

Mapping the Research Domains of Digital Monitoring: A Systematic Literature Review and Taxonomy

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Abstract. Digital monitoring is increasingly central to modern information systems, enabling continuous observation of assets, processes, and services through real-time data collection. Although advances in analytics and machine learning support data-driven decisions, monitoring, analytics, and decision-making are still often developed in isolation, limiting effective integration. This study maps digital monitoring research, classifies monitoring characteristics, and identifies gaps in linking monitoring with decision-making. Using a PRISMA-based Systematic Literature Review of Scopus-indexed journal articles published between 2020 and 2025, 97 studies were selected and analysed through thematic synthesis. The review shows that digital monitoring spans nine major domains, with infrastructure, environmental, and manufacturing applications most dominant. The study's main contribution is a multidimensional taxonomy that classifies monitoring approaches by monitoring object, mode, analytics type, application domain, and information system orientation. This taxonomy also positions digital monitoring within the evolution of information systems toward decision intelligence. Findings indicate that current research remains largely technical, relying mainly on descriptive and predictive analytics, while integration with decision intelligence is still limited. A notable gap appears in digital service contexts, especially proactive user-experience monitoring in Internet Service Providers (ISP).

Keywords: Digital Monitoring; Decision Intelligence; Systematic Literature Review; PRISMA; Digital Monitoring Taxonomy

1. INTRODUCTION

Digital monitoring in information systems refers to a continuous process of collecting, processing, and presenting data to monitor the condition of systems, processes, and organizational services in real time [1]. Supported by technologies such as the Internet of Things (IoT), smart sensors, and distributed computing platforms, organizations can achieve higher visibility of system performance in a fast and accurate manner. In various studies, digital monitoring has been widely utilized for operational supervision, anomaly detection, and system performance reporting [2], [3].

The advancement of digital technologies has driven the transformation of digital monitoring from merely a technical supervision mechanism into a strategic information source within information systems. The integration of IoT, sensors, and real-time data enables organizations not only to monitor system conditions but also to support data-driven decision-making processes. In addition, the use of data analytics and machine learning has increasingly evolved to extract patterns and generate predictions from monitoring data. This transformation indicates that digital monitoring has strong potential as a key component in supporting decision intelligence within information systems.

However, prior studies indicate that the integration between digital monitoring, analytics, and decision-making remains partial. Most studies still focus on improving prediction accuracy and monitoring system efficiency without linking monitoring outputs to actionable recommendations that can support decision-making. As a result, digital monitoring is still largely treated as a standalone technical function rather than an integrated component of decision-support systems.

Several studies reinforce this condition. Dong et al. (2021) and Yousefpour et al. (2021) developed deep learning-based predictive models for slope deformation and bridge erosion monitoring; however, the outputs are limited to numerical predictions without actionable recommendations [4], [5]. Ren et al. (2022) and Seshan et al. (2024) proposed water quality monitoring systems based on edge computing, yet these systems are not integrated with operational decision-making processes [6],[7]. In the context of communication networks, Yang et al. (2020) and Dornala & Senthilkumar (2025) developed

anomaly detection systems using fog computing and network traffic analysis; however, these approaches remain reactive and do not support preventive interventions [8],[9].

Furthermore, digital monitoring research is still dominated by physical infrastructure and industrial system domains, which primarily focus on device and system performance. In contrast, digital service domains that emphasize service quality and user experience remain relatively underrepresented. This limitation is evident in studies that have not successfully integrated technical indicators such as Quality of Service (QoS) with user perception indicators such as Quality of Experience (QoE), particularly in digital service contexts such as Internet Service Providers (ISP) [10], [11], [12], [13]. This condition indicates that user experience has not yet become a central component in the development of monitoring systems.

Based on these conditions, a research gap exists in the systematic integration of digital monitoring, analytics, and decision-making. In addition, there is still a lack of studies that comprehensively map digital monitoring research domains, classify monitoring approaches, and identify future directions toward proactive, adaptive, and user-oriented systems.

Therefore, this study aims to conduct a Systematic Literature Review (SLR) to comprehensively map the research domains of digital monitoring. The main contribution of this study lies in the development of a multidimensional taxonomy that classifies digital monitoring approaches and connects monitoring characteristics with information system orientation. Furthermore, this study identifies research gaps related to the integration of monitoring, analytics, and decision-making within service-oriented information systems. Specifically, the contributions of this study include: (1) the development of a multidimensional digital monitoring taxonomy; (2) research domain mapping and gap identification; and (3) the formulation of future research directions toward adaptive information systems driven by decision intelligence.

2. METHODS

This study employs a Systematic Literature Review (SLR) approach to identify and synthesize research related to digital monitoring. To ensure transparency and

reproducibility, the review process follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [14]. In addition, this study refers to the SLR guidelines proposed by Kitchenham and Charters (2007) [15], while data analysis is conducted using a thematic synthesis approach as described by Thomas and Harden [16].

2.1 Research Design and Workflow

This study consists of several stages: (1) formulation of research questions; (2) design of the literature search strategy; (3) identification and screening of articles; (4) data extraction and coding; and (5) thematic synthesis and taxonomy development. These stages are designed to ensure a systematic, transparent, and reproducible research process.

2.2 Search Strategy

The search strategy in this study is designed using a restrictive approach to ensure that the selected articles explicitly address the relationship between digital monitoring, analytics, and decision-making. This approach is adopted because the objective of the study is not only to map digital monitoring research in general, but also to specifically identify the integration of monitoring with analytics and decision intelligence within the context of information systems. The literature search was conducted in the Scopus database on January 29, 2026, using the following query:

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("digital monitoring" OR "system monitoring" OR "service monitoring" OR "real-time monitoring" OR "performance monitoring" OR "quality monitoring")AND("decision intelligence" OR "decision support" OR "decision-making" OR "intelligent decision*" OR "data-driven decision*" OR "automated decision*")AND("analytics" OR "data analytics" OR "machine learning" OR "artificial intelligence" OR "predictive model*" OR "intelligent analytic*")
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The use of a query that requires the simultaneous presence of these three concept groups aims to ensure conceptual alignment between monitoring, analytics, and decision-making, thereby strengthening the validity of the taxonomy development and research gap identification. Consequently, the selected articles are not limited to technical monitoring studies but also include those that explicitly relate monitoring outputs to analytical processes and decision-making mechanisms.

Although this approach may exclude studies that discuss monitoring without explicitly using analytics or decision-related terminology, it is maintained to ensure consistency with the research objectives. Therefore, the findings of this study should be interpreted within the scope of digital monitoring research that explicitly integrates analytics and decision intelligence.

2.3 Inclusion and Exclusion Criteria

Inclusion and exclusion criteria were defined to ensure that the selected articles are relevant to the research objectives and the information systems context. The inclusion criteria consist of: (1) journal articles indexed in Scopus; (2) publication period between 2020 and 2025; (3) subject areas including computer science, engineering, and decision sciences; (4) English language; (5) availability of full-text; and (6) articles addressing digital monitoring, data analytics, or data-driven decision-making. Furthermore, studies involving the use of analytics or machine learning on monitoring data and those relevant to information systems or digital service contexts were also included.

The exclusion criteria include: (1) studies focusing solely on technical aspects without implications for decision-making; (2) articles that do not involve analytics or decision-related processes; (3) non-journal publications such as conference papers, non-systematic reviews, and editorials; and (4) articles with limited full-text access.

The use of open access as a selection criterion is based on methodological considerations to ensure that all selected articles can be analysed comprehensively, particularly during data extraction and thematic coding. Full access is necessary to maintain analytical consistency, depth, and transparency in the SLR process. However, this criterion may introduce selection bias, and therefore the findings should be interpreted as representing the accessible body of literature rather than the entire population of digital monitoring research.

2.4 Screening and Selection Process

The article selection process follows the PRISMA stages: identification, screening, eligibility, and inclusion, as illustrated in Figure 1.

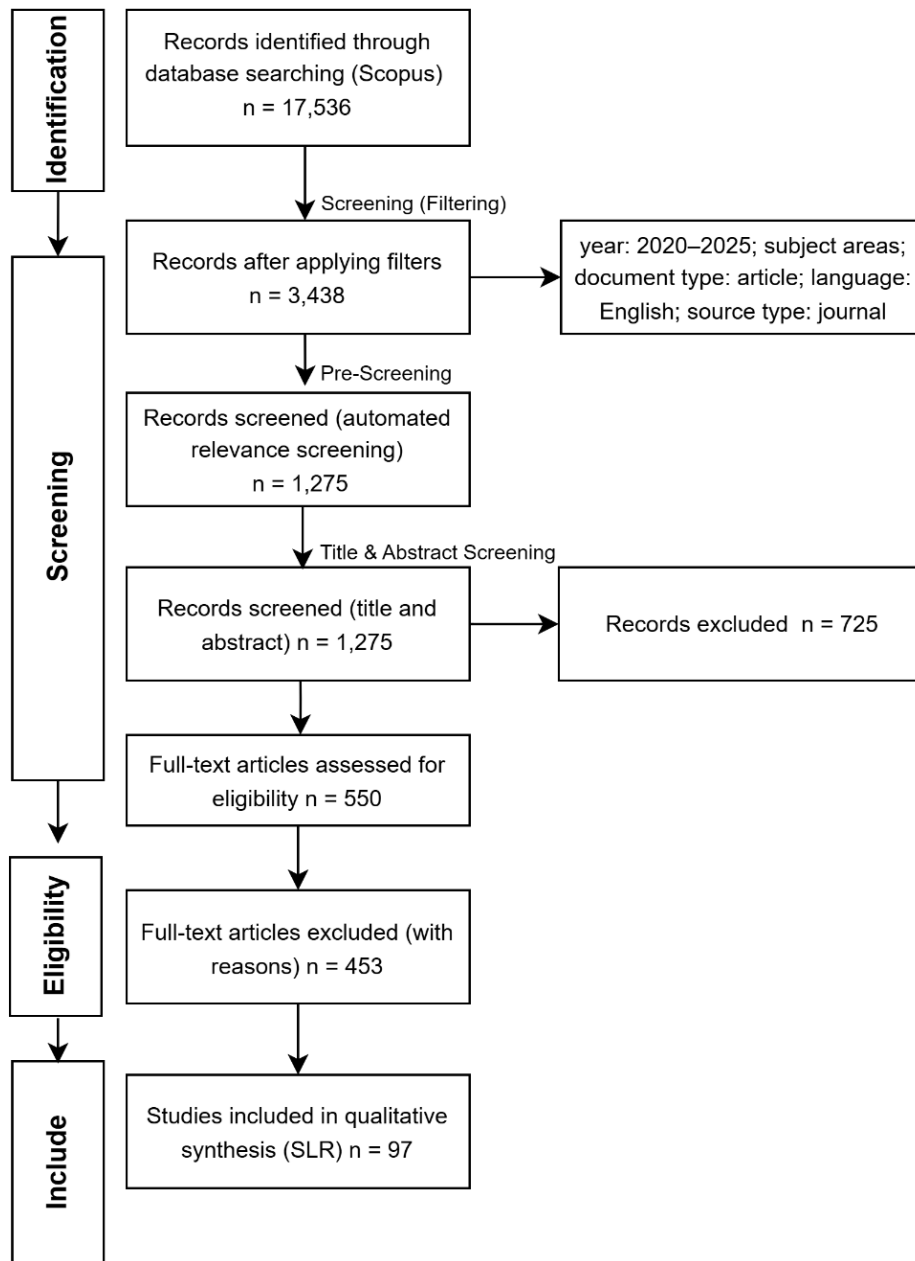


Figure 1. PRISMA Flow Diagram

During the identification stage, the initial search in the Scopus database yielded 17,536 records. After applying the initial inclusion criteria, the number of articles was reduced to 3,438. In the screening stage, an automated-assisted pre-screening process was conducted using artificial intelligence (AI) as a preliminary filtering mechanism. At this stage, abstracts were analysed using a keyword-based and semantic context approach to identify the presence of key concepts related to digital monitoring, analytics, and

decision-making. Articles that met the initial relevance criteria were retained, while irrelevant articles were excluded, resulting in 1,275 articles.

To ensure validity and reliability, the results of the AI-assisted pre-screening were further validated through manual screening by the researchers. This involved evaluating titles and abstracts based on the predefined inclusion criteria. During this process, 725 articles were excluded due to lack of relevance. In the eligibility stage, full-text assessment was conducted on 550 articles to ensure comprehensive alignment with the research objectives. A total of 453 articles were excluded at this stage. Finally, in the inclusion stage, 97 articles met all criteria and were included as the final dataset for the systematic literature review.

2.5 Data Extraction and Thematic Synthesis

Data analysis was conducted using a thematic synthesis approach involving three stages of coding: open coding, axial coding, and selective coding. In the open coding stage, each article was analysed to identify key concepts related to digital monitoring. In the axial coding stage, these concepts were grouped into categories based on conceptual similarity and functional relationships.

In the selective coding stage, these categories were integrated to develop a multidimensional taxonomy consisting of five main dimensions: monitoring objects, monitoring modes, types of analytics, application domains, and information systems orientation. Each dimension of the taxonomy was derived from consistently observed patterns across the analysed articles, ensuring traceability from the data to the conceptual framework.

2.6 Research Questions

This study was designed to address the following research questions (RQs):

- RQ1 : What research domains have been explored in digital monitoring studies?
- RQ2 : How can digital monitoring be classified based on monitoring objects, monitoring modes, analytics types, application domains, and information systems orientation?
- RQ3 : What research gaps exist in the integration of digital monitoring, analytics, and decision-making mechanisms, particularly in the development of proactive monitoring based on user experience?

3. RESULTS AND DISCUSSION

3.1. RQ1: What research domains have been explored in digital monitoring studies?

Based on the results of the Systematic Literature Review of 97 selected articles, digital monitoring research exhibits a diverse distribution across domains. The domain mapping results indicate that digital monitoring research is dominated by nine main clusters, namely: Structural/Civil Engineering Monitoring (20 articles), Water/Wastewater and Environmental Monitoring (18 articles), Manufacturing/Industrial Monitoring and Predictive Maintenance (12 articles), Smart City/Urban Infrastructure (10 articles), Healthcare/Medical Monitoring (9 articles), Digital Twin and AI/ML Frameworks (9 articles), Supply Chain/Cold Chain Logistics (8 articles), Energy/Power Systems Monitoring (7 articles), and Network/Telecommunication/ISP Monitoring (4 articles). The distribution of digital monitoring domains is presented in Table 1.

Table 1. Distribution of Digital Monitoring Research Domains

No	Domain	Number of Articles
1	Structural/Civil Engineering Monitoring	20
2	Water/Wastewater & Environmental Monitoring	18
3	Healthcare/Medical Monitoring	9
4	Manufacturing/Industrial Monitoring & Predictive maintenance	12
5	Smart City/Urban Infrastructure	10
6	Supply Chain/Cold Chain Logistics	8
7	Energy/Power Systems Monitoring	7
8	Network/Telecom/ISP Monitoring	4
9	Digital Twin & General AI/ML Frameworks	9

The distribution presented in Table 1 indicates that digital monitoring research is still predominantly concentrated in domains related to physical infrastructure and industrial systems. This dominance suggests that current research primarily focuses on monitoring assets and technical systems with quantitatively measurable parameters. In contrast, service-oriented digital domains, such as telecommunications and service information systems, remain relatively underrepresented in literature. This finding highlights an

imbalance in research focus, where technical aspects are more extensively explored than service-oriented and user experience-based perspectives.

3.2. RQ2: How can digital monitoring be classified based on monitoring objects, monitoring modes, analytics types, application domains, and information systems orientation?

The results of the literature analysis indicate that digital monitoring research can be classified into a multidimensional taxonomy consisting of five main characteristics. Based on monitoring objects, the studies focus on assets, operational processes, and services. Based on monitoring modes, three main approaches are identified: periodic, near real-time, and real-time monitoring, with an increasing trend toward the adoption of real-time monitoring driven by the advancement of IoT technologies. From an analytical perspective, literature is dominated by descriptive and predictive analytics, while prescriptive and adaptive analytics remain relatively limited. In terms of application domains, digital monitoring is widely implemented in infrastructure, manufacturing, logistics, public services, as well as healthcare and environmental sectors. Meanwhile, from an information systems perspective, digital monitoring research is still largely dominated by monitoring-oriented systems and decision support systems.

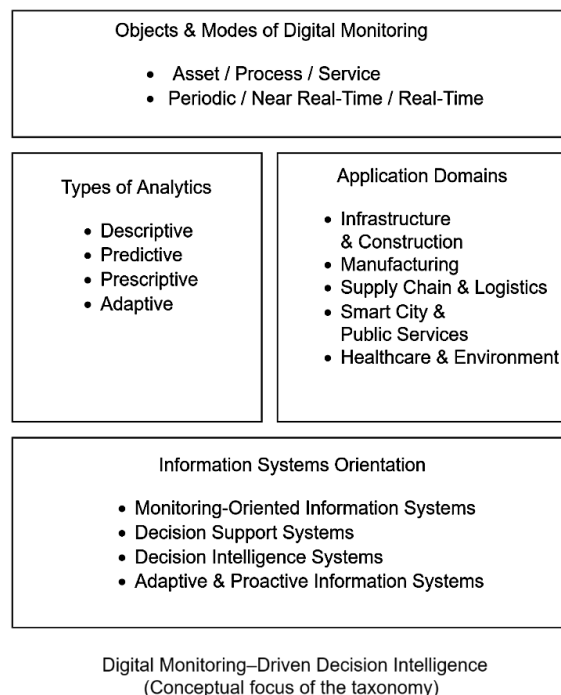


Figure 2. Multidimensional Taxonomy of Digital Monitoring

The taxonomy presented in Figure 2 not only serves as a classification scheme but also represents a conceptual structure that illustrates the relationship between monitoring characteristics and information systems orientation. Specifically, each dimension of the taxonomy can be utilized as a framework to classify emerging studies, identify the position of research within the evolution spectrum of information systems, and explore under-investigated areas within the design space, particularly in relation to the integration toward decision intelligence systems. The visualization of the multidimensional digital monitoring taxonomy is presented in Figure 2.

3.3. RQ3: What research gaps can be identified in the integration of digital monitoring, analytics, and decision-making mechanisms, particularly in advancing proactive monitoring grounded in user experience?

To address Research Question 3, an analysis was conducted on the distribution of articles based on domain, monitoring mechanism (reactive and proactive), and the type of ground truth employed. The results of this classification are presented in Table 2.

Table 2. Distribution of Articles by Domain, Monitoring Mechanism, and Ground Truth (N= 97)

Domain	Monitoring Mechanism	Ground Truth	Number of Articles	Authors and Publication Year
Non-ISP	Reactive	Non-Customer Complaints	82 (84.5%)	[6],[17],[10],[7],[18],[19],[20], and others
		Customer Complaints	0	
	Proactive	Non-Customer Complaints	11 (11.3%)	[4],[5],[21],[22],[23],[24],[25],[26],[27],[28],[29]
		Customer Complaints	0	
ISP/Telecommunication	Reactive	Non-Customer Complaints	4 (4.1%)	[8],[9],[30],[31]
		Customer Complaints	0	

Domain	Monitoring Mechanism	Ground Truth	Number of Articles	Authors and Publication Year
		Non-Customer Complaints	0	
	Proactive	Customer Complaints	0	Research Gap (No studies meet the following criteria: Domain: ISP; Mechanism: Proactive; Ground Truth: Customer Complaints)

Based on Table 2, digital monitoring research is still predominantly dominated by reactive approaches in non-ISP domains, accounting for 84.5%, followed by proactive approaches in non-ISP domains at 11.3%, and reactive approaches in ISP/telecommunication domains at 4.1%. The visualization in Figure 3 reinforces this finding by showing that the distribution of studies is highly concentrated in the Non-ISP Reactive Non-Complaint category (84.5%). This finding indicates that most studies still focus on post-event detection (reactive monitoring), rather than on preventive approaches based on predictive analytics or user experience.

Furthermore, within the analyzed corpus of literature, no studies were found that explicitly integrate proactive monitoring in the ISP domain with customer complaint-based ground truth. This finding indicates a potential research gap, particularly in the integration of proactive monitoring and user experience as a basis for decision-making. However, this finding should be interpreted within the context of the search design and selection criteria applied in this study.

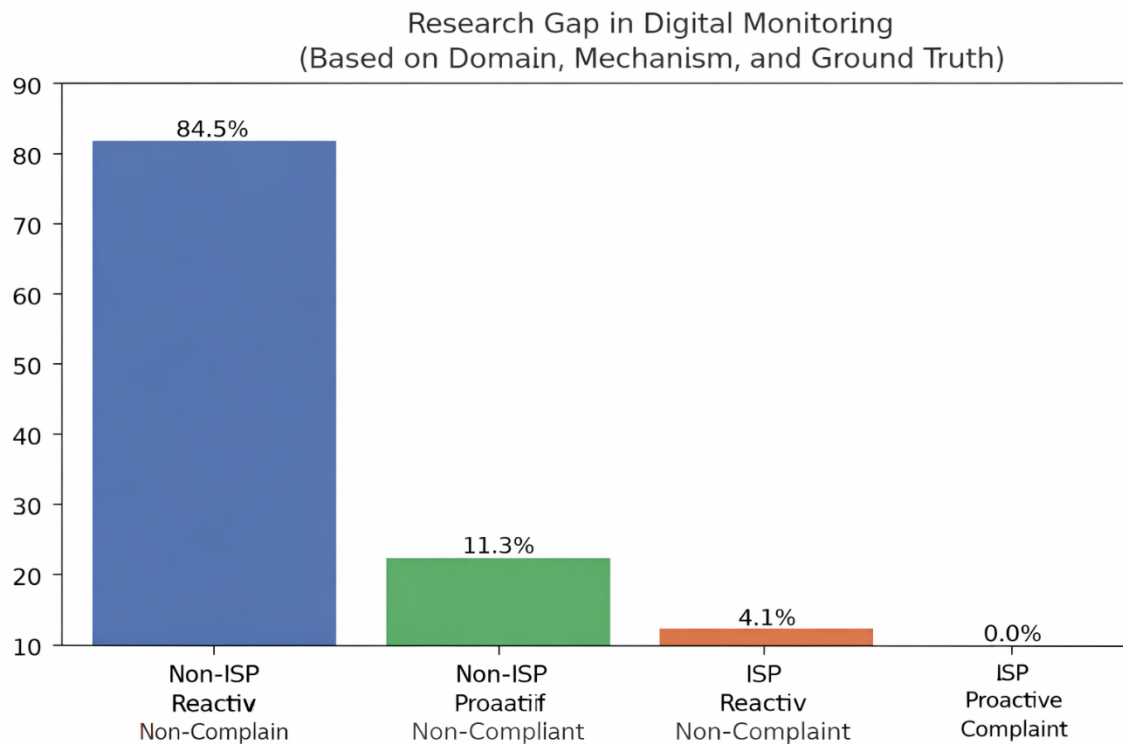


Figure 3. Research Gaps in Digital Monitoring Based on Domain, Monitoring Mechanism, and Ground Truth

3.4. Discussion

The findings of this study indicate that digital monitoring research is still predominantly concentrated in infrastructure and industrial system domains. This dominance can be attributed to the characteristics of these domains, which involve structured and quantifiable monitoring parameters, making them more readily integrated with sensor technologies, IoT, and data-driven analytics. In addition, the level of technological maturity in these domains is relatively higher compared to digital service domains. In contrast, service-oriented domains, particularly Internet Service Providers (ISP), remain underrepresented in the literature. This limitation is largely due to the complexity of integrating technical indicators such as Quality of Service (QoS) with user perceptions such as Quality of Experience (QoE), which are inherently subjective and difficult to model. As a result, most studies continue to focus on technical aspects rather than user experience.

From a methodological perspective, the findings also reveal that monitoring approaches are still largely dominated by reactive mechanisms. This indicates that digital monitoring has not yet fully evolved toward proactive and adaptive systems. The limited number of studies on customer complaint-based monitoring suggests that the integration between operational data and user experience has not yet become a primary focus in the development of information systems. These findings are consistent with prior studies indicating that digital monitoring remains primarily oriented toward technical performance and has not been fully integrated with intelligence-driven decision-making mechanisms. Nevertheless, this study contributes by proposing a multidimensional taxonomy that links monitoring characteristics with information systems orientation.

The proposed taxonomy (Figure 2) can be positioned as a conceptual framework that not only classifies existing studies but also supports researchers in identifying future research opportunities. Each dimension of the taxonomy provides an analytical perspective that can be used to evaluate the position of a study and to identify underexplored combinations across dimensions. Accordingly, the taxonomy serves as a conceptual tool for understanding the evolution of digital monitoring from monitoring-oriented systems toward decision intelligence systems.

Furthermore, the gap analysis (Figure 3) indicates that no studies within the analysed corpus explicitly integrate proactive monitoring based on user experience in the ISP domain. This finding suggests a potential research opportunity in developing monitoring systems that combine technical data with user experience data. However, this gap should be interpreted within the scope of the analysed literature, which is influenced by the search query design and selection criteria, and therefore should not be generalized as an absolute absence across the entire digital monitoring research field. Overall, the results of this study indicate that the integration of monitoring, analytics, and decision-making remains an emerging research area with significant potential for the development of more adaptive, proactive, and user-oriented information systems.

4. CONCLUSION

This study contributes by providing a structured mapping of digital monitoring research domains through a systematic literature review of 97 Scopus-indexed journal articles

published between 2020 and 2025. The primary contribution lies in the development of a multidimensional taxonomy that integrates monitoring characteristics with information systems orientation, thereby offering a conceptual perspective on the evolution of digital monitoring toward decision intelligence. The findings indicate that most studies remain focused on technically oriented monitoring, with a dominance of descriptive and predictive analytics, while the integration toward adaptive and proactive decision-making remains limited. Within the scope of the analysed literature, this study also identifies a key research gap related to the limited exploration of proactive monitoring based on user experience, particularly in digital service domains such as Internet Service Providers (ISP). However, this finding should be interpreted within the context of the search design and selection criteria applied in this study. Accordingly, future research is encouraged to integrate technical data with user experience-based indicators to support the development of adaptive and decision intelligence-driven information systems.

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