1016/j.technovation.2022.102482.
[10] D, P.M. Talburt, John R. Pullen, Evaluating and Improving Data Fusion Accuracy, in: G.L. Bossé Éloi, Rogova (Eds.), Information Quality in Information Fusion and Decision Making, Springer International Publishing, Cham, 2019, pp. 295–326, https://doi.org/10.1007/978-3-030-03643-0_14.
[11] L. Yu, Y. Lu, X. Zhu, Smart hospital based on internet of things, J. Networks 7 (2012) 1654–1661.
[12] A. Holzinger, C. Röcker, M. Ziefle, From smart health to smart hospitals, in: A. Holzinger, C. Röcker, M. Ziefle (Eds.), Smart Health: Open Problems and Future Challenges, Springer International Publishing, Cham, 2015, pp. 1–20, https://doi.org/10.1007/978-3-319-16226-3_1.
[13] A. Macías, E. Navarro, P. González, A microservice-based framework for developing internet of things and people applications, in: Proceedings, 2019, p. 31, https://doi.org/10.3390/proceedings2019031085.
[14] Md.M. Islam, S. Nooruddin, F. Karray, G. Muhammad, Multi-level feature fusion for multimodal human activity recognition in Internet of Healthcare Things, Inf. Fusion 94 (2023) 17–31, https://doi.org/10.1016/j.inffus.2023.01.015.
[15] M.A. Becerra, C. Tobón, A.E. Castro-Ospina, D.H. Peluffo-Ordóñez, Information quality assessment for data fusion systems, Data (Basel). 6 (2021), https://doi.org/10.3390/data6060060.
[16] Gartner Inc. and/or its affiliates, Guide 4: what role data fabric will play in your data management. Gartner's Essential Guides for Effective Data Driven Decision Making, 2023. https://www.gartner.com/en/information-technology/insights/data-and-analytics-essential-guides. accessed April 13, 2023.
[17] A. Macías, D. Muñoz, E. Navarro, P. González, Digital twins-based data fabric architecture to enhance data management in intelligent healthcare ecosystems, in: J. Bravo, S. Ochoa, J. Favela (Eds.), Proceedings of the International Conference on Ubiquitous Computing & Ambient Intelligence (UCAmI 2022), Springer International Publishing, Cham, 2023, pp. 38–49.
[18] T. Priebe, S. Neumaier, S. Markus, Finding Your Way Through the Jungle of Big Data Architectures, CoRR, 2022 abs/2201.0.
[19] R. Minerva, G.M. Lee, N. Crespi, Digital twin in the IoT context: a survey on technical features, scenarios, and architectural modelsProcceedings of the IEEE 108 (2020) 1785–1824, https://doi.org/10.1109/JPROC.2020.2998530.
[20] ISO - ISO/IEC 25040:2011, Systems and software engineering — Systems and software Quality Requirements and Evaluation (SQuaRE). Evaluation Process, 2023 n.d. https://www.iso.org/standard/35765.html. accessed March 20,
[21] ISO; IEC, Software engineering — Software product Quality Requirements and Evaluation (SQuaRE). Data Quality Model (ISO/IEC 25012:2008(E)), ISO/IEC, 2008.
[22] B. Khaleghi, A. Khamis, F.O. Karray, S.N. Razavi, Multisensor data fusion: a review of the state-of-the-art, Inf. Fusion 14 (2013) 28–44, https://doi.org/10.1016/j.inffus.2011.08.001.
[23] H. Boström, S.F. Andler, M. Brohede, R. Johansson, A. Karlsson, J. van Laere, L. Niklasson, M. Nilsson, A.S. Persson, T. Ziemke. On the Definition of Information Fusion as a Field of Research, ISIF Perspectives On Information Fusion, 2007.
[24] R. Johansson, A. Karlsson, S.F. Andler, M. Brohede, J. van Laere, M.K. Nilsson, T. Ziemke, On the definition and scope of information fusion as a field of research, Perspectives (Montclair) 5 (2022) 3–12. http://urn.kb.se/resolve?urn=urn:nbn:se:his:diva-21740.
[25] R.J. Abrahart, L. See, Multi-model data fusion for river flow forecasting: an evaluation of six alternative methods based on two contrasting catchments, Hydrol. Earth Syst. Sci. 6 (2002) 655–670, https://doi.org/10.5194/hess-6-655-2002.
[26] F. White, Data fusion lexicon (1991). https://api.semanticscholar.org/CorpusID:60241292.
[27] S. Qiu, H. Zhao, N. Jiang, Z. Wang, L. Liu, Y. An, H. Zhao, X. Miao, R. Liu, G. Fortino, Multi-sensor information fusion based on machine learning for real applications in human activity recognition: state-of-the-art and research challenges, Inf. Fusion 80 (2022) 241–265, https://doi.org/10.1016/j.inffus.2021.11.006.
[28] M.M. Kokar, J.A. Tomasik, J. Weyman, Formalizing classes of information fusion systems, Inf. Fusion 5 (2004) 189–202, https://doi.org/10.1016/j.inffus.2003.11.001.
[29] D. Lillis, On the evaluation of data fusion for information retrieval, in: ACM International Conference Proceeding Series, 2020, pp. 54–57, https://doi.org/10.1145/3441501.3441506/ASSETS/HTML/IMAGES/FIRE20-4-FIG1.JPG.
[30] B. Zitová, J. Flusser, Image registration methods: a survey, Image Vis. Comput. 21 (2003) 977–1000, https://doi.org/10.1016/S0262-8856(03)00137-9.
[31] X. Zhou, W. Liang, K.I.K. Wang, H. Wang, L.T. Yang, Q. Jin, Deep-learning-enhanced human activity recognition for internet of healthcare things, IEEE Internet Things J. 7 (2020) 6429–6438, https://doi.org/10.1109/JIOT.2020.2985082.
[32] S.G. Dastidar, K. Sambhoos, J. Llinas, C. Bowman, Performance evaluation methods for data-fusion capable tactical platforms, in: 2005 7th International Conference on Information Fusion, 2005. https://www.academia.edu/71967024/Performance_evaluation_methods_for_data_fusion_capable_tactical_platforms. accessed March 19, 2023.
[33] R.M. Pereira, D. Bertolini, L.O. Teixeira, C.N. Silla, Y.M.G. Costa, COVID-19 identification in chest X-ray images on flat and hierarchical classification scenarios, Comput. Methods Programs Biomed. 194 (2020), 105532, https://doi.org/10.1016/J.CMPB.2020.105532.
[34] S.A. Kashinath, S.A. Mostafa, A. Mustapha, H. Mahdin, D. Lim, M.A. Mahmoud, M. A. Mohammed, B.A.S. Al-Rimy, M.F.M. Fudzee, T.J. Yang, Review of data fusion methods for real-time and multi-sensor traffic flow analysis, IEEE Access 9 (2021) 51258–51276, https://doi.org/10.1109/ACCESS.2021.3069770.
[35] P. Jackson, J. Musiak, Boeing fusion performance analysis (FPA) tool, in: 2009: pp. 1444–1450.
[36] D. Akselrod, R. Tharmarasa, T. Kirubarajan, Z. Ding, A.M. Ponsford, Multisensor-multitarget tracking testbed, in: IEEE Symposium on Computational Intelligence for Security and Defense Applications, CISDA 2009, 2009, pp. 1–6, https://doi.org/10.1109/CISDA.2009.5356526.
[37] A. Raj, J. Bosch, H.H. Olsson, T.J. Wang, Modelling data pipelines, in: 2020 46th Euromicro Conference on Software Engineering and Advanced Applications (SEAA), 2020, pp. 13–20, https://doi.org/10.1109/SEAA51224.2020.00014.
[38] D.M. Sundaram, M.S. Vidhya, Data lakes-a new data repository for big data analytics workloads, Int. J. Adv. Comput. Res. 7 (2016), https://doi.org/10.26483/ijarcs.v7i5.2714.
[39] M.M. Alvord, F. Lu, B. Du, C.-A. Chen, Big data fabric architecture: how big data and data management frameworks converge to bring a new generation of competitive advantage for enterprises, 2020.
[40] B.R. May, Digital Twins Can Help Turn Manufacturing Data into Insight, Automation World, 2022. https://www.automationworld.com/factory/iiot/article/22171856/digital-twins-can-help-turn-manufacturing-data-into-insight. accessed July 1, 2022.
[41] Microsoft Corp., Batch integration with Azure Data Factory for Azure Digital Twins, Docs.Microsoft.Com/En-Us/Azure/Architecture/Example-Scenario/Iot/Batch-Integration-Azure-Data-Factory-Digital-Twins. (2022). https://docs.microsoft.com/en-us/azure/architecture/example-scenario/iot/batch-integration-azure-data-factory-digital-tw (accessed July 1, 2022).
[42] H, K.S. Jimenez Jaime Ibarra, Jahankhani, Health care in the cyberspace: medical cyber-physical system and digital twin challenges, in: A, H.-F.A, J.H. Farsi Maryam, Daneshkhah (Eds.), Digital Twin Technologies and Smart Cities, Springer International Publishing, Cham, 2020, pp. 79–92, https://doi.org/10.1007/978-3-030-18732-3_6.
[43] Y. Zheng, S. Yang, H. Cheng, An application framework of digital twin and its case study, J. Ambient Intell. Humaniz. Comput. 10 (2019) 1141–1153, https://doi.org/10.1007/s12652-018-0911-3.
[44] A. Macías, E. Navarro, C.E. Cuesta, U. Zdun, Architecting digital twins using a domain-driven design-based approach, in: 2023 IEEE 20th International

Conference on Software Architecture (ICSA), 2023, pp. 153–163, https://doi.org/10.1109/ICSA56044.2023.00022.
[45] K.Y.H. Lim, P. Zheng, C.-H. Chen, A state-of-the-art survey of Digital Twin: techniques, engineering product lifecycle management and business innovation perspectives, J. Intell. Manuf. 31 (2020) 1313–1337, https://doi.org/10.1007/s10845-019-01512-w.
[46] I. Errandonea, S. Beltrán, S. Arrizabalaga, Digital Twin for maintenance: a literature review, Comput. Ind. 123 (2020), 103316, https://doi.org/10.1016/j.compind.2020.103316.
[47] C. Semeraro, M. Lezoche, H. Panetto, M. Dassisti, Digital twin paradigm: a systematic literature review, Comput. Ind. 130 (2021), 103469, https://doi.org/10.1016/j.compind.2021.103469.
[48] B.R. Barricelli, E. Casiraghi, D. Fogli, A survey on digital twin: definitions, characteristics, applications, and design implications, IEEE Access 7 (2019) 167653–167671, https://doi.org/10.1109/ACCESS.2019.2953499.
[49] J. Niles, S. McClure, D. Pouliquen, Reality capture: a digital twin foundation, 2022. https://www.digitaltwinconsortium.org/wp-content/uploads/sites/3/2022/06/Reality-Capture-A-Digital-Twin-Foundation.pdf (accessed September 19, 2023).
[50] B. Guo, Z. Yu, X. Zhou, A data-centric framework for cyber-physical-social systems, IT Prof. 17 (2015) 4–7, https://doi.org/10.1109/MITP.2015.116.
[51] M.S. Hossain, G. Muhammad, A. Alamri, Smart healthcare monitoring: a voice pathology detection paradigm for smart cities, Multimed. Syst. 25 (2019) 565–575, https://doi.org/10.1007/s00530-017-0561-x.
[52] Google Inc, Google Cloud Computing, Hosting Services & APIs | Google Cloud, 2019. https://cloud.google.com/. accessed February 1, 2019.
[53] Inc. Amazon.com, Amazon Web Services (AWS) - Cloud Computing Services, 2019. https://aws.amazon.com/?nc1=h_ls. accessed March 20, 2019.
[54] Microsoft Corp., Microsoft Azure, Microsoft Azure, 2018. https://azure.microsoft.com/.
[55] A. Macías, E. Navarro, An integrated approach for context-aware development, in: Proceedings of the 12th European Conference on Software Architecture: Companion Proceedings, ACM, New York, NY, USA, 2018, p. 47, https://doi.org/10.1145/3241403.3241452. :1–47:7.
[56] A. Dey, G.D. Abowd, D. Salber, A conceptual framework and a toolkit for supporting the rapid prototyping of context-aware applications, Hum. Comput. Interact. 16 (2001) 97–166, https://doi.org/10.1207/S15327051HCI16234_02.
[57] D.G.D. La Iglesia, D. Weyns, MAPE-K formal templates to rigorously design behaviors for self-adaptive systems, ACM Trans. Auton. Adapt. Syst. 10 (2015) 1–31, https://doi.org/10.1145/2724719.
[58] C. Lv, Q. Zhao, Integration of data compression and cryptography: another way to increase the information security, in: 21st International Conference on Advanced Information Networking and Applications Workshops (AINAW'07), 2007, pp. 543–547, https://doi.org/10.1109/AINAW.2007.208.
[59] J.R. Talburt, D. Pullen, M. Penning, Evaluating and improving data fusion accuracy, (2019) 295–326. https://doi.org/10.1007/978-3-030-03643-0_14.
[60] M. Peralta Ascue, Calidad de datos en sistemas de gestión académica universitaria basado en ISO/IEC 25012, Interfases (014) (2021) 65–88.
[61] D. Muñoz, A. Macías, E. Navarro, Diseño e Implementación de un Sistema Ciber-físico-social para la Monitorización y Prevención de Infecciones por COVID-19 en Residencias de Ancianos, XXVI J. Ingen. Ciencia Ingen. Serv. (JCIS) (2022).
[62] Amavir, Residencia de ancianos Amavir Las Hazas Albacete | Amavir, Amavir. Residencias Para Mayores. (2022). https://www.amavir.es/residencia-de-ancianos-albacete-amavir-las-hazas/(accessed May 4, 2022).
[63] I.A. Geisselmann, S.M. Torre, I.G. Molinero, E.M. Calahorro, S.L. Milla, Formas atípicas de presentación de la enfermedad COVID-19 observadas en atención primaria, FMC 27 (2020) 469, https://doi.org/10.1016/J.FMC.2020.06.002.
[64] Microsoft, Microsoft azure well-architected framework - azure architecture center | Microsoft Docs, (2022). https://docs.microsoft.com/en-us/azure/architecture/framework/(accessed May 1, 2022).