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REAL-TIME RELIABILITY MONITORING ON EDGE COMPUTING: A SYSTEMATIC MAPPING

Diván M.J., Shchemelinin D., Carranza M.E., Martinez-Spessot C.I., Buinevich M. **Real-Time Reliability Monitoring on Edge Computing: a Systematic Mapping.**

Abstract. Scenario: System reliability monitoring focuses on determining the level at which the system works as expected (under certain conditions and over time) based on requirements. The edge computing environment is heterogeneous and distributed. It may lack central control due to the scope, number, and volume of stakeholders. Objective: To identify and characterize the Real-time System Reliability Monitoring strategies that have considered Artificial Intelligence models for supporting decision-making processes. Methodology: An analysis based on the Systematic Mapping Study was performed on December 14, 2022. The IEEE and Scopus databases were considered in the exploration. Results: 50 articles addressing the subject between 2013 and 2022 with growing interest. The core use of this technology is related to networking and health areas, articulating Body sensor networks or data policies management (collecting, routing, transmission, and workload management) with edge computing. Conclusions: Real-time Reliability Monitoring in edge computing is ongoing and still nascent. It lacks standards but has taken importance and interest in the last two years. Most articles focused on Push-based data collection methods for supporting centralized decision-making strategies. Additionally, to networking and health, it concentrated and deployed on industrial and environmental monitoring. However, there are multiple opportunities and paths to walk to improve it. E.g., data interoperability, federated and collaborative decision-making models, formalization of the experimental design for measurement process, data sovereignty, organizational memory to capitalize previous knowledge (and experiences), calibration and recalibration strategies for data sources.

Keywords: real-time, system reliability, monitoring, edge computing, systematic mapping study.

1. Introduction. The continuously evolving technological landscape has driven the need for real-time data processing to meet emerging requirements. Consequently, there is a renewed interest in reevaluating real-time concepts and their alignment with advancements and new contexts [1]. These reasons vary, ranging from leveraging up-to-date information about entities to making critical decisions [2 – 4] and mitigating natural disasters [5]. These advancements have paved the way for various monitoring applications in sectors such as retail [6], industry [7, 8], and natural disaster management [9 – 11], among others. In applications directly associated with people (e.g., natural disasters and rescue), real-time represents the difference between whether or not keeping a person alive [10]. To achieve this, the Internet of Things (IoT) has played a crucial role by enabling data processing, sensor integration, storage, and communication systems to be deployed as close to the monitored environment as possible [12, 13]. Simultaneously, Edge Computing (EC) has emerged to enhance resource management and workload processing [14, 15]. This approach has increased computing power, local resource availability, and communication capabilities while enabling effective resource allocation and management within specific events. Various networks, including body sensor networks and road sensor networks, have been developed and deployed as part of a common and heterogeneous infrastructure, each serving different purposes [16].

Real-Time Reliability Monitoring (RTRM), which relies on IoT devices and EC, is based on a crucial assumption – the system is reliable. However, it is important to establish a clear and shared definition of reliability to ensure a common understanding. Reliability refers to the level of achievement at which a system, product, or component meets its functional specifications within specified conditions and time intervals [17]. A reliable system should exhibit maturity, availability, fault tolerance, and recoverability.

Maturity entails meeting the reliability requirements during typical system operation. Availability ensures that the system is operational and accessible whenever it is required. Fault tolerance focuses on maintaining the system's expected functionality even in the presence of hardware or software faults. Recoverability deals with the system's ability to recover affected data and restore the desired state of a component following an interruption or failure event. Therefore, while reliability represents the desired objective, resiliency encompasses the various elements and procedures employed to attain such a status.

In critical areas such as healthcare, real-time analysis relies on the utmost reliability and monitoring. The advent of IoT has enabled the proliferation of sensing applications, leading to increased density and coverage of data collection related to various aspects, such as the impact of particulate matter on people's health. However, it is crucial to acknowledge and address concerns associated with sensor measurements, such as miscalibrations, before making decisions based on such data [18]. The assumptions underlying the measurement process must be precise and treated with the same level of importance as any decision-making process, whether automated or not.

The collection of measures should adhere to certain principles: repeatability (consistent data collection methods), extensibility (ability to accommodate new requirements), clear definition, and alignment with the intended purpose. The measures obtained must be comparable and consistent, reflecting a cohesive and coherent representation of the property being quantified. They should also possess a known degree of accuracy and precision, achieved using calibrated devices (instruments or sensors). When introducing data-driven decision-making [19], decision-makers expect the data to be interesting, consistent, trustworthy, and timely. They seek information, rather than raw data, to inform their decisions across various aspects. This concern becomes even more critical in the context of automated sensor networks, where decision-making processes are automated. Therefore, ensuring system reliability monitoring, along with a robust measurement process, becomes essential.

Given the critical areas (e.g., health) where real-time analysis is applied, reliability and monitoring are mandatory. On the one hand, IoT fostered increasing the density and coverage of sensing applications (e.g., particulate matter and its impact on people's health). On the other hand, sensors suffer from different concerns that need to be considered (e.g., miscalibrations) before deciding based on such data [18]. The underlying assumptions around the measurement process are sharp and must be regarded as in any decision-making process (automated or not). How the measures are collected must be repeatable (i.e., collects data in a compatible way), extensible (e.g., new requirements), defined, and aim guided. The obtained measures must be comparable and consistent (i.e., cohesive and coherent based on the property trying to quantify), with a known degree of accuracy and precision using a calibrated device (instrument or sensor). Always Data-driven decision-making [19] gets introduced, and decision-makers believe that data are interesting, consistent, trust, and timely. Thus, decision-makers expect to use information (and not data) before deciding on any aspect. Now, it extrapolates this concern in automated sensor networks where the decision-making is automated. System reliability monitoring (and the underlying measurement process) becomes essential.

The Systematic Mapping Study (SMS) describes a set of guides to perform a study focused on tracing the evidence in a broad domain, such as RTRM on EC. This approach allows for a preliminary exploration of the topic before delving into specific aspects [20 – 22].

This work contributes in several ways: a) an SMS was conducted, providing a detailed identification and characterization of strategies related to RTRM on EC; b) different approaches focusing on reliability monitoring were identified and characterized; c) a comparative analysis was performed to elucidate the relationship between artificial intelligence, reliability, and monitoring on edge devices; d) the reliability monitoring needs and their impact on automated decision-making processes were analyzed within the context of edge computing.

The study is divided into seven sections. Section 2 provides a summary of related articles that share similar objectives. Section 3 outlines the methodological strategy, including the selected data sources, criteria for article selection, and retention criteria used to compile the final list of articles. Section 4 analyzes the collected documents using the SMS methodology, describing the application of SMS and the analysis of the subjects, along with a scoring model for prioritizing further reading. Section 5 presents a comparative analysis of the main strategies based on the scoring model. Section 6 discusses the results obtained in relation to the research questions. Finally, the study concludes with a section dedicated to presenting the overall findings and conclusions.

2. Related Works. There is a vast number of reviews available on the topics of IoT and EC, particularly related to sensor networks and data gathering for monitoring purposes. However, this section specifically focuses on the most relevant works pertaining to RTRM on EC, which examines system reliability monitoring at an abstract level. The objective is to identify reviews that emphasize reliability as a core concept.

Additionally, the monitoring schema should prioritize the degree to which a system achieves functional specifications under defined conditions within a specific time interval. This means that the system can monitor various entities such as vehicles, trains, roads, outpatients, etc., but the crucial aspect lies in ensuring that the primary monitoring system operates as intended.

In a review by [23], the authors delve into edge computing applications in smart grids and compare their efficiency to traditional systems. They discuss the advantages of employing edge devices in smart meters, which results in improved accuracy, reduced latency, and optimized bandwidth consumption. The article explores various EC-based applications, including the monitoring of transmission lines using Unmanned Aerial Vehicles, video surveillance systems, microgrid systems, and power supply management in charging points. It also discusses RTRM of edge frameworks, the interplay between IoT, EC, and cloud computing, as well as the correlation between productivity and security in smart grids based on EC.

While this review shares similarities in addressing the impact of EC devices on latency, bandwidth, and accuracy, it differs in its primary focus on RTRM as a core concern, regardless of the specific application domain.

In [24], the authors introduce a review of mobile and wearable sensors for data-driven health monitoring systems. They discuss strengths and weaknesses associated with wearable sensors, available alternatives, and monitoring systems. Also, the work addresses data types and issues related to disease diagnosis domains, critical challenges inhibiting sensor-based health monitoring systems, and proposed solutions. As a similarity, it addresses a systematic mapping study on Sensor-based applications and solutions. As a difference, this systematic mapping study focuses on the reliability of EC-based systems and how different works try to achieve defined system requirements.

It discusses the articulation between cloud and EC for cooperating on meteorological radar applications and data interoperability [25]. The authors discuss the main problems of weather radar data quality control and different scenarios where edge and cloud computing are complimented for data quality control. The article introduces and contrasts various techniques for data quality control jointly with the challenges and association with edge-cloud cooperation. As a similarity, the review focuses on real-time alternatives to deal with data quality control and the associated implementation (and not the data gathering itself). As a difference, this SMS addresses the system reliability considering different data collection strategies (e.g., push-based, pull-based, hierarchical variations, etc.) jointly with the decision-making process and how to implement actions to keep aligned reliability requirements.

In [26], the authors discuss the impact of information and communication technologies on Digital Twins as a Service (DTaaS). They substantiate the increasing interest in the industrial field due to technologies related to EC, network function virtualization, and 5G. As a similarity, it analyses the latency, data rate, reliability, and scalability requirements in different functionalities related to digital twins (i.e., monitoring, simulation, and operation). However, it limits the level of scalability outlined based on use cases. As a difference, this work discusses the SMS of the RTRM on EC as a central concept, analyzing research volume, types of applications, data collection strategies, and decision-making approaches (e.g., centralized, distributed, etc.).

3. Methodology. SMS proposes a set of directives to specify an action protocol to analyze the shell of a topic. It is beneficial in those areas where a topic is extensive and needs to be reduced based on determined criteria [20 – 22]. This way, after the topic's shell is known and described, it is feasible to explain it before focusing on further detailed analysis.

Figure 1 outlines a Business Process Model and Notation (BPMN) diagram depicting the crucial steps and activities related to the SMS. First, the aim that guided the study was defined jointly with the Research Questions (RQ). An essential aspect was to cover the purpose through RQs before advancing; In other words, the research questions should add different approaches to explore the topic based on the objective. After that, it chooses the databases where the inquiries will be executed. In this sense, every RQ is translated as a part of the search string and suited to the particularities of each chosen database, incorporating the filtering criteria.

This way, the final search strings (suited to each chosen database, including the filtering criteria) were run on each database. Then, the results were processed and reduced through established criteria.

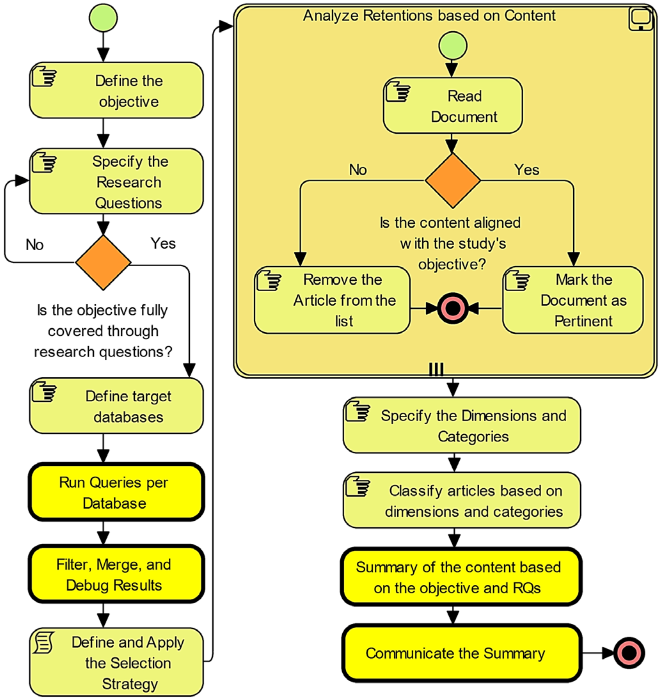

Fig. 1. Crucial Steps of the Systematic Mapping Study, using the BPMN notation

It is worth mentioning that database results were unified in a single list. Then, a quick analysis removed the duplicate records from the list while the selection criteria were defined. The retention criteria focused on the wished properties in articles to sustain the analysis based on coverage and the study's objective. At the same time, those that did not meet the requirements were separated, which helped debug the results and obtain a debugged list.

The next step was to read each article from the debugged list. Records were kept depending upon whether the contents were related to the study objective and the associated points of view (e.g., perhaps an article figured in the list because keywords were present, but the content could mention them as a related example – or potential application – without specific details on the topic). After analyzing every article, a unique list of articles aligned with the objective and proposed questions was produced.

The next step aimed to define dimensions and categories for analyzing those articles from the list. On the one hand, dimensions describe a broad perspective from research questions, while the categories focus on specific content in the dimension. For instance, a dimension could analyze the approaches used for monitoring the system's reliability; however, categories could indicate different typologies for implementing the monitoring, such as "Push-based, Pull-based, distributed, or centralized." Once the dimensions and categories were specified, they helped to classify the articles in the list. Then, articles were summarized, organized, and communicated through the conclusion in alignment with the study aim.

This section is organized into four sections. The first section specifies the study aim and research questions. The second focuses on the search strategy, target databases, and how to suit the search string in each case. The third one discusses the selection process. The last part of this section makes explicit the limitations and potential biases of this study.

3.1. Research Questions. RQ emerged naturally from the defined aim to define the analysis perspectives and describe the broadness of the search strategy. As it was introduced, the objective of this SMS resided in identifying and characterizing the IoT-based RTRM strategies, which have implemented a measurement process to study the effects of the particulate matter on human health.

The first one was *What is the volume of research on Artificial Intelligence (AI) applied to RTRM on edge devices?* (i.e., RQ1). It is focused on exploring the main concentration of AI-related techniques on current reliability concerns and challenges. It is interesting to review and characterize the current trends. Also, it is worth analyzing the reasons behind the topics with the closest attention in contrast to those with the lowest popularity.

The second question was *What kind of AI approaches are used for reliability monitoring on edge devices?* (i.e., RQ2) The inquiry aims to dive into the different approaches used for reliability monitoring. It could be associated with a holistic approach or dive into some reliability sub-attributes such as maturity, availability, fault-tolerance, or recoverability. Thus, methods could refer to the data processing mode (i.e., online or offline), how metrics are collected (i.e., push or pull), etc.

The third question analyzed the relationship between AI approaches and Data-driven decision-making. It was "*Are the AI approaches related to some real-time decision-making strategy?*" (i.e., RQ3). In this perspective, the underlying assumption implies there is an AI approach guided by data and applied to some situations. Thus, the research question focused on the articulation between the AI model and the Decision-making strategy.

The fourth question advocated for the data collection methods and the articulation with Real-time Reliability Monitoring. This question was *What data collection methods are used for implementing RTRM on eEC?*" (i.e., RQ4). These aspects are worth considering due to the edge challenges such as device heterogeneity, device distribution, data ownership, data sovereignty, etc.

The last research question was *What are the main applications of AI-based RTRM on EC?* (i.e., RQ5). In other words, the idea is to dive into kinds of applications, fields, areas, or subjects where RTRM gets required, and the AI models represent a positive plus. Thus, the characterization of such applications would allow extracting features under interest.

From the research questions, the idea was to identify the concepts involved in each question to delineate the query strings. Thus, once the query strings were identified, they were adapted following the syntaxis of each queried database [21].

Table 1 describes the keywords surged from each research question, defining the alternative terms for known concepts such as Reliability. While the research questions indicate each complementary perspective under analysis based on the aim of the view, keywords allowed for addressing such views converting them into conceptual search strings to locate articles satisfying each view (acting as decision criteria) [22]. Keywords related to AI, RTRM, Strategy, Reliability, and EC emerged from RQ1 to analyze the articulations between the devices, collecting systems, and those AI approaches to monitor them [27 – 29]. Keywords associated with the types and uses emerged from RQ2, intending to analyze the alternative approach for reliability monitoring [30 – 31]. Keywords about AI, Decision-Making, and Relationship get derived from RQ3 to explore the articulation between knowledge (or previous experiences) and decision [32 – 34]. Keywords related to the data collection use and reliability used from RQ4 to analyze the common collection methods and the reliability monitoring [35 – 37]. Keywords associated with the applications surged from RQ5 [38 – 40].

Table 1. Keywords related to Research Questions

RQ	Keywords
1	**AI** (alternatively “Artificial Intelligence,” “Machine Learning,” “Expert Systems,” “Agents,” “Case-based Reasoning,” “Linked Systems,” “Optimization,” “Automated Planning and Scheduling,” or “Computer Vision”), **Real-time**, **Reliability** (alternatively “Maturity,” “Availability,” “Fault-Tolerance,” or “Recoverability”), **Monitoring** (alternatively “Observation” or “Monitor” or “Observability”), **Strategy** (alternatively, “Approach,” “Method,” “Procedure,” “Scheme”), and “**Edge Computing**”.
2	*Kind* (alternatively, “Class,” or “Category,” or “Type”), *AI*[1], *Approach*[1], “*Used for*” (alternatively “Applied to”), *Reliability*[1], *Monitoring*[1], and “*Edge Computing*”.
3	*AI*[1], *Approach*[1], *Relationship* (alternatively “Association”), *Real-time*, *Decision-making*.
4	*“Data collection” (alternatively “data gathering”), Strategy*[1]*, “used for”*[1]*, Real-time, Reliability*[1]*, Monitor, “Edge Computing”.*
5	*Applications (alternatively “Use Case”), AI*[1]*, Real-time, Reliability*[1]*, “Edge Computing”.*

[1] As defined in previous research questions

Table 2 describes the conceptual search string derived from keywords in Table 1.

Table 2. Conceptual Search String

Terms	Structure
Common	(“Artificial Intelligence” or “AI” or “Machine Learning” or “Expert Systems” or “Agents” or “Case-based Reasoning” or “Linked Systems” or “Optimization” or “Automated Planning and Scheduling” or “Computer Vision”) and “Real-time” and (“Reliability” or “Maturity” or “Availability” or “Fault-Tolerance” or “Recoverability”) and (“Monitoring” or “Monitor” or “Observation” or Observability) and (“Strategy” or “Approach” or “Method” or “Procedure” or “Schema”) and (“Edge Computing” or “Edge” or “IoT” or “Internet-of-Thing”)
Alternative	(“Kind” or “Class” or “Category” or “Type”) or (“Used for” or “Applied to”) or (“Relationship” or “Association”) or (“Decision-making”) or (“Data collection” or “data gathering”) or (“Applications” or “Use Case”)

Table 2 discriminates between common and alternative restrictions for logical expression. On the one hand, the common terms must be simultaneously present in the abstract, title, or keywords. On the other hand, the alternative terms represent different concepts eventually associated. However, at least one of them must be present in the abstract, title, or keywords jointly with the familiar words.

Thus, an article was retained in the initial result if it contained all the common terms plus at least one alternative term. It is essential to mention that Table 2 describes the conceptual search string, which was fitted to each database’s syntaxis before applying it.

3.2. Search Strategy. The conceptual search string was fitted to each database where the query would be performed. For this study, the digital libraries of IEEE and Scopus were considered. The idea was to provide broad coverage around the published articles related to the subject.

Tables 3 and 4 describe the adaptation of the conceptual search string to the Scopus and IEEE database syntaxes. As it is possible to appreciate, even when the meaning is similar, some syntactic aspects were fitted before running the query.

Table 3. Search String fitted to Scopus Database

Search String
TITLE-ABS-KEY ("Artificial Intelligence" OR "AI" OR "Machine Learning" OR "Expert Systems" OR "Agents" OR "Case-based Reasoning" OR "Linked Systems" OR "Optimization" OR "Automated Planning and Scheduling" OR "Computer Vision") AND TITLE-ABS-KEY ("Real-time") AND TITLE-ABS-KEY ("Reliability" OR "Maturity" OR "Availability" OR "Fault-Tolerance" OR "Recoverability") AND TITLE-ABS-KEY ("Monitoring" OR "Monitor" OR "Observation" OR "Observability") AND TITLE-ABS-KEY ("Strategy" OR "Approach" OR "Method" OR "Procedure" OR "Schema") AND TITLE-ABS-KEY ("Edge Computing" OR “Edge” OR “IoT” OR “Internet of Thing”) AND TITLE-ABS-KEY ("Kind" OR "Class" OR "Category" OR "Type" OR "Used for" OR "Applied to" OR "Relationship" OR "Association" OR "Decision-making" OR "Data collection" OR "data gathering" OR "Applications" OR "Use Case")

Table 4. Search String Fitted To IEEE Database

Search String
("All Metadata": "Machine Learning" OR "All Metadata": "Artificial Intelligence" OR "All Metadata": "AI" OR "All Metadata": "Expert Systems" OR "All Metadata": "Agents" OR "All Metadata": "Case-based reasoning" OR "All Metadata": "Linked Systems" OR "All Metadata": "Optimization" OR "All Metadata": "Automated Planning and Scheduling" OR "All Metadata": "Computer Vision") AND ("All Metadata": Reliability OR "All Metadata": Maturity OR "All Metadata": Availability OR "All Metadata": "Fault-Tolerance" OR "All Metadata": Recoverability) AND ("All Metadata": Monitoring OR "All Metadata": Monitor OR "All Metadata": Observation OR "All Metadata": Observability) AND ("All Metadata": Real-time) AND ("All Metadata": "Edge Computing" OR "All Metadata": "Edge" OR "All Metadata": "IoT" OR "All Metadata": "Internet of Thing") AND ("All Metadata": Strategy OR "All Metadata": Approach OR "All Metadata": Method OR "All Metadata": Procedure OR "All Metadata": Schema) AND ("All Metadata": Kind OR "All Metadata": Class OR "All Metadata": Category OR "All Metadata": Type OR "All Metadata": "Used for" OR "All Metadata": "Applied to" OR "All Metadata": Relationship OR "All Metadata": Association OR "All Metadata": "Decision-making" OR "All Metadata": "Data collection" OR "All Metadata": "Data gathering" OR "All Metadata": "Applications" OR "All Metadata": "Use case")

3.3. The Selection Process. This SMS focused on consolidated research written in English and published in journals. It did not consider those articles related to conferences (except extended versions), abstracts, posters, general surveys, reviews, or similar. Thus, it assumes the consolidated research is published in journals and written in English, pursuing international visibility. In this sense, the idea focused on getting an updated perspective about consolidated research strongly associated with Edge-aware systems for RTRM. For sure, this decision implies a bias around the review.

Thus, the initial result list was filtered, retaining articles written in English and coming from journals. Also, surveys and reviews were kept out, fostering access to the source.

Once results from each database were obtained and filtered, a unique list was generated from the fusion of the previous ones. Over this new list merging results from each database, only one copy of duplicate records was kept.

After that, each article's abstract was read in the list to confirm whether it was retained or not according to the search string. That is to say, the searched terms (i.e., keywords) could be present in the abstract just as a mention but not as a core subject. Just articles addressing as a core subject those aspects indicated in the keywords introduced by research questions (Table 1) were retained. In this way, a debugged list for its analysis was reached. This aspect incorporated subjectivity derived from the author's criteria in this work, which was understood as a potential bias.

3.4. Biases and Limitations. The primary underlying assumption throughout this work was that consolidated results from research lines were published in journals. For this reason, no conference papers and other kinds of publishing were considered. Also, previous reviews were supposed to only partially analyze the core aspect of real-time system reliability, avoiding intermediaries.

English is assumed to be the common language to internationalize the research results.

The limitation of the systematic review is associated with biases. The inclusion/exclusion criteria and the selection of databases compound a set of elements that could be naturally subjective due to the authors' perception. This work was limited to articles published in journals and available on IEEE and Scopus databases. Even when the work tried to get a broad scope, it is not a warranty that the universe of articles is considered.

4. Description of the Approaches. This section is broken down into three sections to describe the implementation of SMS, jointly with the analysis of topics and the proposed order to introduce each obtained work from the queries.

4.1. Implementing the SMS. The queries ran in their respective databases on December 14, 2022. After the initial results, the indicated filters were applied (i.e., limiting to journal articles written in English, etc.), obtaining a partial list of a) *IEEE*: 22 records and b) *Scopus*: 42 records. In this way, 64 records initially satisfied the search requirements.

Each query's result was stored in an Excel file organized by the origin database, and each item was individually inspected to verify that it was associated with a journal article. If a record was not associated with a research article from a journal, it was removed from the list.

Table 5 shows the reasons and quantities for each record's retention jointly with the removal. On the one hand, those records referred to RTRM based on EC were retained. On the other hand, documents associated with the following types were removed 1) *Duplicated*: The same article was available in the IEEE and Scopus results. Only one copy was retained; 2) *Not related content*: The article specifically did not refer to RTRM based on EC. Keywords were only mentioned in the narrative; 3) *Proceedings*: It was not an article but a conference proceeding; 4) *Review*: The article was not a research article. It contained a survey or review of the subject but not how to monitor the system reliability through EC in real-time.

Table 5. Results

	Scopus	**IEEE**
Retained	34	16
Duplicated	0	6
Not Related	8	0
Proceedings	0	0
Review	0	0
Total	*42*	*22*

Thus, 58 records were retained from the different databases, removing eight duplicates and obtaining 50 unique articles (See the first line under the caption in Table 5).

4.2. Dimensions and Characteristics. From the research questions, it was possible to define the dimensions associated with each one jointly with the categories to classify each record from the 50. Table 6 describes the dimensions and categories established by each research question to address the synthesis process indicated in Figure 1.

Table 6. Dimensions and Categories

Research Question	**Dimension**	**Categories**
RQ1	Research	Artificial Intelligence, Real-time, Reliability, Monitoring, Edge Devices
RQ2	Approach	Push-based, Pull-based, Distributed, Centralized
RQ3	Decision-Making	Centralized, Federated, Collaborative
RQ4	Methods	Direct Push, Direct Pull, Hierarchical Push, Hierarchical Pull, Query-based local
RQ5	Applications	Area, Subject

About RQ1, the approaches were 1) “*AI*” when models are applied to monitor, analyze, or forecast some properties associated with the system reliability, 2) “*Real-time”* when data are processed and analyzed when they arrive, 3) “*Reliability”* when the monitoring strategy monitors the system reliability itself in addition to the application aim, 4) *“Monitoring”* indicates a formalized strategy to observe (continuously and actively) the system's reliability, 5) “Edge Computing” when edge devices are articulated with the monitoring strategy focused on the system reliability. RQ2 refers to the approach used for monitoring the system’s reliability. It could be “*Push-based”* when the edge devices push data to a reliability monitoring component; “*Pull-based*” when a reliability monitoring component scratches data from the edge devices to ensure the system's reliability; “*Distributed*” when the reliability monitoring is associated with some swarm intelligence where data are kept on the origin; “*Centralized*”: It indicates an approach where system reliability monitoring is associated with a central component, and edge devices play the role of obedience. RQ3 was associated with the decision-making strategy, indicating “Centralized*”* for those strategies where a significant piece makes decisions based on collected data, “Federated” when the decision-making strategy implies a set of autonomous and distributed features which decide based on some consensus and feedback mechanism between them, and "*Collaborative*" is when two or more components exchange data and knowledge optionally before choosing between them. In this approach, collaboration is optional. A system component could act unilaterally or with a few other devices. RQ4 was focused on the data collection strategy and decision-making process. "*Direct Push*" indicates data are pushed to a central reliability monitoring component without intermediaries or data aggregation. "*Direct Pull*" is associated with a centralized reliability monitoring component scratching data directly from the data sources. "*Hierarchical Push*" is when data walks through a data processing hierarchy from the data source until reaching the wished reliability control level. "*Hierarchical Pull*" focuses on data traveling in a data processing hierarchy, but a certain reliability control level pulls data from the source in stages. "*Query-based local*" indicates that data resides locally (never moved), and the data source only answers queries using the local data. Finally, RQ5 was related to the applications. Thus, "*Area*" represents the field in which the system reliability monitoring is applied, while "*Subject*" refers to the specific application.

Using the ISSN (International Standard Serial Number) associated with the journal of each selected article, the quarter to which the journal belongs was obtained from Scimago Journal and Country Rank (SJCR) [41] and incorporated for the analysis. SJCR is a publicly available portal that includes the journals and country scientific indicators created using information from the Scopus database (Elsevier B.V.). The platform uses the Scimago Journal Rank indicator [42] to show the visibility of journals in the Scopus database from 1996. The indicator considers the journal prestige, the number of associated documents in the database, and the citation prestige given by "importance" and "closeness" according to the received citations. Thus, journals could fall into four categories a) Quarter 1 (Q1) indicates the Top-25% percent most visible journals for an area or discipline, 2) Quarter 2 (Q2) represents journals located in the region of (25; 50] %, 3) Quarter 3 (Q3) indicates those journals integrating the zone of (50; 75] %, and 4) Quarter 4 (Q4) composed of journals falling into the interval (75; 100] %. Eventually, it is possible that a journal is not registered or present in the Scopus database (e.g., because it is a new journal); in such a case, missing space is indicated.

Figure 2 describes the distribution by year of the retained articles from the queries, indicating the quarter to which the associated journal belongs. Since 2013 this field has taken sustained growth. As mentioned, the basic Scimago's journal categories go from Q1 to Q4. However, some journals contain a mix of types (e.g., Q1/Q2), indicating that some journal subjects are assessed and fall under a specific category (e.g., Q1). Still, other ones fall under a different category (e.g., Q2). Some journals do not have a Scimago category because they are new. The previous figure indicates this situation under the "Missing" category.

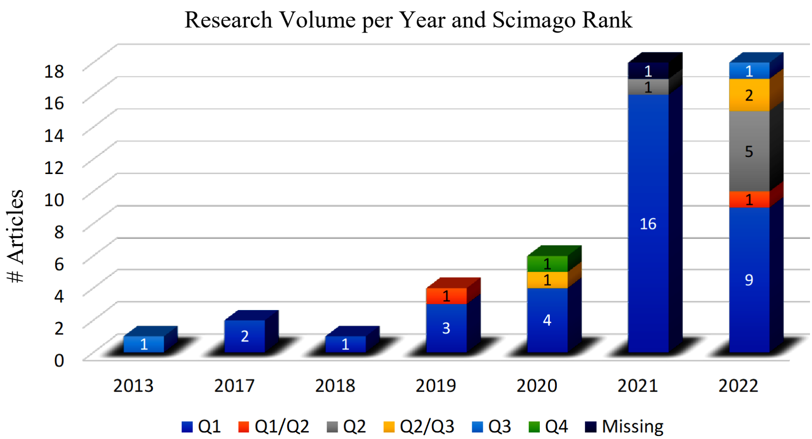

Fig. 2. Articles organized by year and Scimago's quarter to which the journal belongs

Through the individual reading of each article, they were classified according to the categories specified for each dimension. Regarding the research dimension, 74% of analyzed works incorporated some AI model, 94% focused on the real-time aspects, 90% analyzed specific reliability properties, 70% described a formalized monitoring strategy, and 98% explained the articulation between edge devices to IoT and Cloud computing.

The dimension related to the reliability monitoring approach shows that 75.86% of works follow a Push-based strategy. It is logical because there is no control over exogen factors affecting the deployment field (or decisions from third parties) in a distributed and heterogeneous environment. 12.07% of works incorporate a central component for system reliability monitoring. 10.34% of analyzed documents describe a Pull-based associated with the system reliability monitoring component. Lastly, 1.72% of works outline a distributed strategy for dealing with system reliability monitoring.

About the Decision-making dimension, 71.43% of works are associated with a centralized schema to make decisions on system reliability, 17.86% describe a distributed approach, and 10.71% introduced a federated strategy.

From the point of view of data collection methods, 44.23% address the data collection using direct-push strategies, and 42.31% describe a hierarchical-push approach (e.g., using gateways or variations of aggregation schemas). It represents 86.54% of works using push strategies to provide data for system reliability monitoring. 7.69% of results deal with pull-based collection schemas, and 3.85% use a hierarchical-pull approach (i.e., 11.54% of works address the data collection using pull-based methods). 1.92% of results incorporate local data management articulated with the system reliability monitoring component through a Query-based schema.

Figure 3 describes the proportion of application areas based on the general area concept characterized by the fifth dimension.

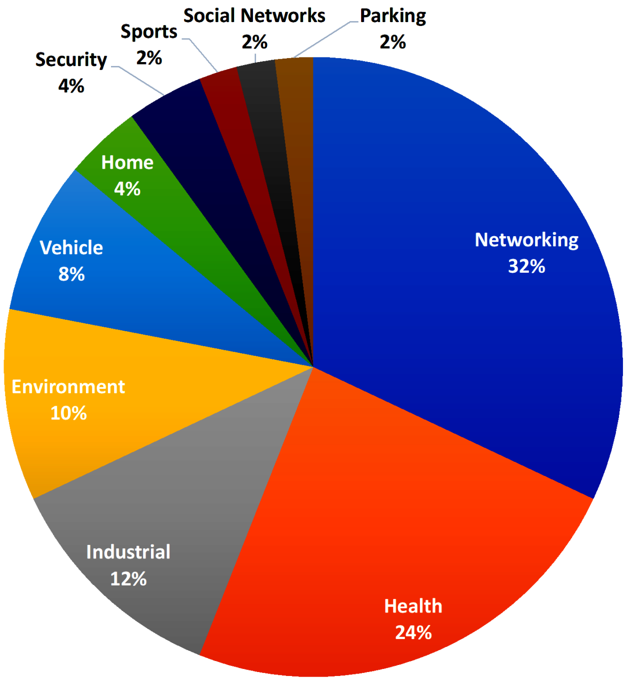

Fig. 3. Main Application Areas

5. A comparative perspective of the main approaches. Each of the obtained articles was synthetically described and analyzed from the dimensions introduced in Table 5. For better organizing, they will be presented according to the generated groups in the previous section and following the order criteria.

5.1. Articles between 2013 and 2019. Table 7 describes articles between 2013 and 2019, ordered by year, quarter, and the number of citations, indicating the decision-making approach.

Table 7. Prioritizing for Articles between 2013 and 2019

Article	Decision-making	Area	Scimago	Citation
IOT system environmental monitoring using IPSO weight factor estimation [43]	2013	Centralized	System environmental monitoring	Q3
Self-regulating supply–demand systems [44]	2017	Collaborative	Energy supply–demand Matching	Q1
Real-Time Signal Quality-Aware ECG Telemetry System for IoT-Based Health Care Monitoring [45]	2017	Centralized	ECG Telemetry System	Q1
PsCPS: A distributed platform for cloud and fog integrated smart cyber-physical systems [46]	2018	Centralized	Cyber-physical Systems	Q1
Contextaide: End-to-End Architecture for Mobile Crowd-sensing Applications [47]	2019	Centralized & Collaborative	Perpetrator Tracking	Q1
Fault-Tolerant mHealth Framework in the Context of IoT-Based Real-Time Wearable Health Data Sensors [48]	2019	Federated & Collaborative	mHealth. Reliability	Q1
QoS-Adaptive Approximate Real-Time Computation for Mobility-Aware IoT Lifetime Optimization [49]	2019	Centralized	Task Schedule based on QoS requirements.	Q1/Q2
Deep Learning for Hybrid 5G Services in Mobile Edge Computing [50]	2019	Centralized	Network. Energy consumption optimization	Q1

Study [43] describes an improvement in particle swarm optimization (PSO). The authors claim that Improved PSO increased the measurement preciseness via weight factors estimated via experimental simulations. It allows the integration of weight factors, information source fusion reliability, information redundancy, and hierarchical structure integration in uncertain fusion cases.

In [44], the authors describe a generic decentralized self-regulatory framework shaped around standardized control system concepts and IoT. It involves a decentralized combinatorial optimization mechanism that matches supply–demand under different regulatory scenarios. Also, they describe an evaluation methodology jointly with the proposal that allows the systematic assessment of constraints.

In [45], it is described the signal quality-aware IoT-enabled electrocardiogram (ECG) telemetry system for continuous cardiac health monitoring applications. It comprises modules such as ECG signal sensing, automated Signal Quality Assessment (SQA), and signal-quality aware (SQAw) ECG analysis and transmission. It aims to design and develop a lightweight ECG SQA method for Real-time classifying based on ECG signals.

It proposes a distributed platform for cloud and fog-integrated smart Cyber-Physical Systems (sCPS), named PsCPS [46]. It can provide services to address integration challenges among multiple clouds, multiple fog nodes, and sCPS subsystems. It comprises agents providing services for cloud and fog-integrated sCPS in the participating nodes. Agents can be developed, implemented, controlled, and managed in different ways (i.e., a set of single agents, multi-agent systems, or hierarchical multi-agent systems).

In [47], the authors introduce a design approach for tracking using Mobile-Crowd Sensing (MCS) for complex processing in real-time named ContextAiDe. It comprises 1) An API for detailing contexts jointly with the MCS applications, 2) A middleware for enabling context-optimized and fault-tolerant distributed executions, and 3) An optimization engine for providing the action paths. The authors claim that the strategy is context-optimized recruitment for the execution of computation- and communication-heavy MCS applications in an edge environment. It analyzes two contexts: a) Exact: which has a set of constraints that must be satisfied, and b) Preferred: which has constraints that may be satisfied to a certain level. Thus, ContextAiDe can optimize the operational overheads to enable real-time operation by adjusting the preferred contexts.

In [48], the authors describe a framework to deal with different concerns associated with mHealth applications. They explain a risk local triage algorithm (Risk-Level Localization Triage – RLLT). It can exclude the control process of patient triage and warn about failures related to wearable sensors. RLLT carries out the initial step towards detecting a patient's emergency case and then identifying the healthcare service package of the risk level. Thus, decision-makers are assisted with hospital selection based on the risk-level package, considering the time to arrive at every hospital related to the patient. Also, a mobile app can connect with the hospital's servers to verify the availability of healthcare services given a risk-level package to guide the feasible options.

In [49], the authors address the mobility-aware network lifetime maximization for battery-powered IoT applications. They focus on estimating real-time computation subject to quality-of-service constraints. They discuss a two-fold strategy. An offline step where a task schedule based on mixed-integer linear programming tries to optimize the network lifetime. An online step deals with a heuristic approach for adapting the task execution based on QoS requirements.

In [50], the authors introduce a strategy to minimize normalized energy consumption. In this context, energy consumption refers to the consumption per bit. The optimization is pursued through optimizing user association, resource allocation, and offloading probabilities subject to the quality-of-service requirements. On the one hand, the mobility management entity manages the user association. On the other hand, every access point determines the resource allocation and offloading likelihoods. A deep neural network is trained offline in a central server based on a digital twin approach representing the current state of the network. Thus, the Mobility management entity uses a DNN model to obtain the user association scheme in real time. Next, an optimization algorithm analyzes the best resource allocation and offloading likelihoods at each access point.

5.2. Articles in 2020. Table 8 describes articles in 2020 ordered by quarter and the number of citations, indicating the decision-making approach.

Table 8. Prioritizing for Articles in 2020

Article	Decision-making	Area	Scimago	Citation
Joint Optimization of Offloading Utility and Privacy for Edge Computing Enabled IoT [51]	Centralized & Collaborative	Network. Resource Optimization	Q1	102
Towards collaborative intelligent IoT eHealth: From device to fog, and cloud [52]	Centralized & Collaborative	ECG-based arrhythmia detection	Q2/Q3	47
A Joint Deep Learning and Internet of Medical Things Driven Framework for Elderly Patients [53]	Centralized	Elderly Patients Monitoring	Q1	46
AI-Enabled Reliable Channel Modeling Architecture for Fog Computing Vehicular Networks [54]	Centralized	Vehicular Monitoring	Q1	26
Quantum computing-inspired network optimization for IoT applications [55]	Centralized	Sensor Networks > Improve the RT Data accuracy	Q1	23
Research on environmental monitoring trend analysis based on internet of things visualization technology [56]	Centralized	Environmental Monitoring	Q4	1

In [51], it gets described as a two-phase offloading optimization strategy. It aims for joint optimization of offloading utility and privacy in the Edge. The Resource utilization maximization is reached through a Utility-Aware Task Offloading (UTO) method. On the other hand, a balance between privacy preservation and execution performance is achieved using a mutual optimization method.

In [52], it describes a holistic AI-driven IoT eHealth architecture based on the concept of the Collaborative Machine Learning approach. Intelligence is distributed across different layers: Devices, Edge/Fog, and Cloud. The proposed approach enables healthcare professionals to continuously monitor the health-related data of subjects anywhere at any time, providing real-time actionable insights for improving decision-making. The proposal is applied to the ECG-based arrhythmia detection case study.

In [53], the authors describe a sustainable, reliable, and optimized strategy for cardiac activity monitoring based on wearable sensors and image processing in elderly patients. A self-adaptive power control-based Enhanced Efficient-Aware (EEA) approach improves energy consumption and battery lifetime. In this context, it introduces a framework and architecture for cardiac image processing based on deep learning and the Internet of Medical Things. Sustainability and reliability are described around a model for optimizing battery usage and network optimization.

In [54], the authors propose an AI-based, Reliable Interference-free Mobility Management Algorithm (RIMMA) for fog computing intra-vehicular networks. Contributions are organized around four main axes. The first one they claim is that RIMMA, jointly with fog computing, improves computation, communication, cooperation, and storage space. The second one, it gets proposed a reliable and delay-tolerant wireless channel model with better QoS for passengers. The third one is a reliable and efficient multi-layer fog-driven inter-vehicular framework. The fourth one works on the QoS optimization based on mobility, reliability, and packet loss ratio.

In [55], a Quantum Computing-inspired Optimization (IoT-QCiO) technique is introduced. It focuses on maximizing Data Accuracy (DA) in a real-time environment of IoT applications. The proposed model adds quantum formalization of sensor-specific parameters to quantify IoT devices in terms of Sensors in the Vicinity (SIV) and Optimal Sensor Space (OSS). The algorithm optimization is based on data cost, accuracy, and temporal efficiency.

In [56], it introduces an environmental monitoring trend analysis algorithm based on the Internet of Things visualization technology. The proposed algorithm first divides the environmental monitoring area into several different clusters. Different types of sensors provide environmental data that are associated with a group. A mobile agent node is responsible for a monitoring area. It aims to build a two-dimensional positioning table based on the network energy consumption. Thus, it applies the Rosen gradient projection method for choosing the optimal path. With such information, it builds the mobile plan for data collection and forwarding to the control center. Finally, data are centrally analyzed by the control center.

5.3. Articles in 2021. Table 9 describes articles in 2021 ordered by quarter and the number of citations, indicating the decision-making approach and application area. Works with at least one mention are incorporated into the table, and the other ones are outlined in this section after those related to the table are presented.

Table 9. Prioritizing for Articles in 2021

Article	Decision-making	Area	Scimago	Citation
Digital electronics in fibers enable fabric-based machine-learning inference [57]	Centralized	Digital Electronics in fibers	Q1	27
A Smart, Efficient, and Reliable Parking Surveillance System with Edge Artificial Intelligence on IoT Devices [58]	Centralized	Parking Surveillance	Q1	26
Enabling Secure Authentication in Industrial IoT with Transfer Learning Empowered Blockchain [59]	Federated & Collaborative	Secure Authentication	Q1	20
Development of a speed invariant deep learning model with application to condition monitoring of rotating machinery [60]	Centralized	Machinery Clever Monitoring.	Q1	15
IHSF: An Intelligent Solution for Improved Performance of Reliable and Time-Sensitive Flows in Hybrid SDN-Based FC IoT Systems [61]	Federated	Congestion Control	Q1	11
An IoT-based deep learning approach to analyze indoor thermal comfort of disabled people [62]	Centralized	Indoor Monitoring	Q1	10
Fog-centric IoT based smart healthcare support service for monitoring and controlling an epidemic of Swine Flu virus [63]	Centralized	Monitoring of Swine Flu Virus	Q2	8
Intelligent system of game-theory-based decision making in smart sports industry [64]	Centralized	Athlete Performance Monitoring	Q1	5
Learning Spatiotemporal Latent Factors of Traffic via Regularized Tensor Factorization: Imputing Missing Values and Forecasting [65]	Centralized	Road Status Forecast	Q1	5
Hybrid Auto-Scaled Service-Cloud-Based Predictive Workload Modeling and Analysis for Smart Campus System [66]	Centralized	Scalability. Workload Management	Q1	5
Real-time energy consumption detection simulation of network node in internet of things based on artificial intelligence [67]	Centralized	Network. Resource Monitoring	Q1	4
Monitoring Cyber SentiHate Social Behavior During COVID-19 Pandemic in North America [68]	Centralized	Online Social Network Monitoring	Q1	3
Random Forest for Data Aggregation to Monitor and Predict COVID-19 Using Edge Networks [69]	Centralized	COVID-19 Monitor and Prediction	Missing	3
Scheduling Observers over a Shared Channel with Hard Delivery Deadlines [70]	Centralized	Sensor Network Monitoring & Optimizing	Q1	2

Continuation of Table 9

Article	Decision-making	Area	Scimago	Citation
Energy-Aware Distributed Edge ML for mHealth Applications with Strict Latency Requirements [71]	Federated & Collaborative	Epileptic seizures prediction	Q1	2
Information Security Monitoring and Management Method Based on Big Data in the Internet of Things Environment [72]	Centralized	Environmental Monitoring	Q1	2
Task Allocation Mechanism for Cable Real-Time Online Monitoring Business Based on Edge Computing [73]	Centralized	Cable Real-time Online Monitoring Business	Q1	1

In [57], the authors discuss the fabrication approach of digital fibers and its impact on Data Sensor-based decision-making using machine learning. Measures are collected from devices in the thread and stored locally in the same yarn. It allows reaching intra-fiber communications between devices via digital signals. A pre-trained CNN model gets embedded in the fiber and articulated to local data for decision-making.

In [58], the authors discuss the feasibility of using edge computing for intelligent parking occupancy detection using the real-time video feed. It incorporates AI at the edge by implementing an enhanced Single-Shot multi-box Detector (SSD).

The article introduces an authentication strategy supported by Transfer Learning and Blockchain (ATLB) [59]. On the one hand, blockchain technology is applied to privacy preservation and avoids central control in industrial applications. On the other hand, it builds trustworthy blockchains for privacy preservation in industrial applications. In terms of privacy preservation, it introduces different blockchains (e.g., inner and outer) for user authentication strategies to deal with collusion and Sybil attacks. A user-per-region credit approach allows for improving authentication accuracy. It uses transfer learning to minimize the training times between regions.

In [60], the authors describe dealing with model invariance to changing speed via a deep learning method. It can detect a mechanical imbalance (i.e., targeted fault) under varying speed settings. They study speed invariance by processing experimental data obtained from a motor test bed. Also, time-series and time-frequency data are applied to long short-term memory and convolutional neural network, respectively, to evaluate their performance.

In [61], the authors introduce an approach named an Intelligent Solution for Improved Performance of Reliable and Time-sensitive Flows (IPRTF) in Hybrid SDN-based Fog (IHSF) computing IoT systems. The proposal is composed of three solutions. The first one is related to an algorithm to deploy Software-defined Network (SDN) switches between legacy switches to improve network observability. The second one is associated with a {K}-nearest neighbor regression algorithm to Real-time prediction of the legacy links reliability at the SDN controller based on historical data. Thus, the SDN controller can make timely decisions, improving system performance. The third focuses on a Reliable and Time-Sensitive Deep Deterministic Policy Gradient (RT-DDPG) algorithm. It optimally computes forwarding paths in hybrid SDN-F for time-critical traffic flows generated by IoT applications.

In [62], a new learning model is proposed using a deep neural network. The outlined model can predict the indoor thermal comfort of people with different abilities in real time to facilitate remote monitoring. The data collection approach can focus on targeted data before moving them to cloud servers for further analysis.

In [63], the authors explain a fog-centric IoT-based intelligent healthcare support service to monitor and control the Swine Flu virus epidemic. They introduce a framework articulated with fog computing for delay-sensitive applications. Also, they describe the feasibility of using a hybrid classifier to classify the swine flu patient at an early stage and generate alerts to the health officials and patients' guardians.

In [64], an IoT-inspired framework gets proposed for real-time athlete performance analysis. Data from IoT devices represent the base for quantifying the athlete's performance in terms of probability parameters of Probabilistic Measure of Performance (PMP) and Level of Performance Measure (LoPM). The authors introduce a two-player game-theory-based mathematical framework for efficient decision modeling by monitoring officials.

In [65], the authors address the challenge of missing data or noisy information in the context of real-time monitoring. After addressing the previous concerns, the underlying idea is to forecast a city’s road status (e.g., congestion). A directed graph models the road network; the nodes are intersections, while the edges represent road segments. The authors assume a set of sensors deployed in the city aligned with the road network. They propose a Temporal Regularized Tensor Factorization (TRTF) framework to account for the spatial structure and temporal dependencies. Also, they describe a data-driven graph-based autoregressive model where weights are learned from data to account for positive and negative correlations.

In [66], it gets introduced a bursts-aware auto-scaling strategy for detecting bursts on dynamic workloads based on resource estimation, decision-making scaling, and workload prediction. The authors pursue keeping the Quality of Service (QoS) through a hybrid auto-scaled service cloud model dealing with horizontal and vertical scaling concerns. It is addressed through an ensemble algorithm for estimating defined workloads. It allows anticipating the resource management associated with workloads and load balancing for horizontal auto-scaling.

In [67], an artificial intelligence-based Internet of Things control method is proposed. It is aware of the information transmission topology structure to analyze the total energy consumption of the node during transmission. Thus, it estimates the load in each communication cycle to study the energy consumption control of multiple and single transmission path nodes. It fosters the improvement of the resource schedule and energy consumption in mobile network nodes.

In [68], the authors describe a framework for online social network real-time monitoring. It allows for data acquisition, processing, interpreting, and decision-making on the fly when data arrives. Bidirectional Encoder Representations from Transformers (BERT) are applied for natural language processing. BERT-based classifiers discriminate hate and sentiments considering iconic emotions (e.g., emojis). Supervised and unsupervised models are complementarily used for online analysis the social behavior.

In [69], the authors describe an e-healthcare framework based on edge computing. It aims to monitor online health data to predict the risk level of COVID-19 patients. A gateway is incorporated to synthesize data based on the original ones, transmitting those meaningful based on the statistical mean. It allows for minimizing data transmissions from every patient (saving energy), optimizing bandwidth use, and avoiding unnecessary redundancy. Geo-distributed edge servers are used to predict the risk level of each patient with Random Forest (RF) using the synthesized data.

In [70], the authors introduce a framework to formulate the Observer Selection Problem (OSP) through which the controller schedules a sequence of observations that maximize its knowledge about the system's current state. The transmission among observers, controllers, and actuators gets carried out through ultra-low-latency wireless communications. The proposed algorithm systematically prunes the search space to improve the knowledge based on the current situation. The authors claim that its work differs from others because of the extent of the controller's knowledge about the state of the system it controls. Alternative approaches work on real-time communications in that communication reliability is monitored by packet loss or error rate.

In [71], the authors describe an approach for gathering latency requirements of mHealth applications based on user equipment and edge server computing under energy constraints. On the one hand, the authors address an optimization problem to locate the feature extraction and classification process cleverly between the user equipment and edge devices. It is a Power-aware optimization approach where the inferential mechanism is as close to the user as possible.

Paper [72] describes a framework for real-time environmental monitoring based on IoT. It addresses the basic principles of constructing the evaluation index system while introducing and outlining a reference architecture.

In [73], the authors describe a task allocation mechanism for cable real-time online monitoring business based on edge computing. They define a task allocation model based on the linear distribution characteristics of the cable, the edge node's statuses, the task processing overhead, and the scheduling strategy of delay-sensitive tasks. Next, they introduce a task allocation strategy based on improved discrete particle swarm optimization. The authors claim that the system focuses on the job queuing problem in edge nodes and the optimized task allocation problem among edge nodes.

In [74], it gets presented a strategy for generating a Device-Specific Identifier (i.e., IoT-ID). It captures the device's characteristics and can be used for device identification. The underlying assumption is that IoT-ID is based on Physically Unclonable Functions (PUFs). Thus, it is possible to exploit variations in the manufacturing process to derive a unique fingerprint for integrated circuits. The authors claim that the strategy is non-invasive and can be invoked using simple software APIs running on components of COTS (Commercially Off the Shelf). Among the mentioned properties, they highlight the following: constructability, real-time, uniqueness, and reproducibility.

5.4. Articles in 2022 and the beginning of 2023. Table 10 describes articles in 2022 and the beginning of 2023 that have received at least one citation. This section will initially describe those articles. Next, it is outlined the remaining works (without received citations).

In [75], the authors refer to the impact of the Point of Presence (PoP) in healthcare and how it gains importance as wearable devices and mobile apps are entrusted with RTRM and diagnosis of patients. Novelty relies on the utility value of sensors data improvement through the Laplacian mechanism of preserved Personally Identifiable Information (PII) response to each query from the Edge Open and Distance Learning (ODL).

In [76], the authors address a framework to optimize energy efficiency, battery lifetime, and reliability for intelligent and connected healthcare. It explains the Adaptive Transmission Data Rate (ATDR) mechanism that works on the average constant energy consumption by varying the active time of the sensor node. It allows for optimizing the energy over the dynamic wireless channel. It explains a Self-Adaptive Routing Algorithm (SARA) to adopt a dynamic source routing mechanism with an energy-efficient and shortest path.

Table 10. Prioritizing for Articles in 2022 – 2023

Article	Decision-making	Area	Scimago	Citation
Emphasizing privacy and security of edge intelligence with machine learning for healthcare [75]	Federated	Patient Monitoring	Q2	13
AI-driven adaptive reliable and sustainable approach for internet of things enabled healthcare system [76]	Centralized	Body Sensor Network	Q2/Q3	8
Smart IoT and Machine Learning-based Framework for Water Quality Assessment and Device Component Monitoring [77]	Centralized	Water Quality Assessment	Q1	5
An innovative edge-based Internet of Energy solution for promoting energy saving in buildings [78]	Centralized	Domestic Energy Saving	Q1	5
Data fusion-based machine learning architecture for intrusion detection [79]	Centralized	Intrusion Detection	Q2	5
Real-Time Fault Detection and Condition Monitoring for Industrial Autonomous Transfer Vehicles Utilizing Edge Artificial Intelligence [80]	Federated	Industrial Autonomous Transfer Vehicles	Q1/Q2	3
Clinical Care of Hyperthyroidism Using Wearable Medical Devices in a Medical IoT Scenario [81]	Centralized	Clinical Care of Hyperthyroidism	Q2	2
MABASR - A Robust Wireless Interface Selection Policy for Heterogeneous Vehicular Networks [82]	Centralized	Selection Policy for Heterogeneous Vehicular Networks	Q1	1
Online Partial Offloading and Task Scheduling in SDN-Fog Networks with Deep Recurrent Reinforcement Learning [83]	Collaborative	Workload Orchestration	Q1	1
Hybrid multi-objective-optimization algorithm for energy efficient priority-based QoS routing in IoT networks [84]	Collaborative	Congestion Control	Q2	1
A Novel CNN-TLSTM Approach for Dengue Disease Identification and Prevention using IoT-Fog Cloud Architecture [85]	Centralized	Dengue Disease Monitoring	Q2/Q3	1

In [77], an IoT-based real-time framework is outlined to perform water quality management, monitoring, and alerts for taking actions based on contamination and toxic parameter levels, and device and application performance as the first part of the proposed work. Machine learning models analyze water quality trends and device monitoring and management architecture. It is supported by a data push strategy associated with dashboards and rules working on a cloud platform.

In [78], it gets introduced the M2SP-EdgeIoE system focused on domestic energy saving and monitoring. It contemplates data collection, Data-based non-intrusive load monitoring, anomaly detection (using Autoencoders), and a data-guided recommender system for improving energy consumption.

In [79], the authors discuss the methodology of Real-Time Sequential Deep Extreme Learning Machine (RTS-DELM) implemented in wireless IoT enabled sensor networks for the detection of any intrusion activity. They claim to reach an approach that not only makes the casting of parallel data fusion networks but also renders their computations more effective.

In [80], it gets explained as a generic real-time fault diagnosis and condition monitoring system. It uses edge AI complementarily to the monitoring and proposes a data distributor open-source middleware platform called FIWARE. The application field is related to those autonomous transfer vehicle (ATV) types of equipment targeting a smart factory use case. Anomaly detection in ATVs is analyzed through a deep learning-based fault diagnosis method performed in the Edge AI unit. At the same time, results are sent to the storage through a data pipeline.

In [81], the authors describe a monitoring strategy monitor for patients with hyperthyroidism based on wearable medical devices. An architecture based on gateways articulates different levels of devices that communicate fused data streams (enriched by a metadata-based data model). It is supported by MQTT and RTMP protocols for messaging and video transmissions.

In [82], the authors describe a Multi-Armed Bandit Adaptive Similarity-based Regressor (MABASR) for interface selection. The interface selection policy is analyzed and learned through the relationship between channel quality parameters and uplink data rate.

Study [83] proposes a computational offloading and CPU resource scheduling method for minimizing energy consumption. It considers off-loadable and non-off-loadable tasks to characterize and optimize the allocation. On the one hand, a node will contribute to a common goal based on cooperation without any assumption about previous knowledge of statistics or global observations. On the other hand, it applies a deep recurrent Q-network (DRQN) to address partial observability, improving the computational complexity.

In [84], it gets explained the Energy-Efficient Priority-based Multi-Objective QoS routing (PMQoSR) mechanism. It aims to ensure energy and

QoS in IoT networks. The proposed system regulates the routing performance based on the QoS parameters, using an optimization technique for three hybrid algorithms (WLFA-Whale Lion Fireworks optimization algorithm with Fitness Function Routing mechanisms). The WLFA focuses on preventing congestion and minimizing localization errors by using and selecting the shortest path through the network.

In [85], an IoT-based proposal is outlined for monitoring Dengue disease. Data-based diagnosis is based on a Hybrid CNN with Tanh Long and Short-Term Memory (TLSTM) using the Adaptative Teaching Learning based Optimization algorithm.

In [86], the authors propose a routing protocol for IoT networks with low power consumption. A secure RPL (Routing Protocol for Low power Lossy network) protocol is introduced to work on congestion control in IoT environments. Authors describe 5 phases a) All nodes register in the sink node, which computes a hash based on the provided data (ID, IP, MAC, Rank, and PUF); b) It gets presented a Multi-context aware parent selection using fuzzy logic; c) The congestion detection is based on agents; d) A lightweight CNN is applied for deep packets analysis; e) An adaptative trickle timer works based on different parameters such as traffic intensity, etc.

In [87], the authors introduce a routing schedule method based on Time-sensitive networking (TSN) for IIOT applications in underground mining. It discusses two alternatives to face the challenge associated with delays, walls, and sensor data collections a) a greedy algorithm based on the shortest distance, and b) a heuristic algorithm based on ant colony optimization.

In [88], the authors introduce a resource-efficient reliability model for MAS (Multi-Agent System) IoT systems for monitoring purposes. The proposed model starts with SLA requirements and characterizes it under the assumption of linear time complexity. It provides simplicity of computations and input metrics for aligning values in each range. Thus, it evaluates the time complexity, producing a measurement associated with the reliability of the model application.

In [89], the authors describe an identification method for rail vehicle running state using Tiny Machine Learning (TinyML). An IoT system is proposed focused on sizing and low energy consumption for data collection through Micro-Electro-Mechanical System (MEMS) sensors. The authors introduce a neural network (NN) model based on acceleration data for classifying the running states of rail vehicles. It represents a two-step approach where the model (i.e., NN) is trained after that is deployed on edge devices. An offset time window strategy addresses sensor results from edge devices and is uploaded to the cloud for visualization and analysis.

In [90], it presents a unique IoT-based sensor node framework (aka, iThing). It aims to predict the onboard battery State of Health (SOH) and Remaining Useful Life (RUL) with the least computational and memory load. The SOH and RUL prediction are implemented through a random learning-based method using the voltage and health metrics of the device.

In [91], and in [5], it gets described as an edge analytics-assisted monitoring solution to monitor several physical activities of the patient. It focuses on determining physical inactivity from their daily routine. It wears wearable sensors to monitor physical movements and GPU for efficient data processing. The study pursues to calculate the scale of the physical inactivity of the patient to make real-time health suggestions.

In [92], it gets proposed how well-established data management techniques from the fields of computer science can be applied to data management for hydrological modeling. It is not a real-time approach but takes advantage of metadata modeling to enrich primary data from sensors. Data are complemented with spatial and temporal information that supports different decision-making models (e.g., upstream drainage area determination).

In [93], shown how the Gulf of Mexico Avian Monitoring Network members used structured decision-making to identify bird monitoring priorities by using multiple tools and techniques to clearly define the problem and stakeholder objectives and to identify bird monitoring priorities at the scale of the entire northern Gulf of Mexico region to coordinate the process of broad-scale monitoring programs to address management, restoration, and scientific questions in other ecosystems and for other taxa.

Study [94] focused on the use of big data in the decision-making processes of healthcare management, the abovementioned three aspects significantly affect the identification of management models, the distribution of responsibilities among professionals (therefore the evaluation of the partial results of each area responsibility) and the processes of allocating resources within the health-care organization.

6. Results and discussions. Independently of the year, citations, and decision-making strategy, this section focuses on answering every research question introduced in Section III and breaks down accordingly.

6.1. RQ1: Research Volume. The research volume in RTRM on EC is associated with fields like Networking (32%), Health (24%), Industrial (12%), Environment (10%), and Vehicle (8%), among others, as shown in Figure 3. Only those five fields represent 86% of the research volume and catch the scientific community’s interest.

Figure 4 indicates a surface diagram contrasting the publishing year jointly with the citation volume and Scimago’s quarter. As it is possible to appreciate, on the one hand, the intense research on the specific subject started to take an interest in 2013, with many citations focusing on Q1 journals. Even more, the volume of citations for recent years (e.g., 2021 and 2022) is close to the oldest works, which indicates an active development in the area. On the other hand, the citation over time shows an interesting growing perspective and opportunities in a context where the software and products reach (or propose) different As-a-Service strategies. Reliability is essential for achieving availability and scalability together [95].

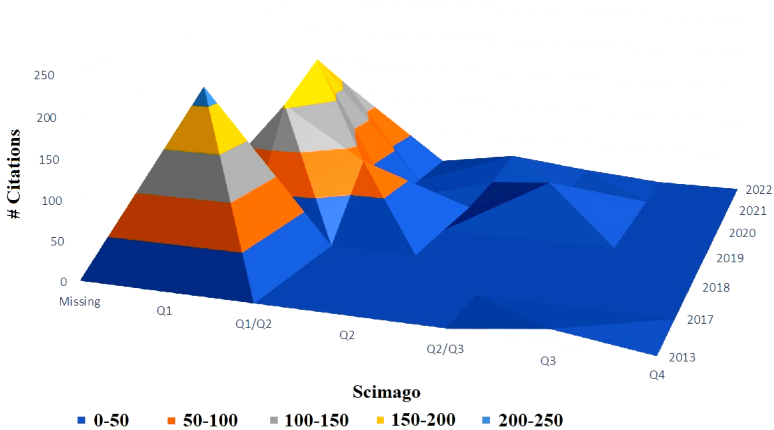

Fig. 4. Main Application Areas

Figure 5 shows that those results related to the research subject are published mainly in Q1 journals (70%), which are associated with a severe and strict publishing process jointly with a high interest in them from the scientific community and practitioners due to the quality of the content. It implies that the subject is worthy of addressing, while challenges and concerns are shared between stakeholders.

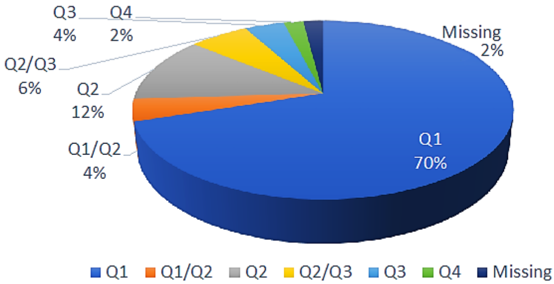

Fig. 5. Research Volume per Scimago Quarter

6.2. RQ2: System Reliability Monitoring Approaches. Figure 6 describes the proportion of data strategies associated with the AI models in reliability working on EC.

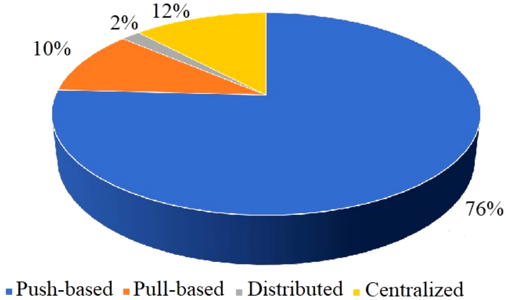

Fig. 6. Proportion of Data Strategy Related to AI Models in Reliability

The heterogeneous and distributed context in which EC is deployed implies that data interoperability is mandatory. In this context, how data is collected from heterogeneous data sources is essential to reach the aim and make proper decisions based on the last known data. According to analyzed works, 76% of the systems use push-based strategies for RTRM, while 12% use a centralized approach. Only 10% address this challenge through a Pull-based process because it requires specific entity data under monitoring and specific communications requirements (not always available depending on the use case or scenario in which a solution is deployed). 2% introduced a distributed schema where data are local to the data source, and the interaction with the reliability component was guided through queries. Thus, the reliability component sends a query. At the same time, the answer is replied to using local data (with its limitations of it because the data are always partial to the data source).

Figure 7 describes the evolution of RTRM strategies over time. As it is possible to appreciate, it was focused on Push-based strategies between 2013 and 2019. In 2020, a centralized approach indicated a possible necessity of consolidation before making decisions around the system's reliability.

However, it additionally emerges Pull-based and distributed techniques between 2021 and 2022. In the end, there is no good or bad alternative because it would depend on the use case and kind of application that defines the specific monitoring requirements. It implies that a Pull-based approach could be interesting to watch distributed data centers because they could support Virtual Private Network (VPN) connections. Still, it would not be the best approach in Low-cost, tiny, distributed devices focusing on body sensor networks.

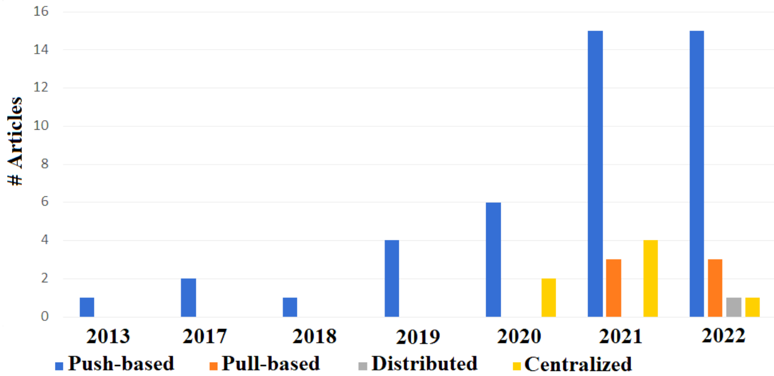

Fig. 7. Evolution of the Reliability Monitoring Strategies over Time

6.3. RQ3: Decision-making strategies. Even when edge computing is associated with a heterogeneous and distributed environment where data interoperability and data quality play an essential role, the main proportion of the system reliability decision-making approaches has been focused on centralized models from 2013 until now (Figure 8). It is a complex scenario because the ability to data analysis, make decisions, and act accordingly depends on a central component or element. Even when the central element could be redundant among other aspects, the figure of a central dependency is contradictory with the reliability perspective and a potential limitation to address the system scalability and high availability.

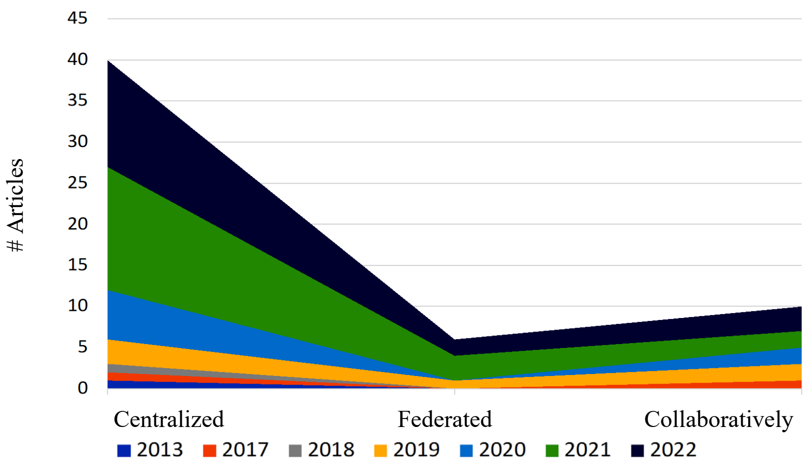

Fig. 8. The proportion of AI and Decision-making approaches per year

However, Federated and Collaborative decision-making approaches are taking interest from 2021 onwards. They propose a system in which the decision-making articulates alternative heterogeneous components monitoring different points of view in a distributed context and the possibility to collaborate, keeping a certain level of local autonomy.

The necessity of collaboration and avoiding central control has influenced Blockchain-based technologies significantly [96]. The idea is that the database content does not depend on a unique stakeholder; on the contrary, any addition or modification (or deletion) requires consensus among the participants. In the reliability context, it could be an exciting approach that the relative importance of each element in the complete system reliability could weigh.

6.4. RQ4: Data Collection Methods. Figure 9 describes the evolution of data collection methods associated with real-time monitoring systems. It was dominated by Direct and Hierarchical Push-based strategies between 2013 and 2020. Nevertheless, Direct-pull and Query-based approaches emerged as an alternative in 2021. 2022 is a context dominated by the Push approaches (be they hierarchical or not). It is consistent with the kind of areas in which the research volume is focusing, i.e., Networking (32%), Health (24%), Industrial (12%), Environment (10%), and Vehicles (8%).

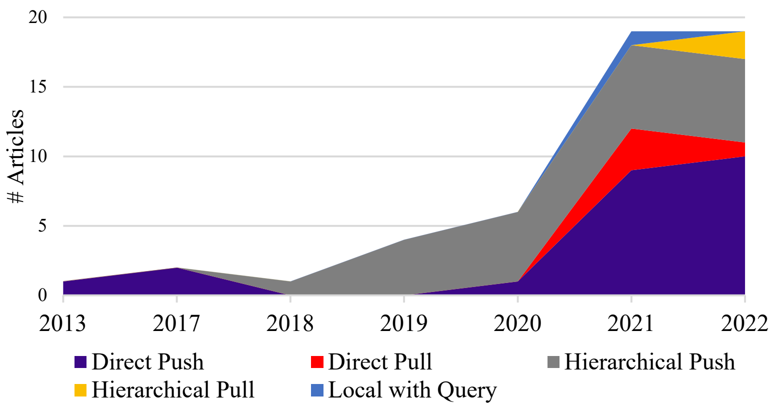

Fig. 9. Evolution of Data Collection Methods for Monitoring Reliability

An aspect worthy of mentioning is that independently of the increment of the research volume in this area, the push-based data collection approaches have become a central aspect to consider. On the other hand, those aspects related to data confidentiality, data sovereignty, and data ownership remain the main challenges and concerns.

6.5. RQ5: Applications. Figure 10 shows a tree map focusing on the main application areas dimensioned based on the citation volume, while inside each room, the most cited subjects are drawn per area.

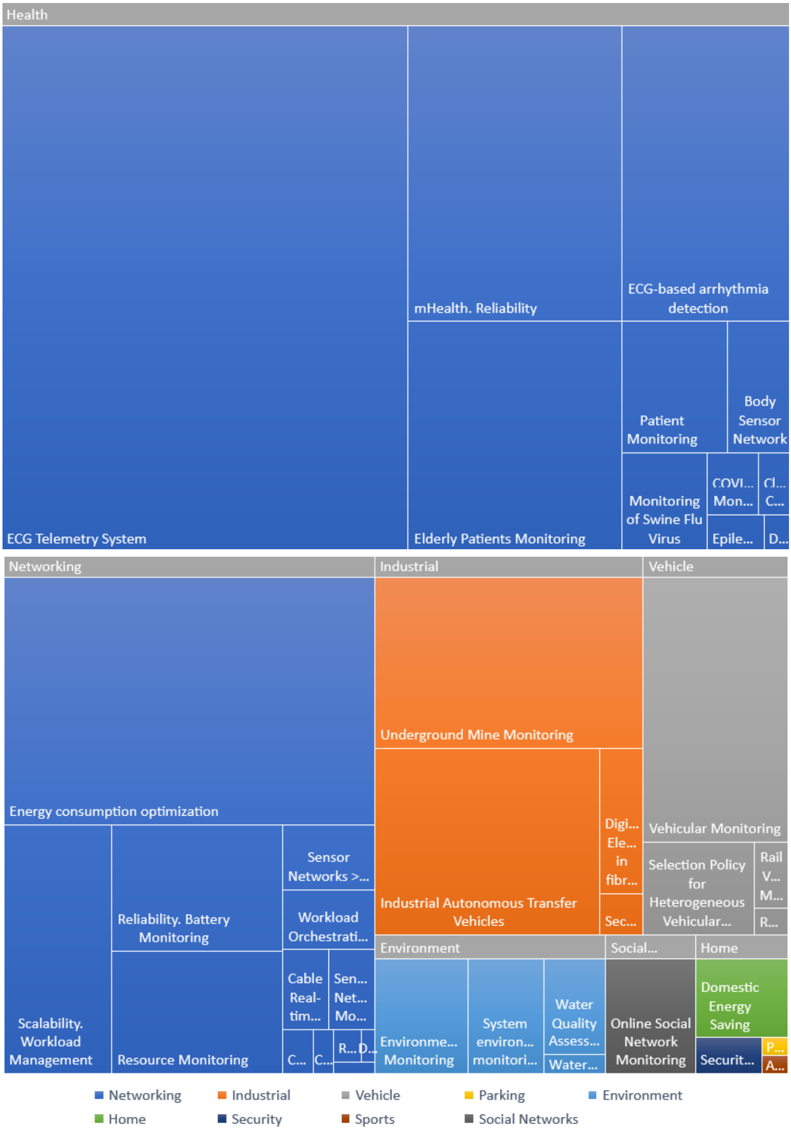

Fig. 10. Main Subjects per Area based on the Citation Volume

In the networking field, the highest cited works are related to resource optimization, task scheduling, energy saving, and data accuracy. On the other hand, the health field focused on ECG telemetry systems, mHealth Reliability, arrhythmia detection, and patient monitoring.

An exciting work (worthy of reading and capitalizing) is introduced in the industrial field related to digital electronics in fibers. It gathers reliability, AI, and local data processing embedded in clothes fibers. Security authentication, machinery monitoring, and energy supply-demand matching are also addressed.

As it is logical, the vehicle field focused on vehicular monitoring, road status monitoring, and parking surveillance. Analogously, environmental areas focus on environmental and water monitoring due to its importance to people´s health and relative impact.

Figure 11 outlines the evolution of application areas per year. It is not strange that the beginning is associated with environmental monitoring because it comes naturally from the IoT environment and the possibility to implement real-time monitoring systems at a relatively low cost [18].

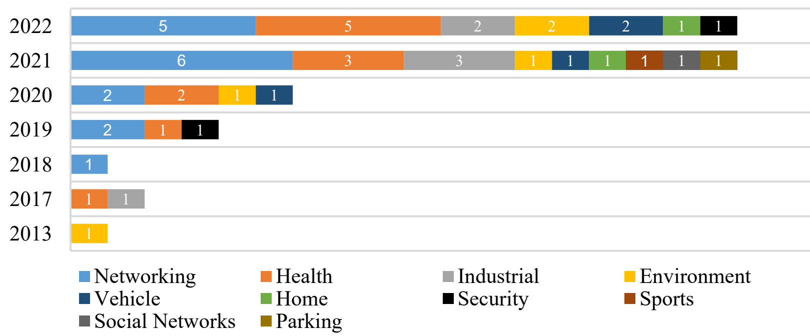

Fig. 11. Application Areas per Year

However, the interest in the application on networking and health has been worthy of highlighting since 2018 onwards. The last three years have provided the context to extend the applications and increase the aspects to be analyzed under the reliability light.

6.6. General Considerations. After the analysis of the different research questions and the involved articles, it emerges essential aspects that are worth mentioning:

1. A few works mentioned using metadata to enrich sensor data to improve the data and automatic interpretation [81], [92]. It is essential to ensure semantic data interoperability because it directly knocks the heart of

system reliability due to the Data-driven decision-making approaches. Definitively, it is not a general approach; it constitutes an open subject, a challenge due to its complexity, and an opportunity to improve decision-making in qualitative terms.

2. The analyzed works need more measurement frameworks, or some formalization focused on guiding the experimental design jointly with the measurement process. It is critical because the strong assumption is that data used for system reliability monitoring are trustworthy, consistent (cohesive and coherent), accurate, precise, comparable, calibrated, and opportune. It is a current challenge and an opportunity to improve the current real-time system reliability monitoring systems.

3. Only [52] mentions the idea of calibration, but it is not associated with the data sources but with input features. The calibration process is essential in any device trying to quantify some property under monitoring because it ensures that the device is aligned with a given reference pattern. The system's entropy could affect (directly or not) the system components producing deviations due to the wear. Data-driven decision-making assumes that the consumed information is adequate for supporting the decision process. Calibration strategies in sensible areas like health and networking are an opportunity.

4. The process measurement assumptions are not reviewed. When data is received from different data sources, the decision-maker assumes that the data come from a repeatable measurement process (It is possible to obtain new data with a compatible method), results are comparable (It is possible to contrast numeric values over time), and extensible (It is possible to add a new characteristic to quantify). It represents an opportunity to integrate distributed and heterogeneous environments where reliability needs to be monitored in real-time.

5. Analyzed works discussed collecting and analyzing data for making decisions based on the system's aim. However, they do not add details about how to ensure the system's reliability and how to monitor it. That is to say; they do not say anything about how to ensure that the system requirements work as expected over time. It means that observability focuses on the typical telemetry and derived actions rather than how to ensure that the telemetry strategy and the system requirements are reached consistently over time. The meta-system monitoring needs to be addressed. For instance, observability is crucial for monitoring a certain level of availability for a given service. Still, also it is essential to monitor the process of producing the Service Level Agreement (SLA) that originated the instantiation of the offered service. The first refers to a particular SLA

with a customer, but the second is associated with the matrix producing the offered SLA. Both must be monitored in terms of reliability.

6. In [69], the authors exposed the challenge of similar or redundant readings and the impact on data transmission latency and energy consumption. Semantic data interoperability is only sometimes considered, affecting how to optimize data retention and transmission policies from data sources (independent of the data collection methods). It is aggravated in data fusion scenarios because the potential integrations become relative and vague.

7. In [65], the authors described the data sparsity, incompleteness, and noise challenges due to the quick deployment of cheap sensors on the field. It is a good point because the IoT environment increases device density and coverage. Still, it needs to address the essential aspects of the data meaning and how to use them to support a decision-making process. Data quality aspects [17] could be analyzed more closely with system reliability.

As it is possible to appreciate, there are a lot of ongoing works on RTRM jointly with current concerns and opportunities. There is no standard approach around it, but there are multiple classes of proposals according to use cases or application areas. The subject has grown in importance in the last two years while leading international journals reported results that substantiate such growth.

7. Conclusion. This review showed the broad proposals and approaches of RTRM on EC. Most publications confirm the importance of the subject in areas such as Networking, Health, Industrial, Environment, and Vehicle. Nevertheless, there needs to be more consensus around monitoring reliability, ensuring syntactic and semantic data interoperability, formalizing the decision-making strategies in edge computing, and capitalizing on previous experiences and knowledge.

In terms of research volume, on the one hand, the intense research on the specific subject started to take an interest in 2013, where many citations focus on Q1 journals. On the other hand, the volume of citations for recent years (e.g., 2021, 2022 and 2023) is close to the oldest works, which indicates an active development in the area.

From the perspective of System Reliability Monitoring Approaches (SRMA): a) 76% of the systems use push-based strategies for reliability monitoring; b) 12% use a centralized approach; c) 10% address this challenge through a Pull-based approach; d) 2% introduced a distributed schema where data are local to the data source, and the interaction with the reliability component was guided through queries. The current dominant monitoring approach has been based on the Push strategy since 2013.

A centralized approach has dominated the decision-making strategies for reliability monitoring. However, the federated and collaborative decision-making approaches are taking interest from 2021 onwards. They propose a system in which the decision-making articulates different heterogeneous components monitoring alternative points of view in a distributed context and the possibility to collaborate, keeping a certain level of local autonomy. The necessity of collaboration and avoiding central control has influenced Blockchain-based technologies in this area.

In terms of data collection methods, it is a clear leadership of Push-based data collection methods (hierarchical or not). The non-hierarchical push-based methods represent 52.63%, while the hierarchical approach is associated with 31.58. Thus, in general, the participation of Puh-based data collection methods is 84.21%. The methods to use depend on the use cases and fields, among others. The remaining 15.79% is related to Pull-based data collection methods, composed of 5.26% for Direct Pull-based methods and 10.53% for Hierarchical Pull-based practices.

From the perspective of the application, Networking and Health areas represent 56% of published works. The percentage reaches 78% when the Industrial and Environment sectors are incorporated.

Beyond the research questions, there are essential aspects that need to be mentioned transversally as follows:

– A few works mentioned the use of metadata to enrich data coming from data sources to improve the data and automatic interpretation. Semantic data interoperability is an open opportunity in RTRM systems considering the distributed and heterogeneous environment associated with edge computing.

– Lack of measurement frameworks for formalizing a consistent, extensible, and repeatable measurement process. It represents a concern because it impacts the heart of Data-driven decision-making, but also an opportunity to improve reliability monitoring.

– Calibration is a subject analyzed on the surface in the works. However, it is essential to consider and maintain over time through different recalibration strategies. It is necessary to establish a reference pattern before obtaining measures. Also, this is a central resource when a metric is contrasted to decision criteria through indicators. Any data source (independently of the type) could fail or lose the calibration reference over time due to entropy.

– The underlying assumptions related to the measurement process are not analyzed. Neither is their impact on Data-driven decision-making. Thus, it represents an opportunity to improve reliability monitoring strategies through the online analysis of interest, comparability, accuracy, precision, trust, opportunity, coherence, cohesion, etc. It is a stage in which the strategy could discriminate among data, information, and knowledge.

– The analyzed works focused on the aimed systems and how to collect and analyze data (e.g., patient monitoring). However, they rarely contemplated the meta-system monitoring to say whether (or not) system reliability is working as expected. Thus, meta-system analysis for monitoring different system properties (in addition to reliability) is open in this environment.

– Data ownership, Data sovereignty, Data Confidentiality, and Data Interoperability (Syntactic and Semantic) are rarely analyzed in the context of online reliability monitoring in EC. It represents a huge opportunity to make a difference. The security around the RTRM strategy is an open topic.

Thus, RTRM in EC is an ongoing work. It lacks standards but has taken importance and interest in the last two years. Articles focused on Push-based data collection methods for supporting centralized decision-making strategies. It was concentrated and deployed mainly on networking, health, industrial, and environmental monitoring. However, there are multiple opportunities and paths to walk to improve it. E.g., data interoperability, federated and collaborative decision-making models, formalization of the experimental design for measurement process, data sovereignty, organizational memory to capitalize previous knowledge (and experiences), calibration and recalibration strategies for data sources.

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МОНИТОРИНГ НАДЕЖНОСТИ ПОЛЬЗОВАТЕЛЬСКИХ ВЫЧИСЛИТЕЛЬНЫХ УСТРОЙСТВ В РЕЖИМЕ РЕАЛЬНОГО ВРЕМЕНИ: СИСТЕМАТИЧЕСКОЕ ОТОБРАЖЕНИЕ

Диван М.Х., Щемелинин Д.А., Карранса М., Мартинес-Спессот Ц.И., Буйневич М.В. **Мониторинг надежности пользовательских вычислительных устройств в режиме реального времени: систематическое отображение.**

Аннотация. Данный исследовательский обзор сосредоточен на мониторинге надежности вычислительных систем в режиме реального времени на стороне пользователя. В условиях гетерогенной и распределенной вычислительной среды, где отсутствует централизованный контроль, исследуется использование моделей искусственного интеллекта для поддержки процессов принятия решений в мониторинге надежности системы. Методология исследования основана на систематическом отображении предыдущих исследований, опубликованных в научных базах данных IEEE и Scopus. Анализ проведен на основе 50 научных статей, опубликованных с 2013 по 2022 годы, показал растущий научный интерес к данной области. Основное применение исследуемого метода связано с сетевыми технологиями и здравоохранением. Данный метод нацелен на интеграцию сети медицинских сенсоров и управляющих данных с пользовательскими вычислительными устройствами. Однако этот метод также применяется в промышленном и экологическом мониторинге. Выводы исследования показывают, что мониторинг надежности пользовательских вычислительных устройств в режиме реального времени находится на начальной стадии развития. Он не имеет стандартов, но за последние два года приобрел значительное значение и интерес. Большинство исследуемых статей сосредоточены на методах сбора данных с использованием уведомлений для поддержки централизованных стратегий принятия решений. Однако, существует множество возможностей для дальнейшего развития данного метода, таких как совместимость данных, федеративные и совместные модели принятия решений, формализация экспериментального дизайна, суверенитет данных, систематизация базы данных для использования предыдущих знаний и опыта, стратегии калибровки и повторной корректировки для источников данных.

Ключевые слова: реальное время, надежность системы, мониторинг, вычисления на стороне пользователя, систематическое исследование.

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