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Resilience in Cyber-Physical Infrastructures: R-KPI prioritization, framework development, and case study insights

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ABSTRACT

Critical infrastructures (CIs) embody cyber-physical-social systems (CPSSs) where physical entities are integrated with cyber components, shaping service delivery through end-user behavior. The seamless operation of CIs is vital for society, and the CPSS resilience relies on interdependencies with AI-integrated technologies. The complexity of the system, and the interconnections with other infrastructures, along with the socio-technical transition towards digitization raised the necessity of implementing Resilience Engineering. This motivates exploration of the scientific literature on resilience key performance indicators (R-KPIs) which support strategies for ensuring service continuity. Therefore, this article aims to identify R-KPIs for AI-integrated CIs and prioritize the extracted R-KPIs using a hybrid Multi-Criteria Decision-Making (MCDM) approach. The results show the importance of employing R-KPIs that measure risk probability, energy self-sufficiency level of the system under study, and performance indicators including functionality loss, recovery time, and minimum performance level after disturbance as the most effective R-KPIs in the domain of this study. After identifying and prioritizing the R-KPIs, a general framework is proposed to employ these R-KPIs in modeling the resilience of a CPS. Finally, a case study demonstrates the implementation of the framework and KPIs in a real-life scenario.

1. Introduction

The resilience of critical infrastructures (CIs) is vital for modern societies. CI as cyber-physical-social systems (CPSSs) is influenced by end-user behavior, especially when considering user behavior's impact to proactively detect and respond to potential attacks through data-driven solutions such as digital twin modeling of system resilience [1]. CIs encompass physical assets and systems that provide a necessary service in national, regional, and local scope. The capacity to withstand or to recover quickly from risks is called resilience. Critical infrastructures should be resilient in all aspects from governance to operational level [2].

Prior studies unveiled the efficiency of data-driven solutions to enhance the resilience of cyber-physical systems [3–5]. However, the body of knowledge in AI-integrated CI resilience engineering is not fully defined, and there is a gap in standardized models and performance metrics to quantify the resilience of AI-integrated CIs.

Modeling the resilience of complex systems with physical, cyber, and social dimensions requires identifying relevant criteria. This identification is performed through scenario-based modeling. The existence of diverse Resilience Key Performance Indicators (R-KPIs) for CPSS across different levels and scenarios is the primary motivation for identifying and categorizing system R-KPIs. This study proposes a data-driven approach to enhance CI resilience through three stages. First, a step-by-step guide for modeling CI resilience using R-KPIs will be developed. Second, the study will extract R-KPIs from existing CI literature. Finally, the most effective R-KPIs for CIs integrated with Artificial Intelligence (AI) will be identified through analysis considering application domain, system structure, and data needs.

In the remainder of this paper, Section 2.1 details the research design for this article to reveal the gap in the CPSS resilience body of knowledge along with the material and methods implemented to carry out the research. In Section 3 the structured framework is proposed for

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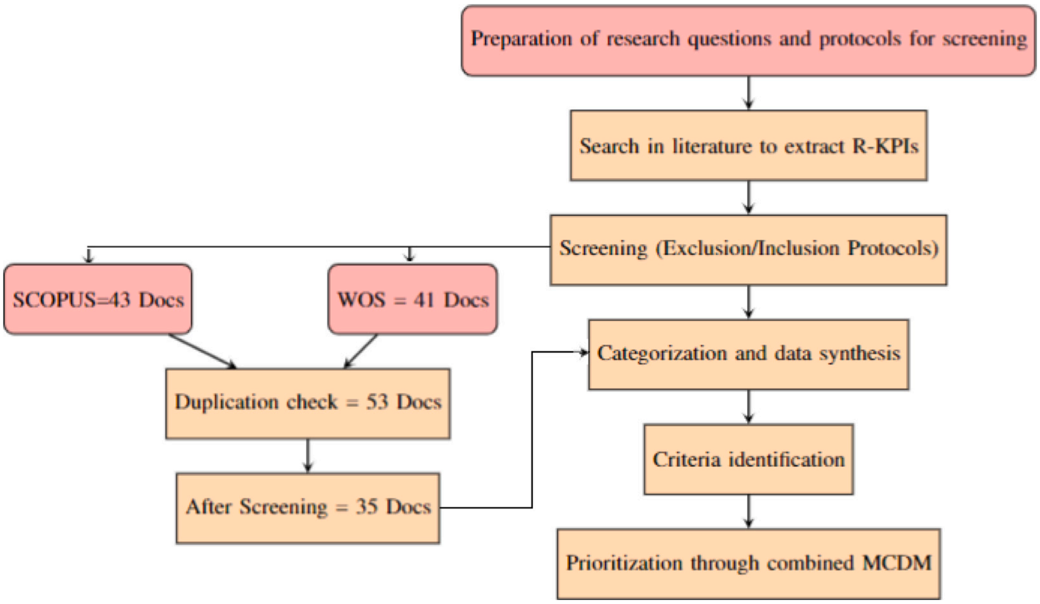

Fig. 1. Research Design. The second step -search in the digital libraries for related documents- is conducted in May 2024.

selecting and implementing R-KPI for CPSS. Section 4 provides results of employing the methodology proposed in this study and further discusses the identified and selected R-KPIs. Then, a real-world case study is presented in Section 5 to further elaborate on the proposed framework. Consequently, the limitations of the current study and future potential developments are presented in Section 6, and conclusion remarks are given in Section 7.

2. Material and methods

2.1. Research design

2.1.1. Problem description

The problem addressed in this article revolves around the identification, characterization, and effective utilization of R-KPIs for CPSSs, particularly focusing on CIs. To contribute to addressing this problem, the study seeks to answer the following research questions:

RQ1 What are the main R-KPIs for the Cyber-Physical Infrastructures (CPIs)?
RQ2 Which are the best R-KPIs for AI-integrated CPIs?
RQ3 What is a model based on R-KPIs for CPIs resilience?

2.1.2. Overall strategy for research

The main contributions of this article through answering the mentioned research questions lie in the identification of R-KPIs for AI-integrated CPSS (with a specific focus on CIs), systematically prioritizing the R-KPIs, and finally furnishing a comprehensive framework for resilience modeling of complex systems across various levels, as explained in Section 3. This framework can be used by researchers and practitioners as a guideline to model the resilience of AI-integrated CIs from macro to micro levels. A case study is also included in the article to illustrate the implementation of the proposed framework.

2.2. Methods and tools

The research methodology comprises a state-of-the-art review and implementation of a combined Multi-Criteria Decision-Making (MCDM). The results heavily rely on the analysis of relevant literature to pinpoint R-KPI in the field of CI resilience. Fig. 1 depicts the research methodology employed in this study for identifying the R-KPIs, outlining its inclusion and exclusion criteria.

2.2.1. Systematic literature review

To extract the R-KPIs of CIs, a literature review was conducted within Scopus and Web of Science. The documents included scientific journal articles, reports, books, building rating systems, and grey literature. We did not narrow the initial research scope by keywords and included all of the documents with three keyword families (acronyms, abbreviations, full form, plural and singular, noun, and adjective, etc.) “KPI”, “Infrastructure” and “Resilience”. The initial Scopus and Web of Science research resulted in 84 documents which after a duplication check decreased to 53 documents. This number of documents suggests a significant gap in the body of knowledge in resilience engineering of critical infrastructures. The exclusion criteria were set to the language of the documents (only English documents were included) and the subject area (Medicine, Chemistry, and Biology are excluded). To identify R-KPIs related to CI resilience, only publications focusing on measurable R-KPIs are included in the final compilation. This study encompasses the breadth of knowledge in CI resilience and discussions on resilience in a broader context. By reviewing the 53 abstracts, we filtered the results to include articles that explicitly identified, listed, or employed measurable qualitative or quantitative R-KPIs.

Fig. 1 depicts the narrowing down process of the review. We conducted an in-depth examination of 3 full-length articles. The data extracted during this phase indicates a growing interest in quantifying the resilience of critical infrastructure. However, it also reveals that the use of R-KPIs for resilience quantification has only recently gained traction, and there are significant gaps in the domains where R-KPIs are identified and applied (Fig. 2).

In this study the methodological tool introduced by Marusic et al. [6] is implemented for sensitivity analyses to assess the quality or risk of bias in the systematic review, providing insights into how sensitivity analysis can be applied to evaluate the robustness of findings in the presence of potential biases. Table 1 shows the results of the sensitivity analysis and shows in this SLR, that the systematic test of the changes to certain aspects (see Table 1 - *Change from Baseline*) of the review does not affect the findings.

A noticeable gap is observed in the application fields, with R-KPIs being quantified in only 7 out of the 11 CI categories outlined in the Directive on the Resilience of Critical Entities [7]. Furthermore, Fig. 3 reveals the high repetition of “data” among the keywords, indicating that the majority of studies are concentrated on enhancing resilience through data-driven solutions. The scope of the articles shows that

Table 1
Sensitivity analysis results for R-KPIs in AI-integrated systems.

Scenario	Key findings	Change from baseline	Implications
Exclude low-quality studies	Results of screening remain dominant; R-KPIs do not change	No change	Findings are robust.
Exclude gray literature	Small studies, reports, and editorial letters are removed.	No change	Findings are robust.
Include recent studies only	The earliest study in the list was published in 2007. Out of the 34 entries, 28 were published in the last 10 years (2014–2024), and 18 were published in the last 5 years (2019–2024).	Minimal	Findings are not time-sensitive and all are recent studies.

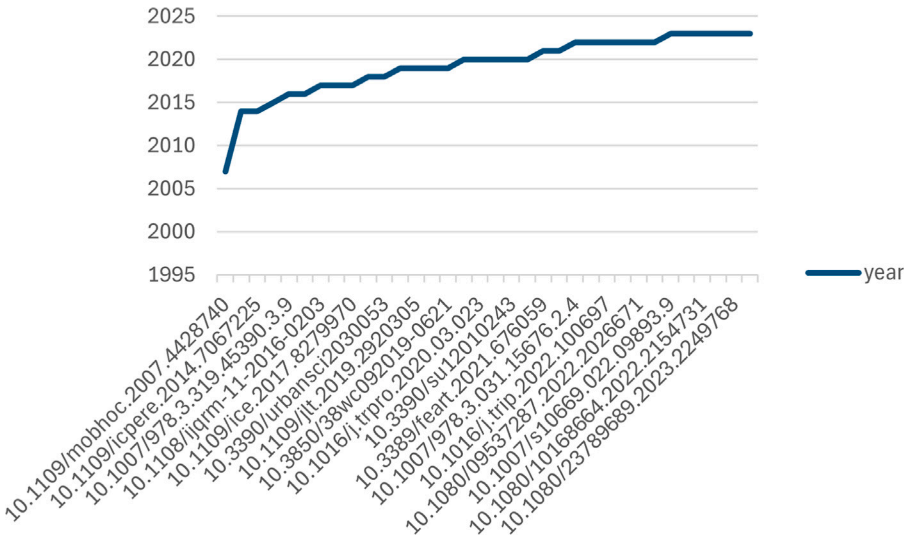

Fig. 2. General results statistics: Published documents per year. The horizontal axis displays the DOI of the documents, highlighting the increasing trend in the year of publication.

the most popular domain is Energy Systems. Following the energy sector, transportation is the second most frequently explored CI. This is primarily because both energy and transportation systems play pivotal roles in supporting various CI networks and are essential for delivering vital services such as healthcare, education, and water systems [8]. Additionally, these sectors underpin economic activities. However, it is crucial to acknowledge that Telecommunication CI catalyzes digitalization and emerging technologies. It is essential to recognize that many cutting-edge technologies, such as Digital Twinning and the Internet of Things (IoT), are shaping the future of industrial automation. Moreover, sectors like energy, transportation, and others will increasingly rely on telecommunication systems to provide their services. Finally, As previously mentioned, resilience modeling is typically scenario-based but some articles proposed R-KPIs of a more general nature, such as the frequency of failures within a specific time frame or the duration and cost of recovery.

2.2.2. Combined multi-criteria decision making for ranking

To rank the R-KPIs, we followed three systematic steps. First, we extracted the criteria suitable for R-KPI selection/ranking from the literature and standards. The list of identified criteria is shown in Table 2. Next, we employed a fuzzy Analytic Hierarchy Process (Fuzzy AHP) to calculate the importance of each criterion, as outlined in Fig. 4. Finally, using the criteria and the weights calculated in the previous step, we applied the fuzzy Technique for Order Preference by Similarity to the Ideal Solution (Fuzzy TOPSIS) method to prioritize the R-KPIs. The steps for fuzzy TOPSIS are illustrated in Fig. 5.

This study follows the broadly used extent analysis method on fuzzy AHP introduced by Chang [13], the outline of which is shown in Fig. 4. Based on Chang's approach, the first step of employing fuzzy AHP is to define the problem and the criteria. In this study, fuzzy AHP is utilized to address the problem of assigning importance weights to the criteria in Table 2. In the second step, the criteria undergo pairwise comparisons. The fuzzy numbers shown in 3 are used to assign linguistic variables to each pairwise comparison. In Step 3, the fuzzy pairwise comparison matrix is formed and the fuzzy extent value is calculated for each criterion. Then, the degree of possibility is calculated for each criterion in Step 4. Consequently, in Step 5, the criteria are compared based on their degree of possibility, and their relative importance weights are calculated accordingly.

Table 2
Criteria for R-KPI selection.

Criteria	Reference
Cost-effectiveness (Implementation/operation costs of KPI)	[9]
Automation (Automated calculation during life-cycle)	[10]
Data management (data availability, data collection, data validity, data storage, and reusability of KPI)	[10]
Manageability (calculable, ease of use of KPI)	[10]
KPI Level (elemental, basic, comprehensive)	[11,12]

For fuzzy TOPSIS, this paper employs Cheng's well-known fuzzy TOPSIS methodology [15], summarized in Fig. 5. First, a decision matrix is established, in which the rows constitute the alternatives (i.e. the R-KPIs) and the columns are composed of the criteria in Table 2. Then, the matrix is filled by scoring each R-KPI with respect to each criterion using the linguistic variables shown in Table 4. Then, using

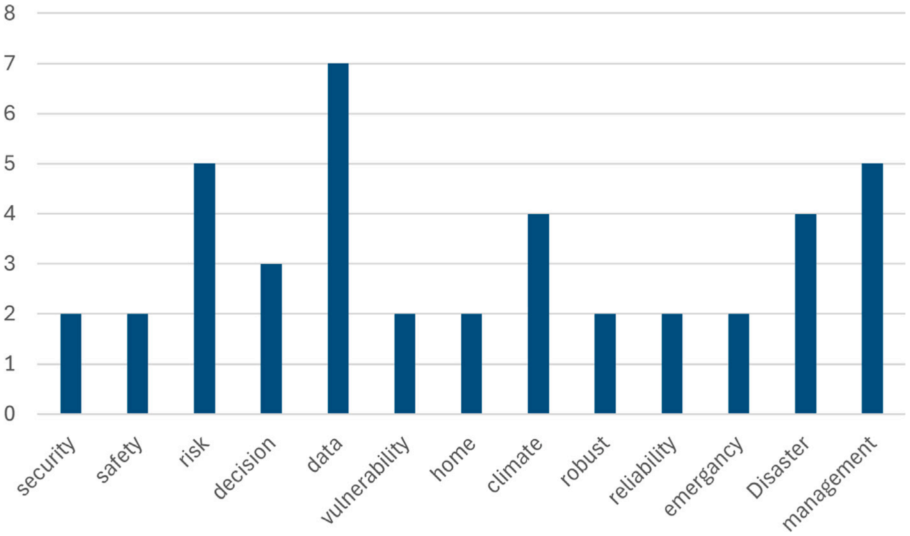

Fig. 3. General results statistics: Commonly used Keywords. The vertical axis indicates the number of times the keyword occurred in the analyzed dataset.

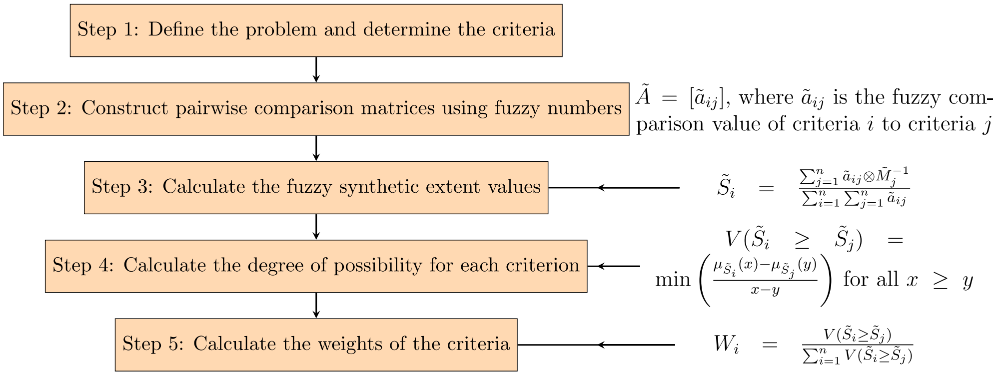

Fig. 4. Outline of the Steps of Fuzzy AHP.

Table 3
Fuzzy numbers for pairwise comparison of criteria based on fuzzy AHP [14].

Linguistic variables	Triangular fuzzy numbers
Low	(0.5, 0.66, 1)
Equal	(1, 1, 1)
High	(1, 1.5, 2)

Table 4
Fuzzy numbers for scoring R-KPIs based on fuzzy TOPSIS [14].

Linguistic variables	Triangular fuzzy numbers
Very low	(0.5, 0.5, 0.6)
Low	(0.5, 0.6, 0.7)
Medium	(0.6, 0.7, 0.8)
High	(0.7, 0.8, 0.9)
Very high	(0.8, 0.9, 0.9)

the criteria's relative weights obtained from fuzzy AHP, the weighted normalized decision matrix is created in Step 2. The Fuzzy positive ideal solution (FPIS) and negative ideal solution (FNIS) are calculated in Step 3. Then in Step 4, the distance of each alternative from FPIS and FNIS is calculated. In Step 5, using these distance values, a closeness coefficient is calculated and assigned to each alternative. Eventually, in Step 6, the alternatives are ranked according to their closeness coefficients.

2.2.3. Data collection

In order to prioritize the defined R-KPIs, they are ranked according to the five criteria shown in Table 2. First, the criteria are given weights based on their relative importance. Then, the weighted criteria are used as inputs in the Fuzzy TOPSIS method to rank the R-KPIs. Data collection in this study was done using two questionnaires. The first collected data on the relative importance of the criteria and the second was concerned with ranking the R-KPIs with respect to the criteria. In total, 12 experts participated in data collection (a group of 12 experts is selected, as Delbecq et al. (1975) [16]) shows this number balances diverse perspectives and efficient decision-making. The interviewees are experts in infrastructure engineering, risk assessment, sustainability, and domain-specific fields like urban planning or cybersecurity. High skills in both qualitative and quantitative methods (all of the interviewees), and experience in research (60% of interviews are from the research community; this majority is because this community is more eager to participate in interviews and share knowledge and experience), along with professional experience are essential criteria for choosing the interviewees.

3. Theory and proposed implementation framework

In this section a conceptual framework is introduced for resilience quantification of CIs. Nevertheless, initially the nature of the system and its dimensions should be identified. Fig. 6 offers a process to understand the type of the system.

Fig. 7 shows the conceptual framework for quantification of the R-KPIs. This framework provides a structured approach to selecting

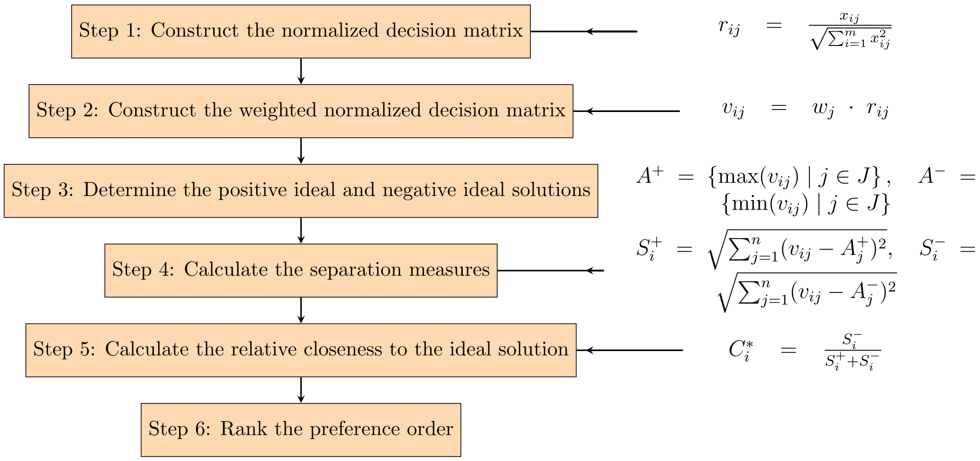

Fig. 5. Outline of the Steps of TOPSIS.

and implementing R-KPIs for CPSs, particularly in CIs where service continuity is essential.

The process begins with the identification of the need for R-KPIs for ensuring that systems can withstand and recover from disturbances. The first step is to determine the type of R-KPIs, which can be either quantitative (e.g., Recovery Time, Minimum Performance After Disruption) or qualitative (e.g., the joint estimation of risk attitudes and subjective probabilities, as discussed in [17], Energy Self-Sufficiency). This classification is pivotal as it defines the nature of the metrics to be used. In Step 3, the flowchart illustrates the assessment of data availability, highlighting the importance of different types of data: Historical Data and Logs (for pre-disturbance KPIs), Real-Time Data (for during-disturbance KPIs), and Post-Disturbance Data (for post-disturbance KPIs). The availability of these data types significantly influences the KPI selection process and the accuracy of resilience measurement.

Following this, the operational state is outlined in Step 4, including Real-Time, Steady State, Transient, and Seasonal conditions. This step is crucial for identifying when the KPI measurements should be taken to accurately reflect the system's resilience in different scenarios. Step 5 is to identify the scale of analysis; to determine whether KPIs should be evaluated at the Component Level, System Level, or System of Systems Level. This classification helps understand the scope of analysis and ensures that the resilience metrics are relevant to the system's complexity. After establishing the scale, the stage of disturbance is determined in Step 6, categorizing KPI measurements into Pre-Disturbance, During-Disturbance, and Post-Disturbance stages. This step ensures that KPIs are appropriately measured based on the system's condition related to the disturbance. The flowchart in Step 7 then guides the selection of appropriate KPIs based on the prioritization criteria derived from earlier sections, allowing decision-makers to scale the importance of each KPI and select those most relevant to the system's resilience needs.

Once KPIs are chosen, Step 8 intends to implement and measure them by collecting data according to the identified stage and operational state, and analyzing it to quantify resilience. This step ensures that resilience metrics are effectively captured and evaluated. Resilience monitoring in Step 9 is emphasized as a continuous process, ensuring that the system's resilience is tracked throughout its lifecycle to adapt to any changes or new disturbances. Finally, the flowchart concludes in Step 9 with improvement strategies, where the results from the KPI calculations are used to identify and implement strategies to enhance resilience. This step includes a feedback loop to re-evaluate and refine the resilience measures based on the outcomes of the improvement strategies.

Table 5
Categories of R-KPIs.

R-KPI category	Description
A	R-KPIs based on Resilience attributes, including response, recovery, redundancy, robustness, and preparedness [18,19].
B	KPIs based on environmental friendliness and Sustainable Development Goals (SDGs) of the United Nations.
C	R-KPIs based on risk and reliability.
D	R-KPIs with a different theoretical foundation.

4. Results and discussion

4.1. Identification and selection of R-KPIs

Regarding the complex nature of quantifying the KPIs for the resilience of AI-integrated CIs and the interrelations between CPSSs that characterize future CIs' main architecture, it is crucial to describe the scope of the R-KPIs and prospective level of the system modeling on which resilience quantification might be implemented.

4.1.1. R-KPIs for cyber-physical-social systems (CPSSs)

In this subsection, we delve into each R-KPI individually. We undertook a comprehensive review of the articles, seeking to extract expert knowledge about each R-KPI. The objective was to interpret the R-KPIs and formulate a theoretical definition that aligns with all articles employing that specific R-KPI.

Insights on the identification of CI R-KPIs are shown in Table 6. The first column in this table represents the DOI (Digital Object Identifier) of each article, while the second column describes the approach that each article employs in defining R-KPIs. Notably, a significant similarity exists in the conceptual basis of R-KPI definitions across several articles. To facilitate a comprehensive understanding, we categorized these approaches into a total of 4 distinct categories based on the definition of the KPIs in the reference article and the way they are measured. The categories are shown in Table 5.

The third column indicates the specific category of the conceptual basis used in each article's R-KPI definition. Additionally, the final column denotes whether the article used R-KPIs in AI-integrated CIs.

The definitions confirm that resilience models are scenario-based. Various scenarios are considered for each dimension of CPSS, and the study of system resilience typically relies on predefined scenarios.

Analyzing the categories reveals the distribution which is also shown in Fig. 8:

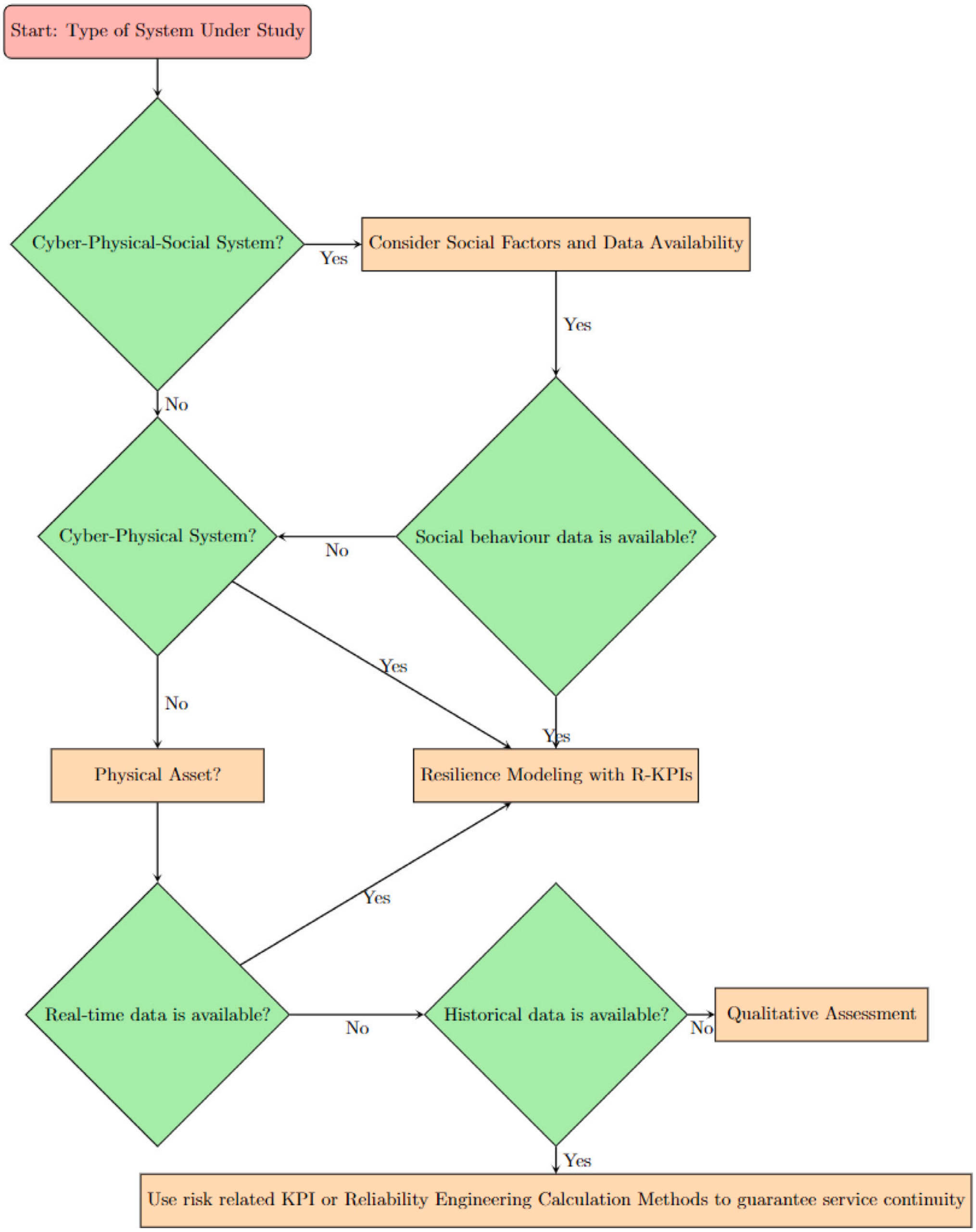

Fig. 6. The type of the complex System.

This indicates that measuring R-KPIs based on risk is the most commonly employed method.

Numerous uses of the risk-based approaches and the incorporation of sustainability as the cornerstone of resilience quantification reveal a robust connection between risk management, sustainability, and the resilience of complex systems. This means a resilience model based on most of the R-KPIs found in the literature contains dynamic and critical components for managing the resilience and security of CIs. The lifecycle of CI operations is characterized by constant changes in technology, external threats, and operational contexts. Conducting risk assessments at various stages of the CI lifecycle is imperative for several reasons [20]. Therefore, the resilience model is also a dynamic one, and the R-KPIs should be monitored and updated continuously with a schedule during the CI lifecycle.

Additionally, new risks may emerge as technology evolves, the threat environment becomes more sophisticated, or the operational environment and industrial best practices undergo changes. Regular reassessment of R-KPIs allows for the prompt identification and documentation of these new factors. Through the timely incorporation of these change factors, organizations can maintain an up-to-date understanding of the resilience of the complex system and tailor their resilience enhancement measures accordingly. Furthermore, an iterative approach to updating the R-KPIs is crucial to ensure the resilience of the evolving systems under socio-technical transformation. Moreover, the CI environment is subject to internal and external changes, such as integrating new data-driven solutions, developments in existing AI implementation, organizational restructuring, changes in regulations, or shifts towards sustainability. These changes can impact the resilience profile of the CI. In essence, an ongoing and iterative approach to resilience modeling through R-KPIs with three risk-related dimensions (physical, cyber, and social risks) during the lifecycle of CI operations is necessary for staying ahead of emerging changes,

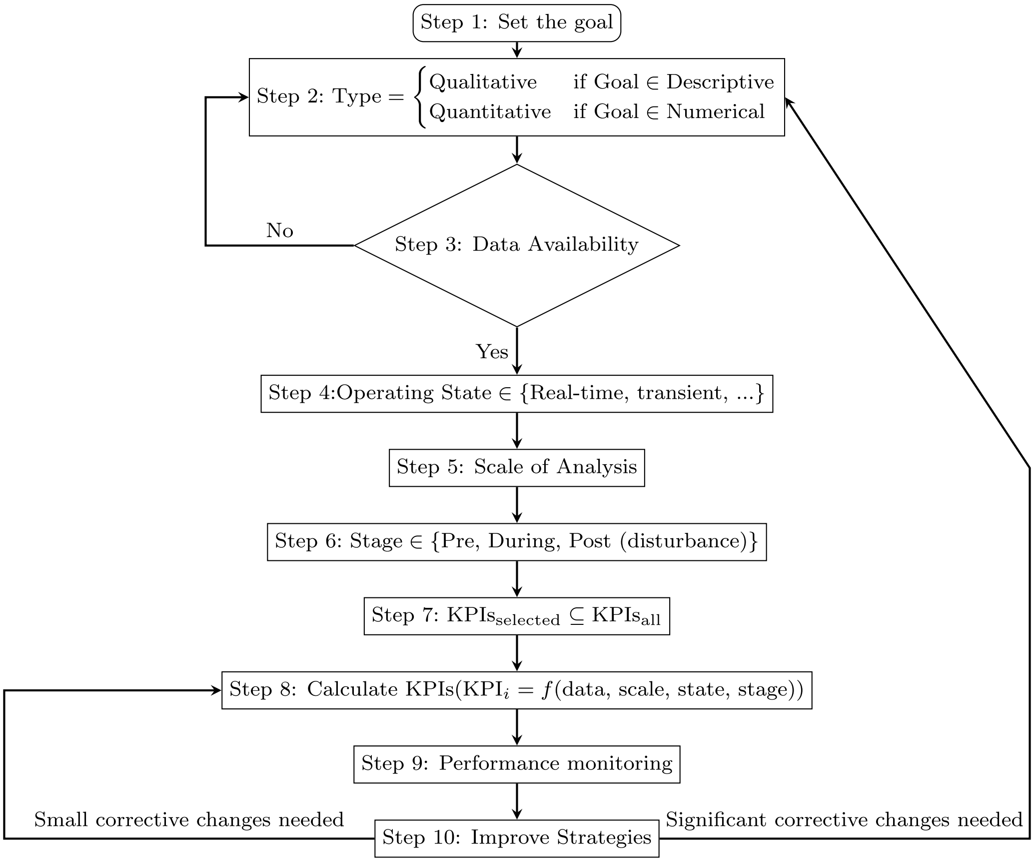

Fig. 7. 10 step process for resilience quantification.

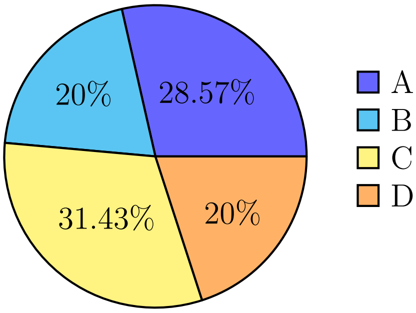

Fig. 8. Distribution of Categories. (The four categories, named A to D, are described in Table 5).

developments, and risks. In the next section, a CPI Resilience quantification conceptual framework is proposed to design resilience models at different levels.

Notwithstanding the emerging trend of considering critical infrastructure (CI) as cyber-physical-social systems (CPSSs), which integrate the social dimension alongside physical and cyber components, this paradigm shift necessitates the inclusion of social factors in the resilience framework.

4.1.2. R-KPIS in different domains

The study of the domain of application of the R-KPIs is crucial as resilience definition and implementation differs across fields. Domain-specific R-KPIs address unique risks ensuring targeted strategies and efficient resource allocation. They also enable benchmarking and continuous improvement tailored to each sector's needs. Table 7 shows the domain of the application of the identified R-KPIs.

The diversity of metrics in Table 7 shows domains like telecommunications and emergency management emphasize recovery time and timely actions, showcasing the importance of responsiveness. In contrast, domains such as environmental science and healthcare prioritize sustainability and risk assessments, reflecting long-term resilience needs.

Context-specific adaptations are also noticed in the R-KPI implementation, for instance, the energy and transportation sectors focus on technical specifications and sustainability due to their critical infrastructure roles. Similarly, public services and education systems incorporate R-KPI related to accessibility and inclusivity.

Studying the cross-domain applications of R-KPI despite differences, a common reliance on risk and reliability assessments (e.g., healthcare, infrastructure, power systems) highlights the universal need to quantify vulnerabilities and measure recovery capabilities.

Application of R-KPIs to policy and practice Table 7 underscores how R-KPI guides strategies across domains, from disaster management to urban planning, supporting evidence-based decisions and enhancing system resilience.

Only 9 out of 34 documents used R-KPIs for Cyber-Physical AI-Integrated Systems as it is shown in Table 8.

The set of articles in Table 8 demonstrates significant achievements through the application of R-KPIs in AI-integrated systems. For instance, [22] highlights the use of AI to improve readiness for catastrophic events by enabling dynamic risk assessment and adaptive learning. Similarly, [24] integrates AI to optimize service delivery platforms, reducing latency and improving user satisfaction.

In the context of sustainability, [26,30] leverage AI to enhance sustainability indexes, driving economic and environmental advancements. Furthermore, [38,39] integrate AI in urban planning and power systems, ensuring better management of resources and increased reliability.

Table 6
The theoretical foundation for measuring R-KPIs (the R-KPIs in rows 4 and 5 are extracted from the same document.).

No.	doi	Theoretical foundation	Cat.	AI
1	[21]	Network resiliency R-KPIs are defined according to recovery time in the event of unpredictable failure of service.	A	NO
2	[22]	R-KPIs are founded on Catastrophe preparedness	A	YES
3	[23]	R-KPIs are based on historic data of failures	B	NO
4	[24]	R-KPIs are based on GHG Emissions, Renewable Energy, Energy Use, and Climate Policy.	B	NO
5	[24]	R-KPIs are based on service delivery time	A	YES
6	[25]	R-KPIs are based on public access to service, alternatives, and the amount of risk sharing	D	NO
7	[26]	R-KPIs are based on sustainability and its indexes	B	YES
8	[27]	R-KPIs are based on climate sustainability and its indexes	B	NO
9	[28]	R-KPIs are based on acting in a timely manner	A	YES
10	[29]	R-KPIs are based on the performance of disaster relief activities	A	NO
11	[30]	R-KPIs are based on sustainability and its indexes	B	YES
12	[31]	R-KPIs are based on risk assessment	C	NO
13	[32]	R-KPIs are based on sustainability and its indexes	D	NO
14	[33]	R-KPIs are based on risk assessment	C	NO
15	[34]	R-KPIs are founded on reliability assessment	C	NO
16	[35]	R-KPIs are based on ancillary service performance	D	NO
17	[36]	R-KPIs are based on risk assessment	C	NO
18	[37]	R-KPIs are founded on reliability assessment and sustainability and risk assessment	B, C	NO
19	[38]	R-KPIs are based on climate sustainability and its indexes	B	YES
20	[39]	R-KPIs are founded on reliability assessment and sustainability and risk assessment	B, C	YES
21	[40]	R-KPIs are founded on reliability assessment and sustainability and risk assessment in the health care system	C	YES
22	[41]	R-KPIs are founded on outage historical data and risk assessment	C	YES
23	[42]	R-KPIs are based on risk assessment	C	NO
24	[43]	R-KPIs are based on risk assessment	C	NO
25	[44]	R-KPIs are based on the education system technical specifications	D	NO
26	[45]	R-KPIs are based on risk assessment	C	NO
27	[46]	R-KPIs are based on Reliability and Environmental friendliness	B, C	NO
28	[47]	No metrics or empirical evidence currently guide the implementation of hubs, so the body of knowledge has a significant gap.	-	NO
29	[48]	R-KPIs are based on technical specifications of traffic engineering	D	NO
30	[49]	R-KPIs are founded on sustainability, social resilience, resource management, and risk assessment	B, C	YES
31	[50]	R-KPIs are based on gas supply chains' resilience	A	NO
32	[51]	R-KPIs are based on risk assessment	B,C	NO
33	[52]	R-KPIs are based on the general notion of redundancy, robustness, and reliability engineering	A	NO
34	[53]	R-KPIs are based on risk assessment	C	NO
35	[54]	R-KPIs are based on a common strategy to assess the network robustness and resilience is to explore the network topology.	A	NO

Overall, the integration of AI with R-KPIs has facilitated advancements across diverse domains, showcasing their value in improving resilience, efficiency, and decision-making. These findings underscore the transformative potential of AI-enhanced R-KPIs in addressing complex challenges.

4.1.3. Optimal R-KPIs for AI integrated CI

In the selected articles, two types of studies on R-KPIs for AI-integrated CIs are identified. The first type introduces and discusses R-KPIs without quantifying infrastructure resilience through specific indicators, focusing on foundational concepts. The second type provides detailed quantifiable R-KPIs and includes case studies in real-world settings, combining theory with practical applications. This categorization highlights the need to bridge theoretical frameworks with empirical evidence to enhance the understanding and application of resilience concepts in CI studies.

The optimal R-KPIs for AI-integrated CIw are selected from the quantifiable R-KPIs that researchers employed in a case study and explicitly described the features in detail. Finally, since the scope is CI resilience, the KPIs that are employed for a post-disturbance condition are shortlisted. For instance, the R-KPIs like social goals of a smart city [38] or climate sustainability indexes [30], cannot provide a measure for the behavior of the system after a disturbance like a cyber-attack, or natural disaster. On the other hand, Aleksandar M. et al. [39], studied the system's resilience before, during, and after disturbances and identified R-KPIs that can reduce the impact of disturbances. These KPIs focus on three areas:

1. **Customer/External Perspective**: Evaluating how disturbances affect the quality of service delivered to customers.
2. **Operator/Internal Perspective**: Assessing how disturbances impact the internal infrastructure and operational efficiency.
3. **Cascading Effects**: For critical infrastructures, it is essential to consider how disturbances can trigger cascading effects that impact interconnected systems.

By addressing these aspects, the R-KPIs help to mitigate the overall impact of disturbances and improve system resilience. Therefore, Table 9 shows the group of R-KPIs that possess all the above-mentioned features.

Table 9 outlines the quantifiable R-KPIs for AI-integrated critical infrastructures (CIs). Energy self-sufficiency measures the extent to which the CI can operate independently from the central power grid. Utilizing off-grid and decentralized renewable sources can enhance this indicator. Minimum Performance refers to the lowest performance level of the system following a disturbance. This metric is crucial for disaster management and system resilience. Recovery Time is the duration required for the system to return to a stable performance level after a disruption. Functionality Loss indicates the system's behavior during the recovery period. For example, it can show whether the performance decreases dramatically and then increases linearly, or if the system's behavior is irregular and requires further study. Probability of Risk represents the frequency of disturbances within a specific period. This can be determined using historical data. In the next section, these KPIs are prioritized through a combined MCDM methodology which is described in Section 2.2. Table 10 presents the definition and significance of the selected R-KPIs. In The following, the theoretical foundation of these R-KPIs is briefly explained and then a detailed implementation methodology for them is proposed in the next subsection.

Probability of risk. As a core part of risk assessment methodologies, the probability of a risk as an R-KPI concerns the likelihood of a failure associated with a specific case that if realized, negatively impacts the system [74]. It is a conventional approach to resilience evaluation that estimates the occurrence of a disturbance using historical incident data. This reliance on historical data is considered the main limitation of employing probability of risk [75]. E. Goforth et al. [41] used seven KPIs based on historical data about outages and unavailability of the system. Table 11 shows the R-KPIs employed in their study.

Energy self-sufficiency. A system component with energy self-sufficiency features has one or several power-generating units independent from other systems. This feature increases resilience performance through improving restoration capabilities when a disturbance occurs [68]. Power disruptions during an incident may lead to cascading effects and energy self-sufficiency prevents such grave impacts. Energy self-sufficiency as an R-KPI reflects the need to minimize disturbance due to unsupplied energy [71].

Table 7
Theoretical foundations for measuring R-KPIs across domains.

No.	DOI	Theoretical Foundation	Domain
1	[21]	Network resiliency R-KPIs are defined according to recovery time in the event of unpredictable service failures.	Telecommunications
2	[22]	R-KPIs are founded on catastrophe preparedness.	Energy
3	[23]	R-KPIs are based on historical data of failures.	Information Technology
4	[24]	R-KPIs are based on GHG emissions, renewable energy, energy use, and climate policy.	Environmental Science
5	[24]	R-KPIs are based on service delivery time.	Service Systems
6	[25]	R-KPIs are based on public access to service, alternatives, and the amount of risk sharing.	Public Services
7	[26]	R-KPIs are based on sustainability and its indexes.	Economics
8	[27]	R-KPIs are based on climate sustainability and its indexes.	Climate Science
9	[28]	R-KPIs are based on acting in a timely manner.	Emergency Management
10	[29]	R-KPIs are based on the performance of disaster relief activities.	Humanitarian Logistics
11	[30]	R-KPIs are based on sustainability and its indexes.	Engineering
12	[31]	R-KPIs are based on risk assessment.	Infrastructure
13	[32]	R-KPIs are based on sustainability and its indexes.	Construction
14	[33]	R-KPIs are based on risk assessment.	Urban Planning
15	[34]	R-KPIs are founded on reliability assessment.	Water Resources
16	[35]	R-KPIs are based on ancillary service performance.	Energy Services
17	[36]	R-KPIs are based on risk assessment.	Wireless Systems
18	[37]	R-KPIs are founded on reliability assessment, sustainability, and risk assessment.	Urban Studies
19	[38]	R-KPIs are based on climate sustainability and its indexes.	Sustainable Cities
20	[39]	R-KPIs are founded on reliability assessment and sustainability and risk assessment.	Power Systems
21	[40]	R-KPIs are founded on reliability assessment and sustainability and risk assessment in the healthcare system.	Healthcare
22	[41]	R-KPIs are founded on outage historical data and risk assessment.	Infrastructure
23	[42]	R-KPIs are based on risk assessment.	Water Management
24	[43]	R-KPIs are based on risk assessment.	Systems Engineering
25	[44]	R-KPIs are based on education system technical specifications.	Education Systems
26	[45]	R-KPIs are based on risk assessment.	Environmental Management
27	[46]	R-KPIs are based on reliability and environmental friendliness.	Power Systems
28	[47]	No metrics or empirical evidence currently guide the implementation of hubs.	Transportation
29	[48]	R-KPIs are based on technical specifications of traffic engineering.	Traffic Engineering
30	[49]	R-KPIs are founded on sustainability, social resilience, resource management, and risk assessment.	Sustainability
31	[50]	R-KPIs are based on gas supply chains' resilience.	Gas Supply
32	[51]	R-KPIs are based on risk assessment.	Earth Sciences
33	[52]	R-KPIs are based on redundancy, robustness, and reliability engineering.	Quality Management
34	[53]	R-KPIs are based on risk assessment.	Decision Sciences
35	[54]	R-KPIs explore network topology for robustness and resilience.	Networks

Table 8
R-KPIs used in AI-integrated systems. The numbers correspond the article numbers in Table 7.

No.	DOI	Description of metric in cyber-physical AI-integrated system
2	[22]	Used to prepare AI systems for handling catastrophic events through robust learning frameworks.
5	[24]	Enhances service delivery optimization in AI-based service platforms.
7	[26]	Evaluates AI-driven sustainability indexes in economic models.
9	[28]	Measures timeliness in AI-enabled emergency response systems.
11	[30]	Incorporates AI to assess sustainability and ensure optimization.
19	[38]	Applies AI to improve climate sustainability metrics in urban planning.
20	[39]	Integrates AI models to evaluate power system reliability and risk.
21	[40]	Utilizes AI to analyze healthcare systems' resilience and sustainability.
30	[49]	AI-driven assessments for sustainability and social resilience.

Table 9
Quantifiable R-KPIs for AI integrated CIs.

Ref	R-KPIs	KPI
[26]	R-KPI(1)	Energy self-sufficiency
[28]	R-KPI(2)	Performance (Min. level)
[39]	R-KPI(3)	Recovery time
[39]	R-KPI(4)	Behaviour during response (Functionality loss)
[41]	R-KPI(5)	Probability of risk
[41]	R-KPI(3)	Recovery time
[24]	R-KPI(3)	Recovery time

Recovery time. The primary objective of resilience-enhancing metrics is to improve the three core capacities of resilience: absorption, adaptation, and restoration. This goal is achieved through the implementation of diverse strategies aimed at strengthening the functionality and performance of CIs, such as incorporating redundancy. Reducing recovery time in CIs is crucial for ensuring swift restoration of services following disruptions. Implementing measures that prioritize the rapid restoration and replacement of impaired components can significantly shorten recovery times. This proactive approach minimizes downtime and enhances overall resilience by enabling the system to bounce back quickly and effectively from unforeseen events. Redundancy is the most well-known strategy to improve this KPI in critical infrastructures, which involves integrating duplicate or backup components and systems. While redundancy safeguards against single points of failure, its primary contribution is in facilitating quicker restoration by providing alternative pathways and resources.

The recovery time after a disruption is a crucial index for CI resilience, particularly in the energy sector due to its direct impact on overall operational resilience. In the aftermath of a disturbance within CI, performance inevitably experiences a decline, reaching its minimum level. Following this critical decrease, there are essentially two potential outcomes. Firstly, the performance may reach zero, resulting in a complete system shutdown— a scenario that is universally deemed unacceptable in any disturbance situation for CIs. Consequently, the system's response to the disturbance may trigger a recovery phase, characterized by an upward trajectory in performance levels. This recovery phase is crucial as it signifies the infrastructure's ability to rebound and stabilize after the initial level of performance. The stabilized performance level, as illustrated in Fig. 10, can assume one

Table 10

Selected R-KPIs definition and significance.

R-KPI	Definition	Significance
Probability of Risk	A potential disturbance is considered a cyber-physical risk and the R-KPI represents the probability of occurrence of the risks in the system. [55,56]	The risk-related R-KPI is directly associated with the service continuity of CIs and is rooted in historical data. The probability of each risk should be calculated individually (i.e. independent from other risks) because the joint probability of risks and cascading effects need to be analyzed separately for CIs). some examples of risks that are studied widely as R-KPI are the frequency of failures within a specified time frame, the issues that quality of service is affected, and issues related to cybersecurity and privacy. [57–60]
Energy self-sufficiency	An R-KPI that measures energy self-sufficiency quantifies the extent to which a system can independently generate and manage its energy needs without relying on external power sources, ensuring continuous operation and stability during external power disruptions. [61–64]	Energy self-sufficiency significantly enhances system resilience by reducing vulnerability to external failures and mitigating cascading effects from power outages. By being less dependent on external power grids, self-sufficient systems can maintain continuous operation and contain disruptions, ensuring greater stability. This autonomy allows for better control and management of energy resources, leading to more reliable and optimized functionality. Additionally, self-sufficient systems can prioritize critical functions during energy shortages and achieve significant cost savings over time. [62,65,66]
Recovery Time (T)	Represents the duration required for the system to recover from a disturbance. [67–73]	Provides a quantitative measure, shedding light on the system's ability to rebound following an incident. [69–73]
Functionality Loss (FL)	Illustrates the extent of functionality loss in the system, irrespective of the system's behavior during degradation and recovery. [67,69–73]	Offers insights into the overall impact on system functionality, encompassing both observable and latent effects. [69–73]
Minimum Performance (Pmin)	Indicates the minimum level of performance achievable by systems. [68–71,73]	The rationale for utilizing this index lies in the complexity of fitting the resilience curve to the dataset derived from IoT sensors embedded in the system. The intricate behavior of the system post-disturbance may lead to the loss of local and global minimums in performance degradation during the polynomial fitting of the curve (see Fig. 9). The Minimum Performance Index is instrumental for decision-makers, enabling them to consider the critical threshold of minimum acceptable performance in CIs. [69–71,73]

of three forms: it may be equal to the prior stable level, higher than the pre-disturbance level, or lower than the pre-disturbance level. This phase is called the recovery phase and represents a critical aspect of the system's resilience.

The concept of recovery time encompasses both the degrading phase, where performance declines, and the subsequent recovery phase, where performance improves and stabilizes. As illustrated in Fig. 10, the recovery time spans from the occurrence of the disturbance to the point of stabilization after the recovery phase. The duration of this recovery time indicates the system's overall robustness and its ability to efficiently restore and stabilize its performance. This is vital for the sustained and reliable operation of CI systems.

Table 11

Examples of probability of Risk KPIs.

KPI	Definition
Frequency (per 100 km-year)	The number of outages divided by km years divided by 100
Frequency (per year)	The number of outages divided by component years
Number of outages	The number of major component-related forced outages
Total outage duration (h)	Total forced unavailable time (i.e., the time required to completely restore a component to service) of the component-related outages
Average outage duration (h)	Total outage duration divided by the number of outages
Median outage duration (h)	50% of the forced unavailability times are greater than this value
Unavailability (%)	The product of frequency and average outage duration in years, expressed as a percentage of the component's population

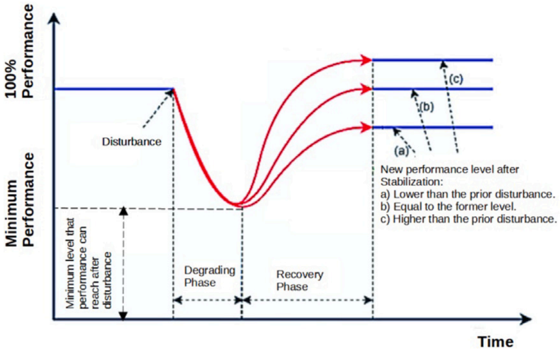

Fig. 9. Illustration of minimum performance level.

Minimum performance level. The determination of the minimum performance level in CIs depends on the inherent design features of the system and the severity of the encountered disturbance. Monitoring this minimum performance level holds crucial significance as it ensures the preservation of essential services vital for the system's proper functioning. The minimum performance level is intricately defined by the indispensable thresholds associated with the societal needs for that particular service. In the event that the minimum performance of a CI descends below this predefined level, it becomes imperative to reassess the response strategy to this risk. Such a proactive approach is essential for safeguarding the reliability and functionality of the CI system, aligning its performance with the crucial needs of the society it serves. Continuous monitoring and adaptive strategies are thus indispensable to maintain the resilience and effectiveness of CI in the face of dynamic challenges. Fig. 9 shows the minimum performance level after disturbance.

Functionality loss. Resilience curves applied across the CI literature are two types. First is the typical representation with a semi-linear degradation and semi-linear recovery phase, and the second is a non-idealized system behavior (Fig. 11). Complex systems can show irregular behavior after disturbance because of their dynamic nature and interdependencies with other CIs. Therefore, it is important to have an index to monitor the loss during the recovery lifecycle. This loss is called the Loss of Functionality [76]. Fig. 12 shows a graphical illustration of Loss of Functionality.

The R-KPIs used in current research to adopted from comprehensive approaches developed for assessing the resilience of CIs in response to specific disturbances [67,68,76–78]. It aims to measure the impact of an earthquake by estimating the predicted degradation in the quality of service provided by the infrastructure, denoted as $Q(t)$. The process is broken down as follows:

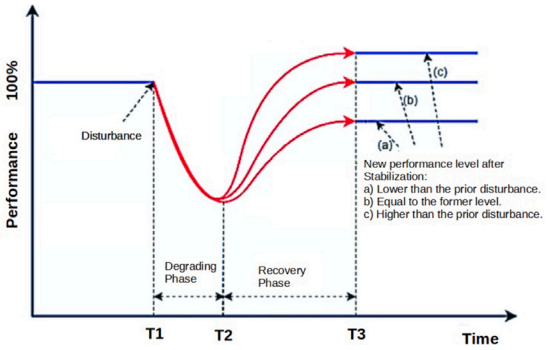

Fig. 10. Illustration of recovery time.

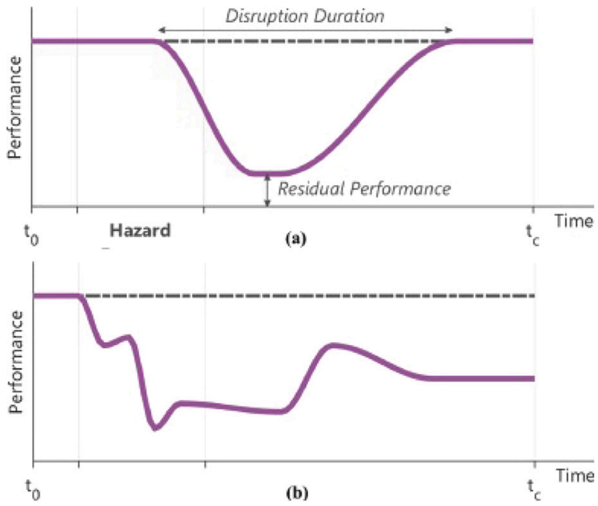

Fig. 11. Graphical illustration of different behaviors after disturbance [74].

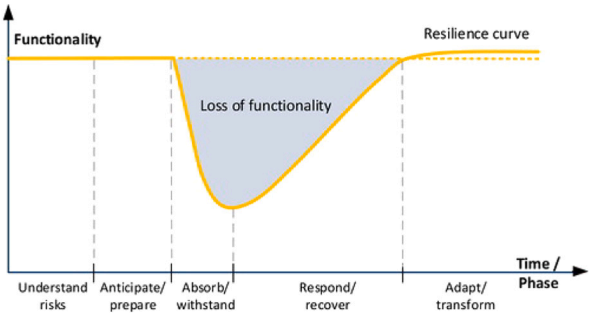

Fig. 12. Graphical illustration of Loss of Functionality [75].

Assuming a disturbance occurs at time t_0, the degradation in service quality is assessed from the moment of the shock (t_0) until the service quality ($Q(t)$) is fully recovered to its pre-disturbance levels at time t_1. This period represents the recovery phase. The measure of Loss of Functionality denoted as LF, is determined by considering how much the service quality degrades during the recovery period regardless of the system's behaviors shown in Fig. 11. The calculation can be expressed as follows:

$$FL = \int_{t_0}^{t_1} [100 - Q(t)]\, dt$$

In simple terms, Loss of Functionality is the difference between the initial service quality at the time of the disturbance (t_0) and the service quality once it has fully recovered (t_1). This provides a quantifiable metric for understanding the impact of the disturbance on the infrastructure's ability to maintain its continuity of service.

Table 12
Weighted criteria used to rank R-KPIs.

ID	Criteria	Normalized weight	Rank
C3	Criticality	0.2357	1
C4	Manageability	0.2215	2
C2	Automation	0.1978	3
C1	Cost	0.1726	4
C5	Level	0.1724	5

Table 13
Final ranking of R-KIPs.

ID	KPI	closeness coef	Rank
R-KPI(5)	Probability of risk	0.83856	1
R-KPI(1)	Energy self-sufficiency	0.77069	2
R-KPI(4)	Behaviour during response (Functionality loss)	0.71756	3
R-KPI(3)	Recovery time	0.53240	4
R-KPI(2)	Performance (Min. level)	0.08251	5

4.2. Ranking results of the R-KPIs for AI-integrated CIs

The result of employing fuzzy AHP on the criteria is shown in Table 12. Consequently, 13 presents the final ranking of R-KPIs.

Table 12 suggests that the highest priority is given to Criticality. This is expected, given the nature of CIs that provide essential services to society and the economy. Manageability comes in as the second highest priority. In the context of AI-integrated CIs, effective data collection, management, and processing are vital. The emphasis on manageability highlights the importance of having robust systems in place for monitoring and maintaining infrastructures. This supports the view that data-driven solutions are essential for handling the complexity of CPSSs to ensure their efficient and effective operation. Automation is ranked third, underscoring its crucial role in modern CI systems. Automation facilitates faster and more reliable responses to various operational scenarios, reducing the dependency on manual interventions. But, interestingly, Cost is ranked fourth. This lower prioritization suggests that, for CIs, the primary concern is ensuring service continuity and system resilience rather than minimizing expenses. Finally, Level is the least prioritized criterion only by a small margin compared to cost. This criterion pertains to the hierarchical importance or operational level within the infrastructure system.

Table 13 shows the ranking result of the selected R-KPIs obtained from the fuzzy TOPSIS method. The top-ranked KPI, Probability of Risk (0.83856), underscores the importance of proactively identifying and mitigating potential threats. Energy self-sufficiency (0.77069) is ranked second, reflecting the critical need for reliable and autonomous power sources. Behavior during response, known as Functionality Loss (0.71756) is the third, emphasizing the importance of minimizing functionality loss during disruptions. Recovery time (0.53240) is fourth, highlighting the need for rapid restoration of services. Lastly, Performance (Minimum level) (0.08251) is ranked fifth, indicating that maintaining a minimum performance threshold, while important, is less critical compared to the other factors. This ranking underscores a comprehensive approach to resilience, prioritizing risk management, energy independence, and effective response and recovery mechanisms.

5. Case study and synthesis of results

5.1. Open data and test condition

This case study utilizes data collected over 152 days from 49 sensors out of 52 (three sensors reported identical values, which suggests there may be an issue with the open dataset) embedded within a centrifugal

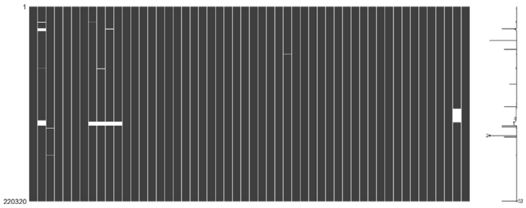

Fig. 13. Missing data in the raw dataset.

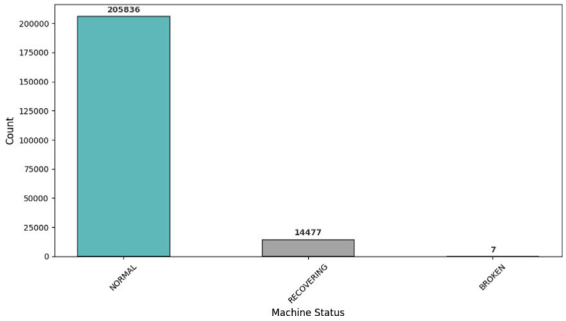

Fig. 14. Operation status of the studied case.

pump. The data is openly available on a Kaggle repository.[1] Notably, some parameters were measured at multiple locations using distinct sensors. The source dataset on Kaggle contains three main data groups:

1. **Timestamp data:** This provides a temporal reference for each data point.
2. **Sensor data (52 series):** This part includes raw sensor readings from all 52 sensors.
3. **Machine status:** This serves as indicating the operational state of the pump and allowing us to identify the disturbance.

This dataset contains measurements from both the driving motor and the driven pump, encompassing various parameters such as vibration, speed, current, power, flow rates, temperature, and pressure. These parameters are captured by different types of sensors including accelerometers, strain gauges, and pressure gauges. This dataset provides a valuable resource for studying pump health and developing predictive maintenance models.

Since the dataset contains raw data collected from sensors in the field, data preparation is needed prior to analysis. The exploratory Data Analysis (EDA) shows the missing data (Fig. 13). After handling missing data and outliers, the failure times are explored (Fig. 14). This data will be used for risk probability calculation.

SENSOR_06 - Motor Active Power - is selected to study the performance of the system and R-KPI quantifications. Monitoring Motor Active Power, measured by `SENSOR_06`, is a key indicator of the motor's operational effectiveness, and deviations from normal power consumption can signal potential mechanical issues or inefficiencies. This importance is supported by the research that highlights how active power analysis can enhance maintenance strategies and energy efficiency in industrial systems [79].

Fig. 15 depicts the system's performance based on SENSOR_06 as a light blue line, indicating the occurrences of full system failures. For this study, only the first failure and subsequent recovery are considered for establishing the resilience curve to facilitate method comparison. However, it is essential to note that there is no data about the implementation of a decentralized renewable energy source, battery, or a local generator for the period of power outage.

5.2. Disturbance scenario and framework implementation

On June 28, 2018, a significant disturbance was observed in the system, which took approximately a week to return to a stable state. During this period, the pump was out of order for maintenance for 5 days. Fig. 16 illustrates the raw data from sensor 06 during this time frame. The data exhibits considerable noise, which complicates the interpretation of the system's behavior.

To better understand the system's resilience, we first applied a rolling window technique to smooth the data. Fig. 17 shows the smoothed curve obtained through this method. While this approach helps visualize the general trend, it may obscure critical details and important data points due to its averaging effect.

To address this limitation, we implemented a Support Vector Machine (SVM) for a more precise polyline fit, which better captures the system's behavior post-disturbance without losing significant data points. Fig. 18 presents the resilience curve fitted using SVM. This curve provides a clearer depiction of the system's recovery trajectory and highlights important data features that might be missed with simpler smoothing techniques.

Based on the available data, we have updated the flowchart for evaluating the R-KPI to better reflect the specifics of our case study. The updated flowchart is shown in Fig. 19 and outlines the revised framework for assessing system resilience. The revised framework incorporates recent data analysis methods and reflects a structured approach for assessing system resilience. It includes information for data availability, disturbance, preprocessing, and R-KPI calculation methods. This framework aims to provide a comprehensive guide for evaluating the system's performance and recovery capabilities. In the subsequent section, we will explore the calculation of the R-KPIs using the SVM-fitted resilience curve to quantify the system's recovery performance.

5.3. R-KPI quantification results

5.3.1. Energy self-sufficiency R-KPI

Going through the data card in the repository, the absence of information regarding decentralized renewable energy sources, battery storage, or local generators for power outages results in an energy self-sufficiency R-KPI of zero. This critical conclusion underscores the urgent need for a redundant electricity source to enhance the resilience of the pumping system.

5.3.2. Risk probability

In the analysis, the percentage of days with pump failures for each month is calculated based on daily observations. Initially, it is determined whether each day had a pump failure by checking if the "machine_status" was "BROKEN" on that day. The number of days with failures and without failures is then counted for each month. The percentage of failure days for each month is computed by dividing the number of failure days by the total number of days in that month and then multiplying by 100.

Finally, the average percentage of failures across all months is computed to understand the overall performance trend (See Table 14). For the given dataset, the average percentage of failures per month is found to be 4.58%, indicating that, on average, 4.58% of the days in each month experienced a pump failure.

5.3.3. Resilience curve and post disturbance R-KPIs

The first post-disturbance R-KPI is Recovery time. Fig. 20 is created based on the sensor data and the recovery time calculation for the observed disturbance period. The scatter plot represents the raw data from Sensor_06, with a red SVM regression curve fitted to the data. The vertical dashed lines indicate key points in the disturbance and recovery timeline:

- **Vertical Line 1 (June 27, 2018, 09:30:00):** Marks the start of the disturbance.

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[1] https://www.kaggle.com/datasets/nphantawee/pump-sensor-data/data

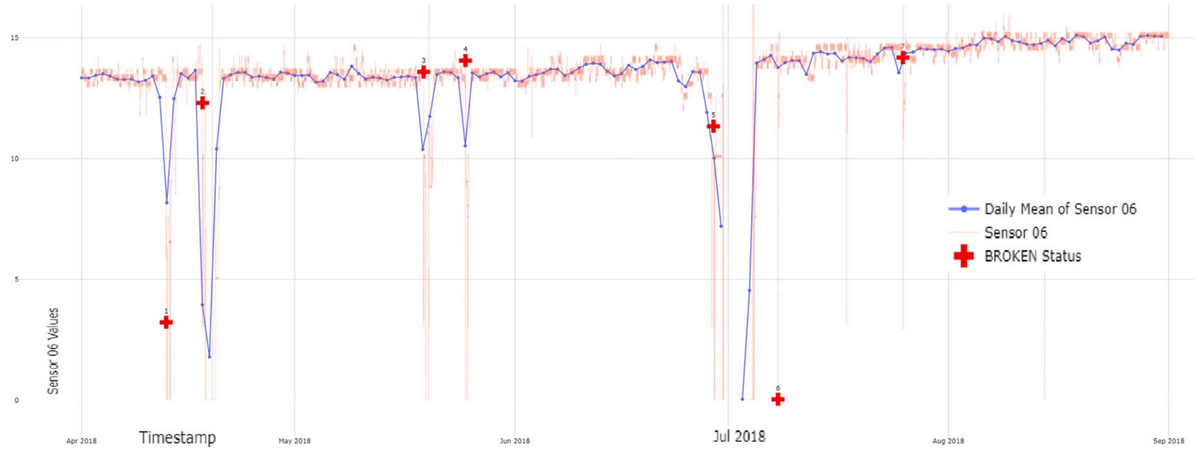

Fig. 15. The system's performance based on SENSOR_06 - Motor Active Power. Failure no.6 which happened in July 2018 will be studied in the current article.

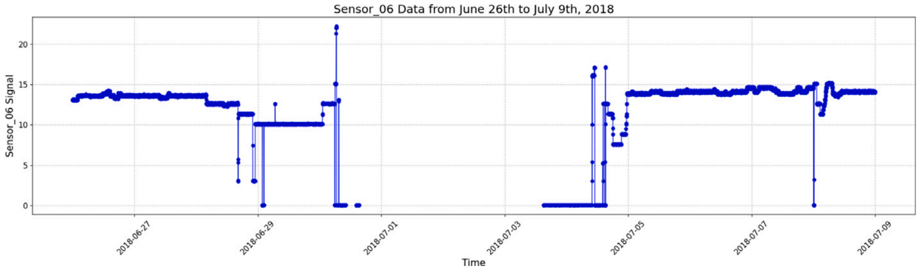

Fig. 16. Raw data from sensor 06 showing the disturbance and recovery period.

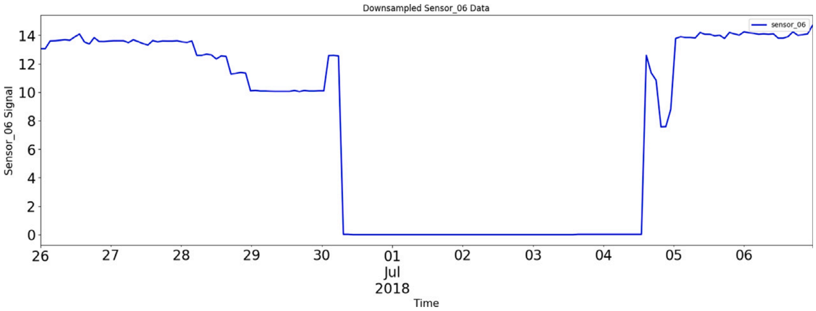

Fig. 17. Smoothed curve using a rolling window method for sensor 06 data.

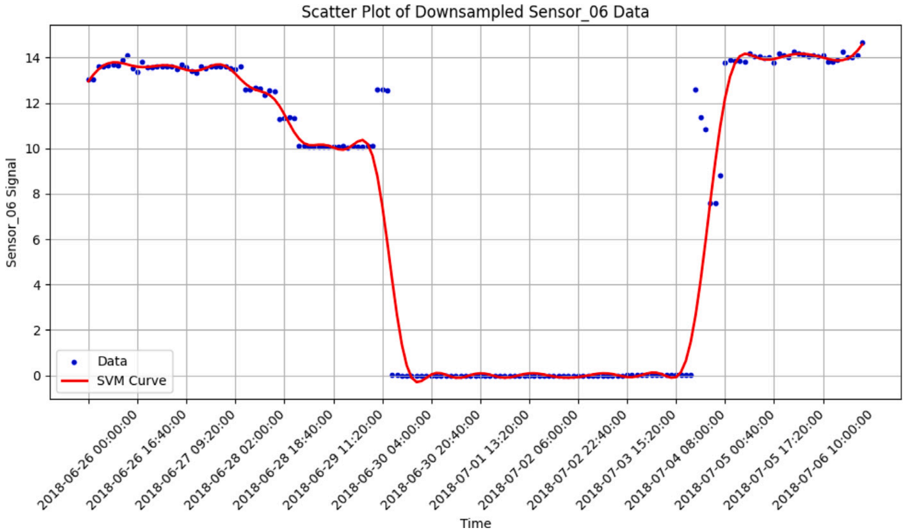

Fig. 18. Resilience curve fitted using SVM, capturing the system's behavior in post-disturbance.

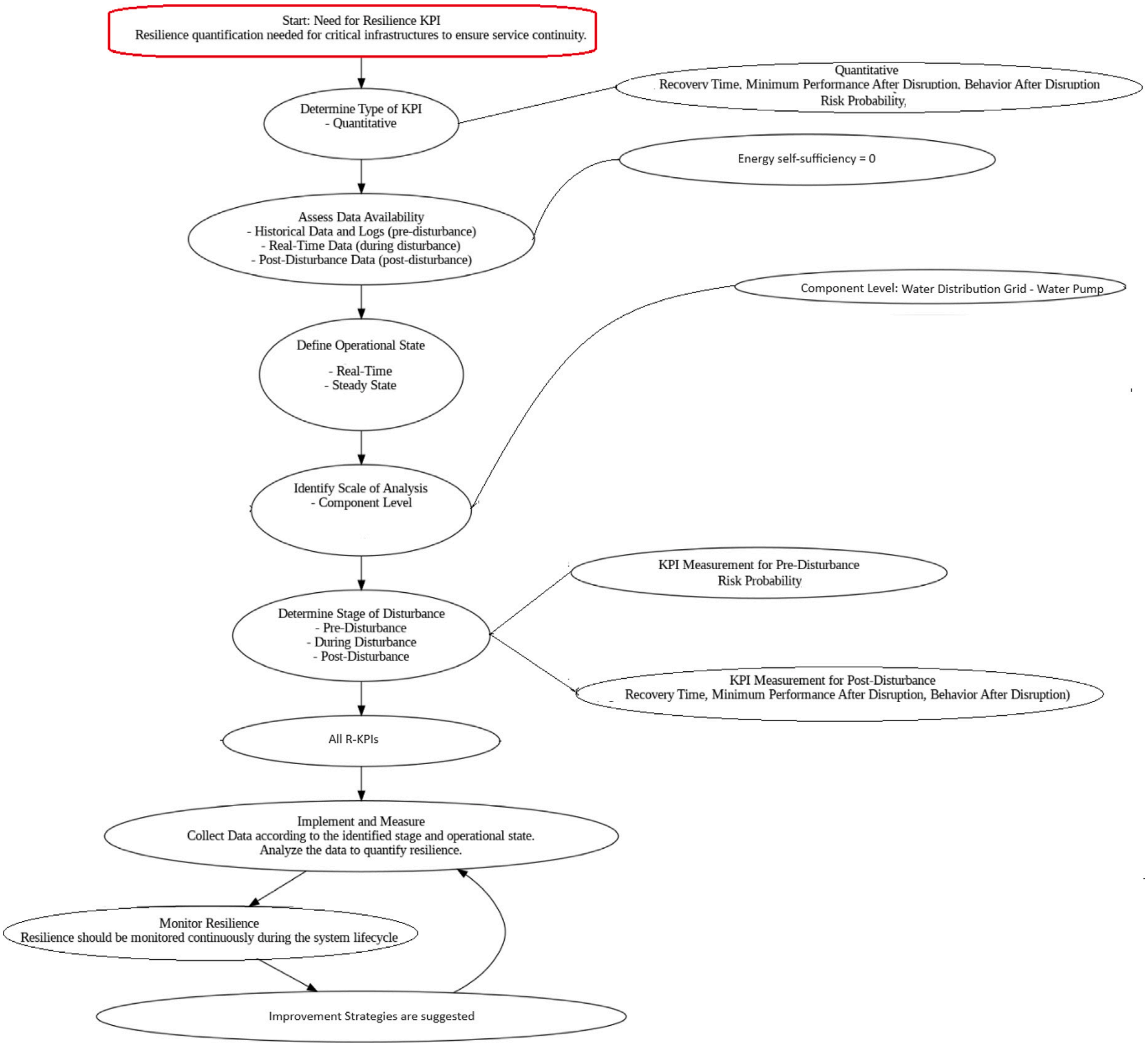

Fig. 19. Updated flowchart of the Resilience Key Performance Indicator (R-KPI) evaluation framework for the case study.

Table 14
Monthly failure data and percentage of failures for the water pump.

Month	Not broken	Broken	Total days	Percentage of failures
2018-04	28	2	30	6.67%
2018-05	29	2	31	6.45%
2018-06	29	1	30	3.33%
2018-07	29	2	31	6.45%
2018-08	31	0	31	0.00%

- **Vertical Line 2 (July 4, 2018, 08:00:00):** Indicates when the disturbance ends and the system returns to stable performance.

The double-headed arrow between these vertical lines highlights the recovery period. The annotation above the arrow shows the calculated recovery duration: **[175.5 h (7 days)]** . This duration represents the time it took for the system to return to a stable state after the disturbance.

In this case study, the second post-disturbance R-KPI reflects the minimum system performance observed after the disturbance. This metric indicates that the system performance has dropped to 0, signifying that the pump has completely failed. The total failure of the pump highlights a significant operational issue, underlining the importance of redundancy and prompt maintenance to prevent extended disruptions in water distribution. Such a decline indicates a severe disturbance in the entire water distribution system.[2]

Fig. 21 illustrates the sensor data and the calculation of functionality loss, which represents the third post-disturbance R-KPI. The scatter plot shows the raw data from Sensor_06, while the red curve represents the SVM regression model fitted to the data. A horizontal red line at $y = 14$ indicates the threshold for evaluating functionality loss. The yellow-shaded area between the SVM curve and the horizontal line highlights the functionality loss during the disturbance period.

The functionality loss quantifies the degradation in system performance due to the disturbance. It is calculated as the area between the SVM curve and the horizontal line that shows where the system is stabilized in Fig. 21, specifically from the disturbance start time (June 28, 2018, 00:30:00) to the disturbance end time (July 5, 2018, 08:00:00). This area is computed using numerical integration techniques. A Python code snippet demonstrates how this calculation is performed (see Appendix).

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[2] Although the data card does not specify whether a spare pump was available, it is common practice in critical water distribution pump stations to have redundant pumps. Redundant systems are designed to ensure continuous operation even in the event of a pump failure, thereby mitigating the impact of such disturbances on the overall system performance.

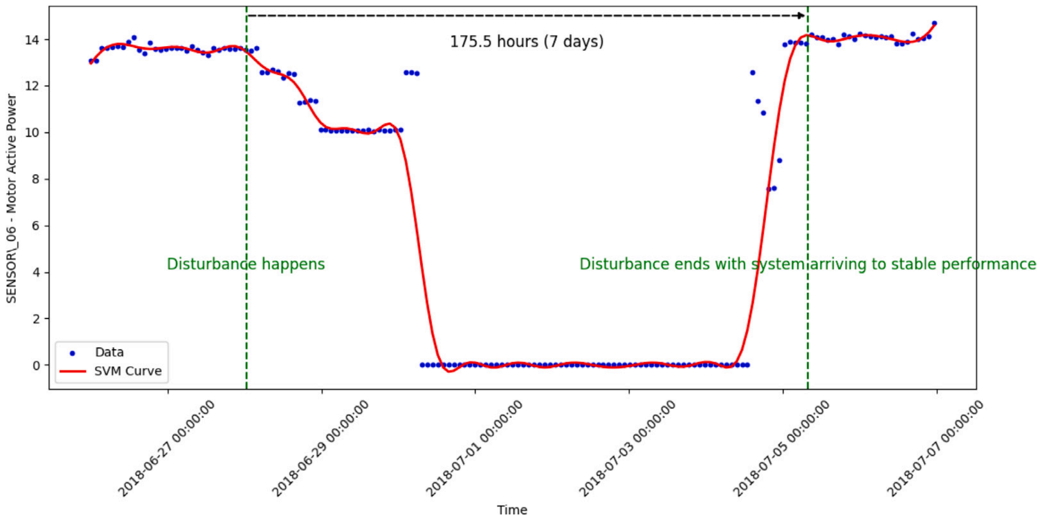

Fig. 20. Post Disturbance R-KPI: Recovery time.

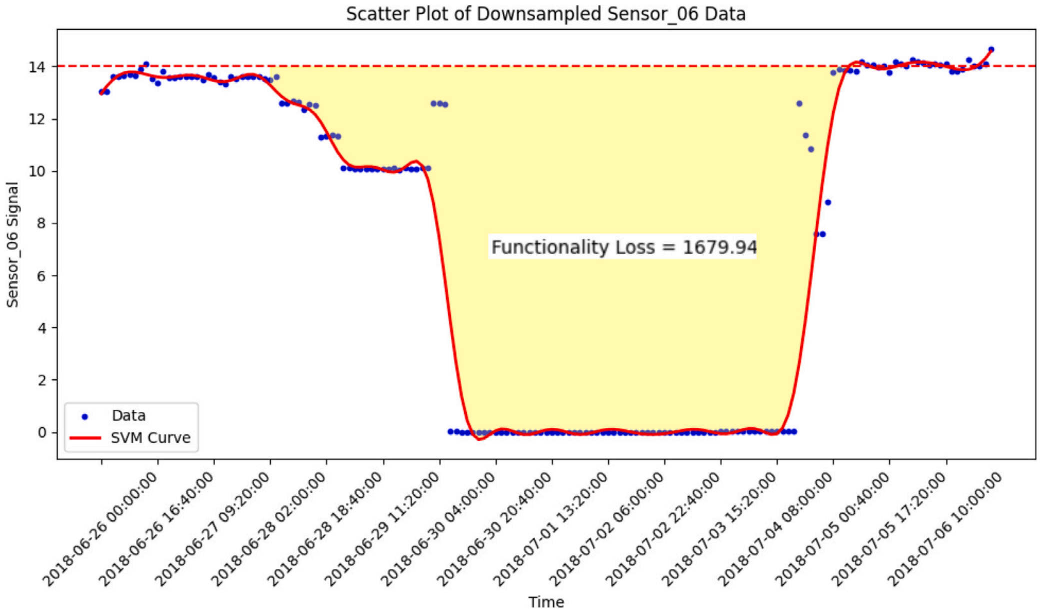

Fig. 21. Post Disturbance R-KPI: Funcionality Loss.

5.4. Resilience improvement strategies

Table 14 presents the percentage of failures for the water infrastructure over the period from April 2018 to August 2018. Although the average percentage of failures per month is relatively low at 4.58%, it is important to note that each month experienced at least one or two failures, with some failures extending for a significant portion of the month. More specifically, there were two long failures in three out of the five months. Even with a low percentage, the substantial duration of these failures indicates that the water pump's reliability needs improvement. The consistent presence of long-duration failures, despite the low failure rate, suggests a need for better preventive measures and maintenance practices to ensure that such issues are addressed more swiftly and effectively.

Energy self-sufficiency is crucial for infrastructures that are heavily dependent on external energy sources. In the current case, the infrastructure consists of a pump in a water distribution system that relies entirely on grid energy. To ensure that the system maintains its minimum performance, especially during energy outages or cyber-physical threats, it is essential to incorporate redundant energy sources. Implementing such redundancy will enhance the system's resilience by providing a backup energy supply, thereby mitigating the impact of power disruptions and ensuring continuous operation even in adverse conditions. Between April 1, 2018, and August 31, 2018, there were seven failures of the water pump. The recovery times for all these failures are presented below, which indicate significant downtime. This extended recovery period underscores the need for a redundant pump and proactive and predictive maintenance strategies. Additionally, the technical department should aim to reduce repair times through various strategies, such as improving training for maintenance personnel, implementing better diagnostic tools, and enhancing the availability of spare parts. The recovery times listed below are extracted from the open dataset.

- Recovery time after failure 1: 944.0 min
- Recovery time after failure 2: 3110.0 min
- Recovery time after failure 3: 1312.0 min
- Recovery time after failure 4: 605.0 min
- Recovery time after failure 5: 8390.0 min
- Recovery time after failure 6: 41.0 min

Table 15
Disturbance types, timestamps, and minimum performance values. The results show that the minimum performance drops dramatically after all disturbances.

Min. Perf. occurance status	Disturbance timestamp	Min performance
Broken	2018-04-12 21:55:00	0.014468
RECOVERING	2018-04-13 11:16:00	0.028935
RECOVERING	2018-04-13 11:48:00	6.438078
RECOVERING	2018-04-13 13:17:00	6.474247
RECOVERING	2018-04-13 13:18:00	6.524884
RECOVERING	2018-04-13 13:32:00	6.553819
RECOVERING	2018-04-13 13:38:00	6.575521

- Recovery time after failure 7: 75.0 min

However, the recovery time in the previous section for a specific failure was calculated by identifying the disturbance using Python code. In our process, the return to a stable performance level is considered the end of recovery, whereas, in the open data, the end of machine repair is considered the end of recovery. This slight difference is important but for resilience calculations, our approach complies with the definition of recovery time for resilience. In summary, the manual checklists and logs are not reliable sources to calculate the R-KPIs and the resilience quantifications may need feature engineering of raw data to comply with the R-KPI definitions listed in Table 10. Since the reasons for the failures and the maintenance procedures are not detailed in the open dataset, further specifics cannot be provided (see Table 15).

The results indicate that the minimum performance drops dramatically following all disturbances. To enhance resilience and mitigate the impact of such performance drops, consider implementing the following strategies:

- *Redundant Systems*: Implement backup systems to take over during disturbances, reducing the impact on overall performance.
- *Real-time Monitoring*: Use advanced monitoring tools to detect disturbances early and initiate preemptive actions to minimize performance drops.
- *Automated Recovery Procedures*: Develop automated recovery procedures to quickly restore performance levels following a disturbance.
- *Predictive Maintenance*: Utilize predictive maintenance techniques to anticipate potential issues and address them before they cause significant performance drops.
- *Load Balancing*: Distribute workloads evenly across multiple systems to prevent any single system from becoming a performance bottleneck.

6. Limitations, challenges and future study

The current article is founded on a state-of-the-art review and knowledge synthesis and R-KPIs prioritization in CPSSs with a focus on AI-integrated CIs. However, a more comprehensive analysis, a deeper exploration of real-life cases, extensive discussion, and validation of the reported R-KPIs in the literature require scenario-based validations. This, therefore, stands as a potential research line for future research. Similarly, the prioritization of R-KPIs also necessitates a scenario-based approach and an in-depth examination through real-life case studies. Criteria extraction and implementation might be subjected to change in some scenarios. This study has the potential to pave the way for future research to fill these gaps and further enrich the knowledge base for quantitative modeling of CI resilience.

According the number of the articles that considered the social aspect, there is a significant gap in considering this aspect and look at the CI from Cyber-Physical-Social lens. because social aspects present significant challenges, particularly in data collection, due to privacy concerns and the complexities of accurately capturing social behavior. While solutions such as leveraging social media data have been proposed, data-driven approaches for CPPSs remain in their nascent stages. Addressing these challenges and developing robust methods for incorporating social dimensions into resilience metrics will be the focus of our next studies.

Table 16
Challenges in using R-KPIs across infrastructures.

Infrastructure	Challenges with R-KPIs
Telecommunications and IT Systems	- Modeling unpredictable service failures and adapting to evolving threats [21]. - Historical data limitations in predicting future disruptions [23]. - Conducting comprehensive risk assessments for wireless networks [36].
Energy Systems	- Balancing sustainability with reliability in predictive models for grid failures [22]. - Integrating environmental friendliness metrics while ensuring grid stability [46].
Healthcare Systems	- Maintaining service continuity during crises with incomplete data on vulnerabilities [40].
Transportation Systems	- Lack of established metrics for designing resilient transportation hubs [47]. - Ensuring robust traffic management through real-time monitoring and simulation [48].
Water Resources and Management	- Integrating data from diverse domains to ensure reliable water supply [42]. - Addressing varying risk profiles of water sources and infrastructure [34].

Table 16 details the challenges in quantification of the R-KPIs in different CIs, reported by empirical studies that should be addressed in future studies.

While the table systematically links infrastructures, challenges, and citations to offer a comprehensive overview of the application and associated complexities of R-KPIs, the following key insights emerge from the analysis:

Telecommunications and IT systems. In telecommunications, R-KPIs often measure network recovery time, but challenges arise in accurately modeling unpredictable service failures. Historical data can provide insights but may not fully capture future disruptions due to evolving technology and threats [21,23]. Similarly, ensuring robust wireless systems requires comprehensive risk assessments to address potential vulnerabilities in infrastructure and cybersecurity [36].

Energy systems. R-KPIs in energy systems face challenges in balancing sustainability and reliability. Catastrophe preparedness KPIs require predictive models that account for natural disasters and grid failures, but the complexity of these systems often limits predictive accuracy [22]. Incorporating environmental friendliness into R-KPIs adds another layer of complexity, as it demands data integration from diverse sources while ensuring grid stability [46].

Healthcare systems. For healthcare systems, R-KPIs need to address the dual challenge of maintaining service continuity and handling resource constraints during crises. Risk assessments are critical but often hampered by incomplete data on healthcare infrastructure vulnerabilities [40].

Transportation systems. In transportation, R-KPIs are difficult to define due to a lack of established metrics. Designing KPIs for hubs and traffic systems requires real-time monitoring and simulation models, but current systems often lack the granularity or coverage to provide actionable insights [47,48].

Water resources and management. Water systems face challenges in applying R-KPIs due to the diversity of supply sources and varying risk profiles. Ensuring reliable water supply often involves integrating data from hydrological, infrastructural, and environmental domains, which can be resource-intensive [34,42].

The case study is primarily focused on the quantification of Resilience Key R-KPIs and the development of a framework for conducting such assessments. It aims to provide a systematic approach to interpreting the results proportionally. However, due to the limitations of the open dataset which does not include detailed information about the root causes of disturbances or the specific recovery measures taken, a deeper analysis of disturbances and the enhancement of resilience strategies is not possible. To advance this field, additional studies are needed to establish thresholds and standardize R-KPI calculations, allowing for a more comprehensive evaluation of resilience and a more effective interpretation of performance results.

In the current article, Functionality Loss is reported but not quantitatively assessed in depth due to the focus on the quantification of R-KPIs. Additionally, there is no predefined threshold for comparing functionality loss directly in the CI Resilience Engineering Body of Knowledge. This raises a critical future study line for researchers and practitioners. However, it is possible to conduct a comparative study by standardizing the functionality losses across the seven disturbances. This approach would involve calculating functionality loss for each disturbance scenario and comparing them to identify the best treatment strategy as a potential threshold. Subsequently, the remaining functionality losses can be compared against this best-performing threshold to evaluate the resilience level of the infrastructure under various scenarios.

7. Conclusions

This study intends to investigate R-KPIs for the CPSSs of CIs to devise a comprehensive framework to identify the R-KPIs and select the most suitable ones, rank them, and provide a case study to use them in the proposed framework.

The background study revealed that the measurement of CI resilience lacks standardization, with notable gaps evident across various domains and dimensions of CI resilience performance and its associated indices.

The results of the systematic literature review within the study reported a list of employed R-KPIs with their characteristics in Table 6. Notwithstanding, a noticeable gap is observed in the application fields, with R-KPIs being quantified in only 7 out of the 11 critical infrastructure categories (categories are outlined in the Directive on the Resilience of Critical Entities). Moreover, a robust connection is identified between risk management, sustainability, and the resilience of complex systems.

Then a hybrid MCDM is used to prioritize the selected R-KPIs in Table 10. The fuzzy-AHP ranking highlights the prioritization of various criteria for assessing R-KPIs in CIs, emphasizing the importance of data-driven approaches. The high priority given to manageability and automation supports this focus, aiming to manage the complexity of modern infrastructures. The lower prioritization of cost indicates a strategic emphasis on resilience and reliability over economic factors, justified by the high cost of failure in critical infrastructures. The balanced weights across all criteria demonstrate a reliable approach to understanding the key factors that enhance the robustness and efficiency of these vital systems..

The ranking results (see Table 13) highlight the crucial importance of KPIs that measure risk mitigation, energy self-sufficiency, and effective response and recovery mechanisms in ensuring the resilience of AI-integrated CIs. Finally, a general framework is proposed to model the resilience of AI-integrated CPSS, specifically focusing on the quantification of CI resilience. This framework is demonstrated through a case study to determine how to discriminate and consciously use R-KPIs for the CPSS resilience assessment.

Based on the outcomes of this paper, several paths for future studies can be imagined. First, instead of MCDM, other qualitative methods can be used to rank the R-KPIs, such as decision trees, Bayesian networks, and machine learning ranking algorithms. Second, the scope of the framework proposed in this study may be expanded to include social and environmental dimensions. R-KPIs representing these dimensions may reflect the sustainable development goals of the United Nations or similar European Union initiatives. Moreover, the applicability of the R-KPIs investigated in this study may be explored in different CI environments.

CRediT authorship contribution statement

Ali Aghazadeh Ardebili: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Marco Boscolo:** Writing – review & editing, Validation. **Antonella Longo:** Writing – review & editing, Validation, Supervision. **Mahdad Pourmadadkar:** Writing – original draft, Validation, Investigation, Formal analysis, Data curation. **Antonio Ficarella:** Writing – review & editing, Validation, Project administration. **Elio Padoano:** Writing – review & editing, Validation, Supervision, Project administration.

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Declaration of competing interest

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

Appendix. Material and tools

The following Python code snippet demonstrates how this calculation is performed:

```python
# Calculate the area between the SVM curve and the horizontal line
mask = (df_rc[’timestamp’] >= disturbance_start) & (df_rc[’timestamp’] <= disturbance_end)
area = np.trapz(np.maximum(0, 14 - y_pred[mask]), x=df_rc[’timestamp’][mask].astype(np.int64) // 10**9)  # Convert datetime to UNIX timestamp for integration
area_hours = area / (60 * 60)  # Convert area to hours assuming the y-axis is in sensor units and time units are in seconds
area_days = area_hours / 24
```

Listing 1: Calculation of the Area Between the SVM Curve and the Horizontal Line

Data and code availability

The dataset and Python code for calculations are available upon request from the following depository: https://github.com/sydalabnavid/Water-Pump-Resilience-KPIs-Calculations.git.

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