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Review Article

A Comparative Literature Review of Data-Driven Decision-Making Phases in Information Systems: Toward an Integrated Six-Phase Framework

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Abstract

This study presents a comparative literature review on data-driven decision-making (DDDM) within Information Systems (IS) and synthesized an integrated framework including six phases to reduce conceptual fragmentation in existing research. Studies published between 2016 and 2025 were systematically reviewed, mapped, and compared, with the evidence consistently presented across six phases: data collection, data preprocessing, feature selection, model development, model evaluation, and decision support. The review is guided by three research questions. RQ1 examines how data quality, governance, privacy and security, and organizational readiness are addressed in the early stages. RQ2 analyses dominant approaches to complexity reduction and model development, highlighting trade-offs among performance, interpretability, and organizational applicability. RQ3 evaluates how reliability is reported and how analytical outputs are translated into actionable decisions, with particular attention to Explainable AI (XAI), Human-in-the-Loop (HITL), and ethical considerations. The findings indicate that key challenges include limited organizational capacity, concerns related to privacy and security, and inconsistencies in data quality. Critical enablers include robust governance structures, analytics literacy, leadership support, and a strong data-driven culture. The proposed framework provides a unified reference model for comparing methods, clarifying inter-phase relationships, and improving transparency and reproducibility in DDDM processes within IS. To support validation against state-of-the-art approaches, the framework is compared with existing pipelines, highlighting differences in governance integration, XAI/HITL incorporation, and controllability mechanisms. Finally, the framework is demonstrated using a case study based on the BTS flight performance dataset, illustrating phase-by-phase implementation and the translation of model outputs into explainable decision support.

Keywords: Data Driven Decision Making; Information Systems; Machine Learning; Data Governance; Explainable Artificial Intelligence.

INTRODUCTION

Data-Driven Decision-Making (DDDM) has become a critical component of Information Systems (IS) because organizations require faster, more accurate and more auditable decisions. However, in practice DDDM often fails not because of the lack of algorithms, but because of the disconnection between the technical phases (data-model-evaluation) and the last phase where the result should become an organizational action (decision support). This creates an "analytics-to-action" gap, where the numerical performance of the model does not necessarily translate into trust, use, and responsibility in the decision. Nowadays, Data-Driven Decision-Making (DDDM) has become a central pillar of Information Systems (IS), because organizations are increasingly relying on analytics, machine learning and decision support systems to increase the efficiency, quality and transparency of decisions [1-4].

However, the literature of recent years shows that DDDM is often treated in a fragmented way, where some papers focus on the analytical culture and the organizational conditions of data use, showing that the analytical culture is more decisive than the centralization of data use to achieve truly "data-driven" decision-making [5-7], then others emphasize the practical obstacles to adoption (e.g., the lack of commitment of top management, privacy/security concerns and technical data vulnerabilities) that block the DDDM chain in organizations [8]. In a parallel context, new studies have proposed frameworks and architectures for decision-making driven by "big data" at the enterprise level [4] and have emphasized that factors such as "data analytics literacy" and alignment with business strategy are causal drivers for effective decision-making based on data [1]. The literature of recent years confirms this fragmentation: one set of studies focuses on analytics culture and organizational readiness (eg the role of management support and perceived data quality), while another set addresses practical barriers like privacy/security and data vulnerabilities [8, 9]. At the same time, the newest works have emphasized the decision-making architectures in the enterprise and the role of "data analytics literacy" as a causal factor of effectiveness. Even with this progress, there are still three clear gaps: (i) there isn't one way to look at the literature from data collection to decision support; (ii) trust/controllability mechanisms (XAI, HITL, ethics) aren't clearly built into the whole process; and (iii) cross-phase relationships (how data quality affects interpretability and adoption) are often talked about but not organized. The fragmented nature of the literature illustrates that Data-Driven Decision Making (DDDM) in Information Systems cannot be understood by analysing analytical culture, organizational barriers, or model performance in isolation. These parts work best when they are all connected from data to decision [10]. Problems that happen early on (like bad data quality and preprocessing) often stay with the project and make it harder to understand, less reliable, and less useful in the real world. We need to look at DDDM as a whole system instead of as separate steps. This lays the groundwork for a phase-based comparative review that makes it easy to find the times when the analytics-to-action gap shows up and the trust mechanisms are always used [11].

Besides this practical gap, the research on Data-Driven Decision-Making in Information Systems is still not very well-organized. Current research often examines isolated elements of the DDDM pipeline, such as analytics culture, data quality, model performance, or decision support, without systematically incorporating these factors across the entire process. As a result, it is difficult to understand how problems in earlier stages, like poor data governance or low preprocessing quality, carry over into later stages and affect how easy it is to understand, how much people trust it, and how well it is used by the organization. This fragmentation makes it harder to put together a clear, complete picture of DDDM in IS contexts and to compare results from different studies [12].

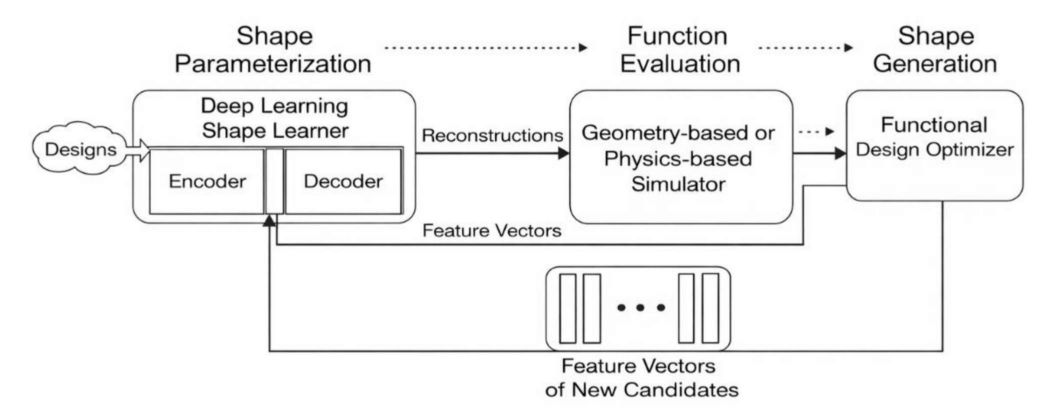

Figure 1. A Deep Learning Framework for Functional Shape Parameterization and Optimization

To address this issue, a phase-based analytical lens is needed not only to organize prior studies, but also to make fragmentation empirically visible. A structured six-phase perspective enables comparison of which parts of the DDDM pipeline are covered by each study, where trust-related mechanisms are incorporated, and how analytical outputs are translated into actionable decision support [13]. In this way, the framework functions as a comparative device for identifying recurrent gaps and cross-phase dependencies within DDDM in Information Systems. In methodological terms, this study extends beyond a purely narrative synthesis by organizing the reviewed literature through a structured phase-based interpretation. This approach increases analytical transparency and supports systematic comparison of how studies address data collection, preprocessing, feature selection, model development, evaluation, and decision support [14]. It also allows identification of whether trust-related mechanisms, such as Explainable AI, Human-in-the-Loop, and ethical considerations, are integrated across the pipeline or treated as isolated elements. In the framework of decision-making systems, by integrating a literature of the years 2024-2025, the focus has been expanded from "analytics" to "action", applying major revisions on Prescriptive Analytics Systems (PAS), where they have clarified the components and archetypes of the systems (advisory, executive, adaptive, self-governing) and have put the human-system relationship (synergy/delegation) in the center as a condition for sustainable organizational decision-making [15, 16]. Also, works on artificial ethics have shown that the principles of fairness, accountability and transparency should be explicitly integrated into the DDDM pipeline, especially when analytics affect decisions with organizational consequences [9].

Another step towards reliability is made through Human Explainable-in-the-Loop (HITL) approaches in dynamic Digital Twins (DDDAS/DT), where interpretability and the analysis of "utility" trade-offs are treated as key mechanisms for reliable and human-controllable decisions [2]. In IS-related domains (eg, health systems), it has also been reported that challenges of data quality and interpretability remain recurring obstacles, even when the benefits of personalization and standardization of decisions are great [3]. Despite this progress, the main gap in the 2024-2025 literature lies in the lack of a unified methodological view that links the key stages of DDDM in IS from data collection to decision support with a single comparative lens. Therefore, this paper constructed a comparative literature review strictly structured according to an integrated framework with six phases: (1) Data Collection, (2) Data Preprocessing, (3) Feature Selection, (4) Model Development, (5) Model Evaluation, and (6) Decision Support [17-23].

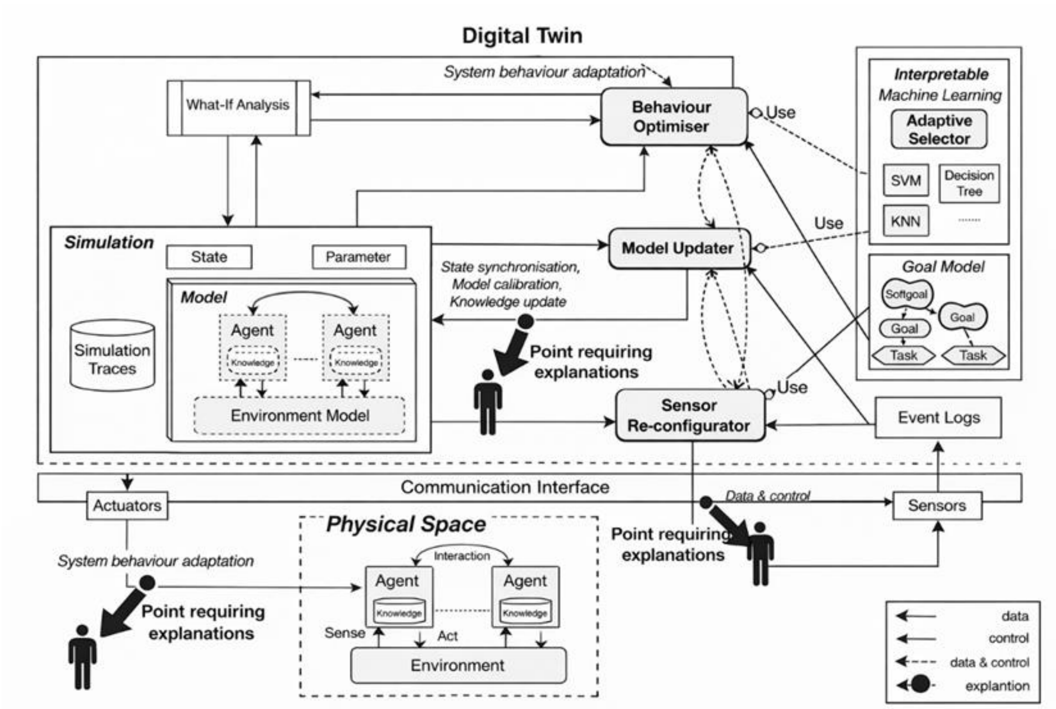

Figure 2. A Human-in-the-Loop Digital Twin Architecture for System Behaviour Adaptation

To address these gaps, this paper conducts a comparative literature review of DDDM in IS (2016–2025) and organizes the evidence according to an integrated six-stage framework. The main contributions are:

The main contributions of this study are fourfold:

- (C1) it introduces a structured six-phase analytical lens for comparing DDDM studies in Information Systems from data collection to decision support;
- (C2) it synthesizes the literature through a comparative phase-based perspective, identifying recurring barriers, enabling conditions, and cross-phase dependencies;
- (C3) it analytically examines the interaction between governance, data quality, interpretability, and decision adoption across the DDDM pipeline;

- (C4) it positions the proposed framework against established pipelines such as CRISP-DM, KDD, and PAS-oriented approaches to clarify its comparative value for IS decision contexts.

Based on these gaps, the study is guided by three research questions that structure the comparative synthesis across the six phases of Data-Driven Decision-Making and explicitly connect technical, organizational, and decision-support dimensions [24-30]. Furthermore, the main aim of the study was to synthesize the evidence, practices and trade-offs reported in recent studies and derive an integrated framework that makes the DDDM pipeline more comparable, transparent and usable for IS.

- RQ1. How are data quality, governance, and organizational readiness (eg, data quality, capacity, privacy/security) addressed in the collection and preprocessing phases, and what are the most commonly reported barriers/accelerators to DDDM adoption in IS? [7].
- RQ2. What methodological approaches dominate for complexity reduction (eg, feature selection/model structuring) and for building analytical models that feed IS decision-making (including PAS/architecture and human–system integration), and how are tradeoffs between performance, interpretability, and organizational applicability justified? [17].
- RQ3. How is the assessment of reliability of results reported and their conversion into action (decision support especially through Explainable AI, Human-in-the-Loop and ethical principles—and which mechanisms increase "trust" and controllability of decisions in IS? [31-36].

Through this study, we were able to map and compare the contemporary IS DDDM literature by consistently organizing it according to an integrated six-stage pipeline, which reduced the conceptual fragmentation reported in separate studies. The study identified critical interdependencies between phases (eg, how governance/data quality and preprocessing conditioned the interpretability and usability of decisions), and systematized the role of socio-technical dimensions (analytical culture, organizational barriers, human-system delegation) in actual DDDM performance.

Also, the paper integrated the 2024-2025 evidence on Explainable AI, Human-in-the-Loop and artificial ethics, positioning transparency and controllability as methodological requirements for the "Decision Support" phase. The paper next outlines the key concepts and gaps in the literature, then describes the review methodology. It subsequently presents the findings by research questions and cross-phase dependencies, develops a conceptual framework, and formalizes the contributions. The final sections discuss implications and future research, and conclude with a summary [19, 20].

LITERATURE REVIEW

Foundation of Data-Driven and Decision-Making in Information Systems

The study is defined in the context of DDDM as a practice where decisions were based on data, analytical models and structured interpretation, linking the analysis process with concrete organizational goals, see Figure 3. In this Information Systems context, DDDM was seen as an extension of classic DSS/BI systems, but with added emphasis on automation, scalability and integration with heterogeneous resources (eg IoT, logs, cloud platforms) [1-3]. Many of the studies had argued that "being data-driven" was not just a matter of technology, but was a combination of data infrastructure, analytical capabilities and how information was transformed into action within work processes [4, 5].

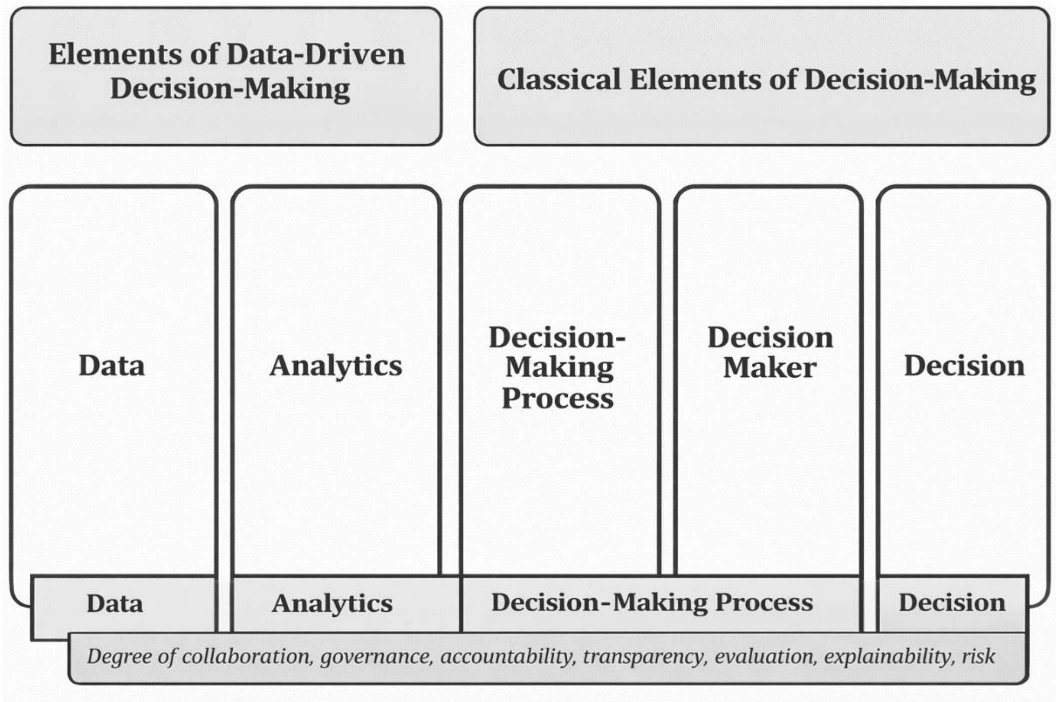

Figure 3. A Conceptual Comparison of Data-Driven and Classical Decision-Making

In recent findings on analytics and data science, DDDM was described as a chain of activities starting from data collection, management and processing, moving to knowledge extraction with statistical/ML models, and ending with decision support with reports, visualizations and recommendations [6, 7]. Also, studies related to prescriptive analytics had emphasized that the most advanced phase of DDDM had not only provided "what was happening" or "what could happen", but had suggested "what should be done", often in interaction with the user and business rules [8, 9]. An important direction of the literature had been the deployment of DDDM in dynamic systems, where the data had arrived in real time and the model had been updated continuously. This approach was clearly illustrated in the concept of Digital Twins and DDDAS, where there was a two-way cycle: sensing-analysis-reshaping, with the possibility of autonomous or interactive decision-making with human-in-the-loop [10, 11]. In this line, the reliability and explainability of the decisions was considered a key condition, because the complexity of the models increased the risk of inappropriate decisions if the reasoning was not understood by people [10, 12]. Through the findings in the literature, we can conclude that DDDM as a socio-technical artifact of Information Systems, has enabled capture, storage and analysis, while organizational structures and roles (e.g. managers, analysts, "integrators" such as controllers) had influenced the way analytical results were translated into decisions [5, 9, 13].

Positioning Against Pipelines and SOTA Frameworks

There are well-known pipelines in the literature for the analytics and knowledge extraction process (KDD and CRISP-DM), which structure the flow from data to model and use. However, in the context of IS, these pipelines often do not make explicit the governance, ethics and human-system interaction (HITL) layer, which are crucial for organizational adoption and decision accountability. Meanwhile, the approaches of Prescriptive Analytics Systems (PAS) and Digital Twins/DDDAS emphasize more the dimension of action and decision delegation, but do not always connect the data cycle (quality, processing, features) with trust and controllability in the same way.

Therefore, an integrated six-stage lens can serve as a "comparative bridge" between classical pipelines and socio-technical approaches, making visible: (i) stage coverage, (ii) trust mechanisms (XAI/HITL), and (iii) how model output becomes a decision [21, 22].

Organizational and Governance Dimensions of DDDM

Organizational studies had shown that DDDM was not automatically increased by technology investments alone, because decision-making behaviors remained intertwined with culture, authority, and human interpretation. A line of works analyzed the role of "analytical culture", where the support of top management and the perception of data quality predicted the growth of analytical culture in the organization [14, 15]. However, it was noted that the centralization of data use was not necessarily associated with increased DDDM, suggesting that formal structures were not sufficient without practical mechanisms of use in decision-making routines [14].

Another important finding was called the "DDDM illusion", where organizations had built analytical capacity but had not really replaced intuition or informal policies in decisions. In that context, digital orientation and the role of controllers as mediators in "sense-making" had been critical to make analytical information usable in a decision-making context [15]. This had shown that the governance of DDDM was not simply the governance of data, but the governance of interpretation and responsibility. In the socio-technical literature, "information for action" was treated as an organizational principle: the quality of data was influenced by the fact of who recorded it and for whom it served. When one group of workers recorded data that guided the actions of another group, problems of quality and mistrust arose, which were mitigated by transparency and co-design of information [16]. As a consequence, the transformation towards DDDM was accompanied by "reskilling/upskilling", because more roles took part in designing the information itself that was used for action [16, 17].

Figure 4 depict a Data-to-Knowledge Decision-Making Framework

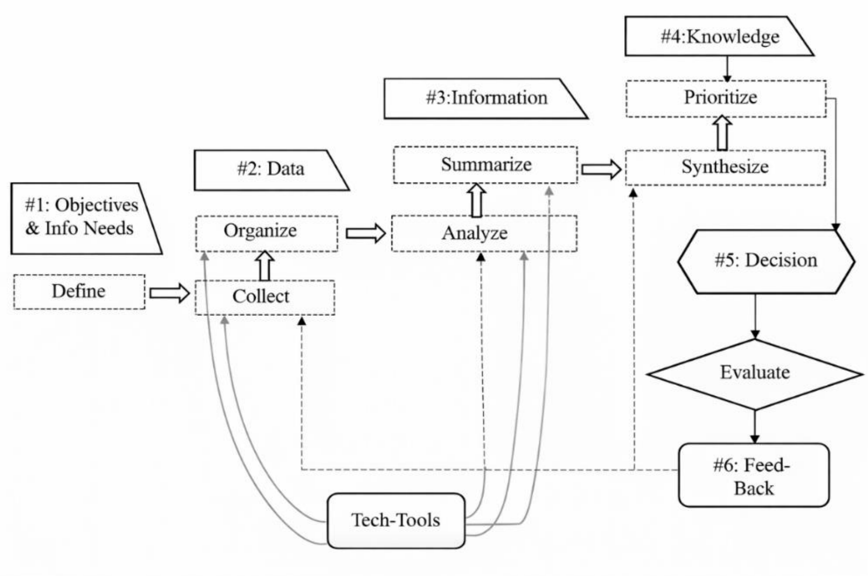

Figure 4. A Data-to-Knowledge Decision-Making Framework

From an Information Systems perspective, governance was also associated with ethics, privacy and impartiality. Works on ethical principles have argued that the integration of "artificial ethics" in analytics has increased accountability, transparency and fairness in decisions, especially in supply chains where parties have different interests [18]. In sensitive sectors such as health, governance has included standardization of indicators, inter-institutional coordination and consensus mechanisms to avoid overlap and data gaps [19]. Several analytical pipelines have been proposed in the literature to structure data-driven processes, including KDD, CRISP-DM, and more recent prescriptive analytics and Digital Twin-oriented architectures. These frameworks provide valuable guidance for data preparation, modeling, and evaluation. However, they differ in the extent to which they explicitly incorporate governance, trust, and decision-support mechanisms. Traditional pipelines such as KDD and CRISP-DM primarily emphasize data preparation, modeling, and evaluation stages, with decision-making often treated as an implicit final step [23]. In contrast, Prescriptive Analytics Systems and Digital Twin approaches emphasize decision execution, human–system interaction, and adaptive feedback loops. Despite these advances, the integration between early data lifecycle stages and decision controllability mechanisms remains inconsistent across studies [24].

This observation suggests that existing pipelines do not fully capture the socio-technical nature of DDDM in Information Systems. In particular, governance, explainability, and Human-in-the-Loop mechanisms are rarely treated as cross-phase elements. Therefore, an integrated phase-based lens is required to systematically compare how studies address the full data-to-decision chain [25].

Data Collection and Data Lifecycle Management

The literature had highlighted that DDDM was conditioned by the way data was collected and managed during the life cycle. In modern systems, data had come from multiple sources: transactional systems, ERP/CRM, IoT sensors, networks, APIs, as well as external sources (e.g. public data, partners) [20, 21]. This variety had increased the need for integration mechanisms, metadata management and versioning, because decisions depended on the origin and context of the data. In practice, lifecycle management included defining data ownership, retention, access and security policies, as well as auditing processes, see Figure 5. In integrated architectures, technologies such as blockchain and IoT were proposed to enable real-time capture, transparency and "trust-less transactions", helping especially in environments where actors did not have full trust among themselves [21].

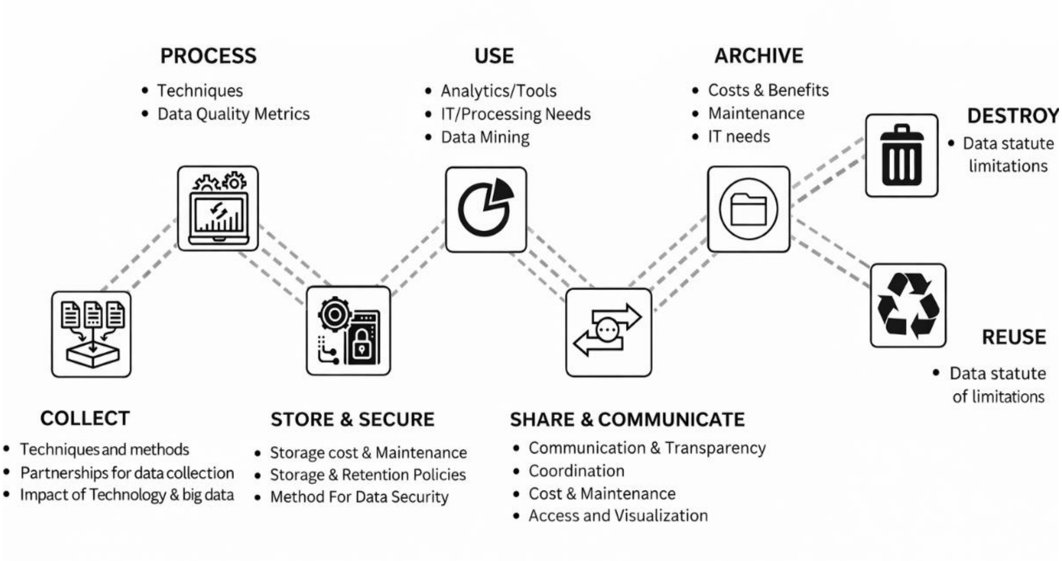

Figure 5. Data Lifecycle Management with Governance and Security Considerations

At the same time, studies have highlighted that these architectures have also brought new risks, such as privacy and cyber security, that should have been managed from the collection stage. In areas such as health, the management of the data cycle was treated as a national system performance problem: overlapping collection, gaps in availability and operational inefficiencies were found to have compromised decision-making. For this reason, a step-by-step approach was used for baseline assessment, collection of candidate indicators, consensus meetings and manuals of procedures for standardization [19]. This organization had shown that lifecycle management was not only technical, but also institutional [16, 22].

Data Preprocessing and Data Quality Enhancement

Studies had shown that the pre-processing stage was crucial to the analytical results, because errors in the data produced errors in the models and, consequently, poor decisions. Processing was focused on cleaning (absences, duplications, outliers), normalization, transformation and integration of data from heterogeneous sources [6, 7]. In systems with operational data, difficulties have come from differences in schemas, different semantics, and different update rates [26]. Classification model development with time-series cross-validation and data preprocessing are shown in Figure 6.

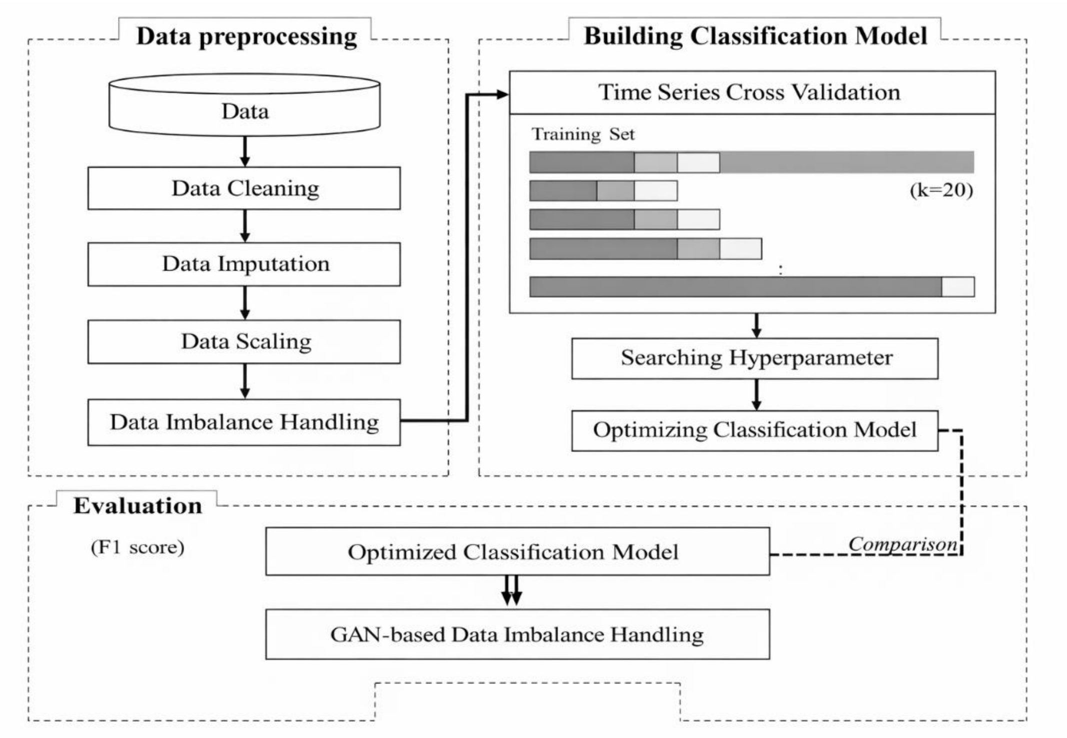

Figure 6. Classification Model Development with Time-Series Cross-Validation and Data Preprocessing

Organizational literature had linked data quality to the way of working: when employees recorded data "for someone else", problems of accuracy and motivation arose, while transparency and joint design of "information for action" improved quality [16]. This meant that data quality enhancement was achieved not only with technical rules, but also with organizational interventions. In studies on the adoption of DDDM in industry, data quality and security/privacy concerns were identified as critical barriers, along with a lack of planning and senior management commitment [23]. These results suggested that "data quality" was a socio-technical variable: it depended on governance, skills and infrastructure. In cause-and-effect analyzes of factors in data-driven organizations, data quality appeared as an "effect" factor, influenced by more basic factors such as analytical literacy and alignment with business strategy [24]. In the contexts of medicine and imaging, data processing also extended to annotation, class balancing, and privacy, because clinical data had been sensitive and often limited to labeling. This made it important to use techniques such as transfer learning, data augmentation or federated learning, in order to maintain quality and confidentiality [25, 26]. In closing, the literature had shown that pre-processing was not a "small technical step", but the foundation that conditioned every subsequent phase of DDDM [27].

Feature Selection and Knowledge Extraction

Literation had treated feature selection as a key mechanism to reduce complexity and increase interpretability. In many domains, the data had high dimensionality (health, IoT, education), and feature selection had reduced unnecessary variables while preserving the main informative signal [6, 27]. This had a direct impact on the performance of the models and their ability to be explained in decision-making [28]. Figure 7 depict the feature-based data mining and knowledge discovery framework.

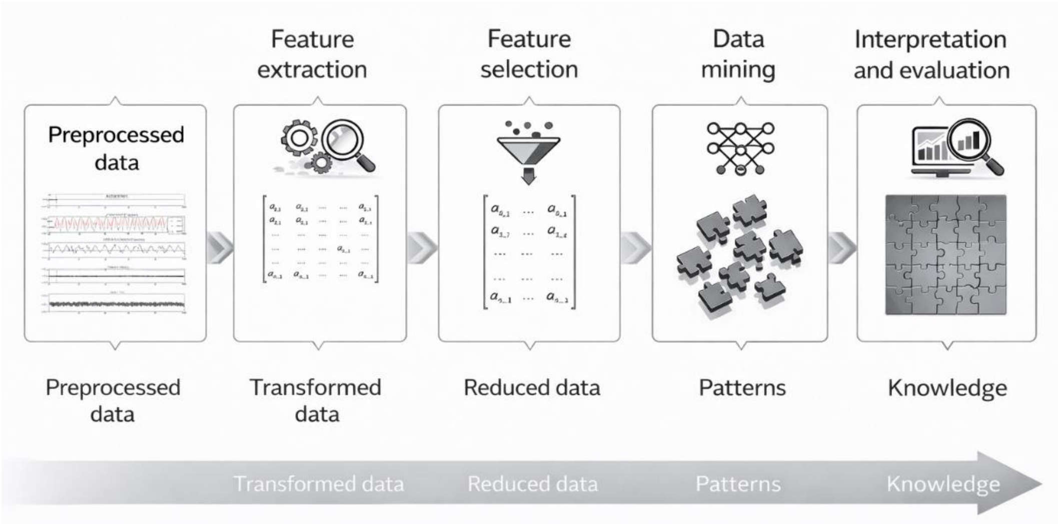

Figure 7. A Feature-Based Data Mining and Knowledge Discovery Framework

In education applications, predictive models have selected characteristics that best explained academic success (prior performance, study gaps, demographic factors), producing not only predictions but also actionable insights for intervention (eg, support for risk profiles) [28]. In medical applications, dimensionality reduction and feature extraction from omics/imaging has been essential for personalized diagnosis, but the literature has emphasized the need to balance automation with clinical interpretability [26], [29]. In systems where decisions had to be justified, the literature on human-in-the-loop and digital twins had asked that feature selection and knowledge extraction not be "black boxes", because people had needed to understand why a model had favored an alternative. Approaches with interpretable ML and goal modeling have helped to make the connection between the characteristics, objectives and utility of decisions [29]. On the other hand, studies on prescriptive analytics have shown that systems have evolved towards combining knowledge extracted from data with business rules, constraints and preferences, turning knowledge extraction into "actionable knowledge" [8, 9]. The literature had moved from feature selection as technical optimization to feature selection as an element of decision governance: it had influenced accuracy, stability, fairness and explainability, becoming a link between data and decisions [30, 31].

Machine Learning and Analytical Models for Decision Support

This section documented that analytical model for decision-making had moved from descriptive to predictive and prescriptive analytics, see Figure 8. ML models had provided predictions and classifications, while prescriptive analytics had recommended actions taking into account objectives and constraints [8, 9].

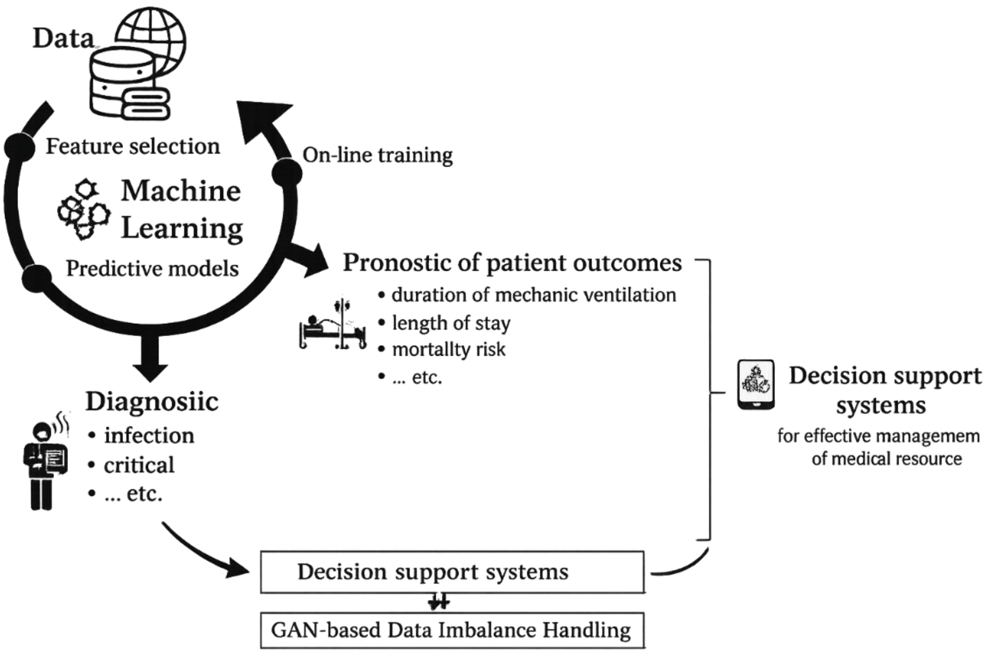

Figure 8. A Machine Learning Framework for Clinical Decision Support and Prognosis

In an IS perspective, PAS was conceived as an artifact with multiple sub-systems and different archetypes (advisory, executive, adaptive, self-governing), which determined how much authority the user had against the system [8]. In different sectors, the literature has brought examples of models: in health, deep learning in imaging has been used for diagnosis and clinical support, including multimodal and privacy-preserving approaches such as federated learning [25, 26]. In hospital processes, hybrid approaches have combined visual analysis, process mining and MCDM (eg PROMETHEE II) to rank solution alternatives and reach consensus faster [30]. In energy, a decision-making tool was built in Python that integrated financial and consumption data to reduce risk and optimize grant-financing [31]. In industry, the Blockchain–IoT architecture was used for real-time capture and autonomous coordination of resources, aiming for agility in management [21].

In the IS MCDM literature, techniques such as AHP, TOPSIS, fuzzy logic and ANP were used for strategic planning, resource allocation, risk assessment and technology selection, increasing the transparency and traceability of decisions [32, 33]. At the same time, studies have acknowledged that ML/AI models have required new infrastructures and capabilities, and that deficiencies in analytical literacy and alignment with strategy have limited the real value of these models [16, 24].

Model Evaluation, Validation and Robustness

The literature had emphasized that the evaluation of models was not limited to metrics such as accuracy, precision/recall or RMSE, but was expanded towards robustness, generalization and reliability in real situations. In prescriptive systems, validation was also related to whether the recommendations were applicable and produced higher utility under realistic constraints [8, 10]. This made it necessary to test with scenarios, sensitivity analysis and comparisons between models. Figure 9 depict the bias propagation and feedback loops in medical machine learning systems.

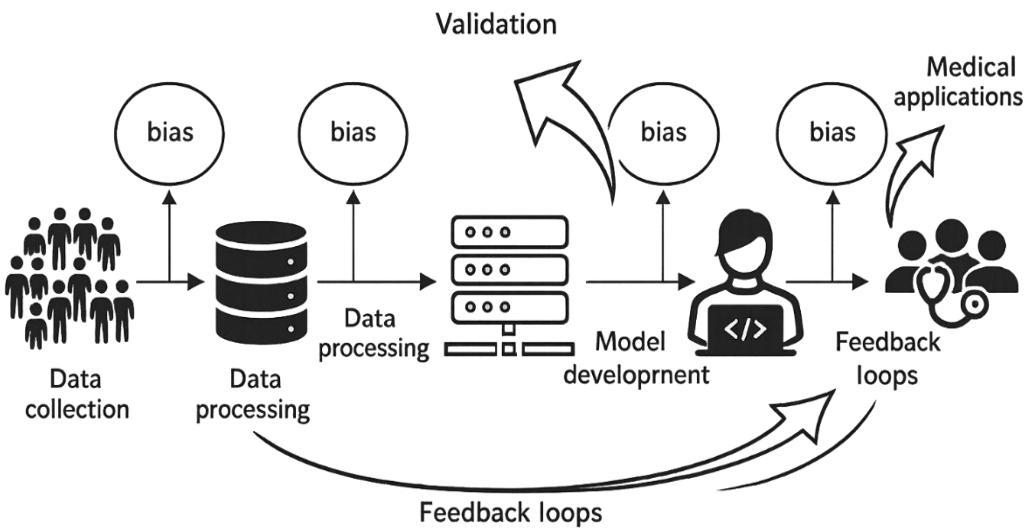

Figure 9. Bias Propagation and Feedback Loops in Medical Machine Learning Systems

In clinical contexts, validation was seen as critical because errors had high costs, therefore, the literature had discussed external validation, bias, and challenges of interpreting deep models [25, 26]. In multi-criteria decision making, studies have used sensitivity analysis and consistency checking to assess the stability of the ranking of alternatives and the reliability of recommendations [31, 32]. In group and fuzzy decision-making models, the literature had emphasized that the uncertainty and heterogeneity of preferences had required special methods for consensus and robustness [34, 35].

In dynamic systems such as digital twins/DDDAS, validation was made even more complex because the model was constantly updated by new data, while re-configuration decisions influenced the sensing process and the behavior of the real system. This had created a need for drift monitoring mechanisms, data quality control and evaluation of decision rationale in real time [32].

Furthermore, the literature had proposed that "robustness" should be understood not only as statistical performance, but as the ability of the system to produce stable, justifiable and safe decisions under variability and uncertainty [8, 10, 23].

From Analytical to Action – Decision Support and Human in the Loop

Many papers have argued that the main gap of DDDM has not been analysis, but the transition from analytical results to action, see Figure 10. In this sense, "information for action" was treated as organizational design: data and visualizations had value only if they were made understandable, reliable and usable by actors who had to act [16]. In organizations, staff participation in designing the information itself has increased, requiring new skills and reflection on the boundaries of what is considered "information for whom" [33].

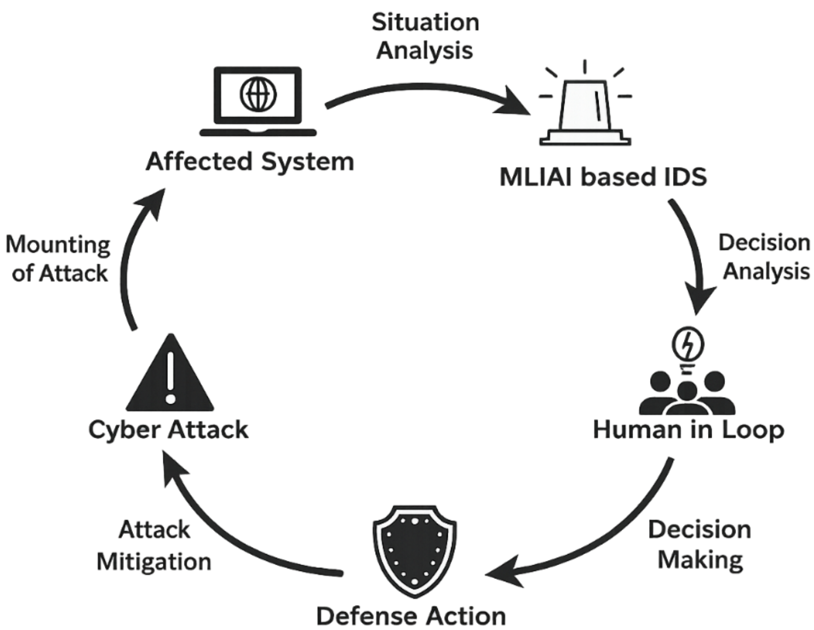

Figure 10. A Human-in-the-Loop ML-Based Intrusion Detection and Defense Framework

This had created issues of delegation, responsibility and "synergy" between the user and analytics [8]. In health, consensus-oriented approaches have used interactive environments (visualization + MCDM) to harmonize stakeholders' perceptions and select implementable alternatives [30, 36]. Human-in-the-loop had become particularly critical in DDDAS/Digital Twins, where reconfiguration decisions had affected model accuracy. The literature had identified that insufficient explainability limited people's ability to evaluate decisions, leading to inappropriate updates and errors that compromised the model. For this reason, the use of interpretable ML and goal modeling was proposed to explain the rationale and utility trade-offs [10]. This had established a bridge between analytics and action: the decision was not considered "output", but part of a cycle where the human had checked, corrected and learned together with the system [8, 10].

Synthesis of Literature Gaps and Motivation for the Integrated Framework

Across the reviewed studies, fragmentation appears not only in research focus but also in phase coverage. Many studies concentrate on model development and evaluation, while fewer address data governance, preprocessing quality, or decision-support implementation. Moreover, trust-related mechanisms such as Explainable AI and Human-in-the-Loop are often discussed independently rather than integrated across the full pipeline. This uneven distribution of focus suggests that DDDM research in IS lacks a consistent end-to-end perspective, making it difficult to compare approaches and identify dominant patterns [34].

By synthesizing the literature, it was noticed that the contributions were distributed in several "islands": some works had been strong in the technical aspect (ML models, prescriptive analytics, digital twins), while others had been strong in the organizational dimensions (analytical culture, governance, reskilling). This had created an integration gap, because many studies had addressed only one segment of the chain, without clearly linking it to other stages of the DDDM process [6, 8, 14, 16]. For example, the literature on analytical culture had shown that centralization did not guarantee DDDM, but had not always operationalized the link with lifecycle management and analytical pipelines [14]. Meanwhile, technical works had optimized the performance of models, but had left less detailed how the results were translated into reliable actions in real organizations [10, 25].

Another gap had emerged in explainability and trust. Even when the models had performed well, the lack of explainability and human-in-the-loop mechanisms had reduced adoption and increased the risk of wrong decisions, especially in dynamic systems [10, 23]. Likewise, the literature on adoption barriers had identified factors such as lack of planning, management commitment and privacy concerns, but often without linking these factors to specific stages (collection, processing, feature selection, development, evaluation, decision) [23, 24].

To make the gap verifiable, this paper operationalizes "fragmentation" through a gap-matrix, where studies are coded according to: (a) the stages they cover, (b) mechanisms of trust (XAI/HITL/ethics), and (c) ways of assessing robustness. This matrix makes it apparent that most studies focus on one segment of the chain, while end-to-end integration and analytics-to-action linkage is rarer. For these reasons, the motivation for an "Integrated Six-Phase Framework" was based on the need for a model that united the technical phases with the socio-technical dimensions: (1) Data Collection, (2) Data Preprocessing, (3) Feature Selection, (4) Model Development, (5) Model Evaluation, (6) Decision Support. This integration was seen as a way to avoid the illusion of DDDM, making it clear that value only came when the entire chain was designed, governed and operated as a single system, with feedback loops and distributed responsibilities [8, 10, 1516]. An overview of the 2016–2025 evolution suggests a shift: the early periods focus on modeling and performance; then the dimension of governance/adoption is added; while 2023–2025 put trust, explainability, HITL and ethics at the center. This justifies the need for the integration framework to be not only a "technical pipeline", but also a "controllable pipeline" for IS decision-making. To make this fragmentation analytically visible, the literature can be interpreted through a structured phase-based perspective. By examining which stages of the DDDM pipeline are covered in each study and whether trust and governance mechanisms are integrated, it becomes possible to identify recurring gaps and cross-phase dependencies. This structured interpretation supports the development of an integrated framework that connects data lifecycle management, analytical modeling, and decision support within a single comparative lens [35, 36].

METHODOLOGY

The reviewed studies were systematically coded using the six-phase DDDM framework to make them more open and analytical. We looked at each study to see if it covered one or more of the following steps: collecting data, cleaning up the data, choosing features, building a model, testing the model, and helping with decisions. Furthermore, studies were classified based on the existence of trust-related mechanisms, such as Explainable AI, Human-in-the-Loop, and ethical considerations. The coding process adhered to a systematic codebook delineating inclusion criteria for each phase and mechanism. To make sure that the studies were consistent, a binary coding method (presence/absence) was used. This phase-based coding made it possible to compare the coverage of the literature, find dependencies between phases, and find gaps that keep happening in end-to-end DDDM pipelines.

Research Design and Review Scope

The study follows a comparative literature review to analyze how Data-Driven Decision-Making (DDDM) is conceptualized, operationalized and evaluated in the field of Information Systems (IS). The aim is to map the research landscape, compare the main approaches reported in the studies and derive an integrated conceptual framework of reference based on the evidence and practices reported in the literature. The paper does not claim to develop a new implemented system or primary empirical benchmark; rather, it consolidates findings, trade-offs, and open gaps emerging from existing studies. To increase transparency and reproducibility, the review was carried out with a documented protocol (search strategy, inclusion/exclusion criteria, two-step screening and coding according to a codebook). The reporting was guided by the principles of systematic reviews in IS (eg PRISMA/Okoli approaches), including a study selection flow diagram.

The review is strictly organized according to a 6-phase DDDM analytical structure, which serves as a methodological lens for comparison and synthesis:

- Data Collection (Data Collection)
- Data Preprocessing
- Selection of features/attributes (Feature Selection)
- Model Development (Model Development)
- Model Evaluation (Model Evaluation)

- Decision Support

The study selection process followed a multi-stage screening procedure. Initially, records were retrieved from the selected databases using predefined keyword combinations. Duplicate records were removed, and titles and abstracts were screened for relevance. Studies that did not address DDDM within Information Systems contexts were excluded. The remaining articles were assessed through full-text review to determine eligibility based on inclusion criteria, including relevance to one or more phases of the DDDM pipeline. This structured selection process ensured that only studies contributing to the understanding of data-driven decision-making phases, governance mechanisms, or decision-support integration were included in the final corpus.

Data Sources and Retrieval

The review covers publications from the period 2016–2025, aiming to capture both fundamental contributions in analytics/ML and DSS in IS, as well as recent developments in data governance, transparency, ethics and Explainable AI / Human-in-the-Loop. The reference corpus for the review consists of primarily peer-reviewed literature: scientific articles and conference proceedings, supplemented by book chapters and technical reports only when necessary for definitions and conceptual basis.

Data Sources and Literature Retrieval Process

Relevant literature was drawn from widely used academic digital databases and libraries in IS and analytics, including:

- IEEE Xplore
- ACM Digital Library
- SpringerLink
- Elsevier ScienceDirect
- Wiley Online Library
- MDPI
- Taylor & Francis / journals indexed in Scopus/Web of Science (when accessible)
- arXiv (for new works not yet fully indexed)

Search and filtering were guided by keyword combinations reflecting the central themes of the paper: Data-Driven Decision-Making, Information Systems, Decision Support Systems, Machine Learning, Feature Selection, Data Governance, Explainable AI, Human-in-the-Loop, model evaluation.

To ensure that the review remains focused on DDDM in IS and avoids “algorithmic-only” papers, the research strategy was built on conceptual blocks directly related to the phases:

- DDDM block (basic concept): "data-driven decision making", DDDM, "analytics-driven decision", "evidence-based decision"
- IS/DSS block (context): "information systems", "decision support systems", DSS, BI, ERP, "IT service*"

- Block of pipeline phases: "data collection", preprocessing/cleaning, "feature selection", PCA, "model development", "model evaluation"
- Reliability and decision-making block: "data governance", explainability/XAI, "human-in-the-loop", transparency, accountability, ethics

Full versions of the queries for each database (with operators, search fields and filters) are documented in the Appendix – Full search strings & replicability pack.

Inclusion and Exclusion Criteria

Studies were included if:

1. address DDDM within an Information Systems context (eg DSS/BI/ERP, IT service management, socio-technical systems), and
2. report elements that can be mapped to at least one of the 6 phases (data → processing → features → model → evaluation → decision making), and
3. provided sufficient methodological clarity for comparative analysis (methods, evaluation metrics, governance/interpretability mechanisms, or structured synthesis).

Studies were excluded if:

- were mainly algorithmic unrelated to IS decision-making,
- the main domain was not relevant to the IS (eg applications completely outside the context of the systems/organisation),
- methodological reporting was missing (without description of the process, metrics or connection to decision-making),
- non-scientific sources were used as main evidence (can only be used for definitions, marked as "background").

The selection process is documented in a PRISMA diagram (records → duplicates → screened → full-text → included). In addition to phase coding (1–6), each study was also coded according to: (i) domain (eg health, industry, education, public sector), (ii) method type (ML, MCDM, PAS/architecture), (iii) trust mechanisms (XAI, HITL, ethics), and (iv) evaluation method (cross-validation, external validation, sensitivity, drift monitoring).

Selection Procedure (Screening) and Selection

The selection was carried out in successive steps:

1. removal of duplicates,
2. filtering by title and abstract for compatibility with DDDM in IS,
3. full evaluation of the text according to inclusion/exclusion criteria,
4. final selection for comparative synthesis and framework derivation.

This process aims to reduce selection bias by prioritizing studies with sufficient content for phase mapping and comparison.

Conceptual Categorization of Literature (Coding According to Six Stages)

Each included reference was analyzed and coded narratively (without tables) being assigned to one or more stages of the 6-stage structure:

1. Data Collection: data sources, integration, quality, completeness, organizational context
2. Preprocessing: cleaning, normalization, transformation, treatment of missingness and noise
3. Feature Selection: dimensionality reduction methods, relevance, interpretability
4. Model Development: classification/regression/prescriptive approach; ML and DSS, hybrid models
5. Model Evaluation (Model Evaluation): validation strategies, metrics, robustness and generalization
6. Decision Support: converting results into recommendations/alerts/action plans; HITL and XAI

The analytical framework of this review is based on a six-phase DDDM structure used as a comparative lens. The framework includes: (1) Data Collection, (2) Data Preprocessing, (3) Feature Selection, (4) Model Development, (5) Model Evaluation, and (6) Decision Support. These phases represent the full lifecycle from raw data acquisition to actionable decision-making. Each selected study was mapped to one or more phases, allowing identification of which parts of the pipeline are most frequently addressed in the literature, see Figure 11. This mapping also enabled examination of how trust mechanisms, governance considerations, and human involvement are distributed across the phases. This coding ensures that each study is evaluated through the same methodological lens and makes comparisons consistent across different contexts.

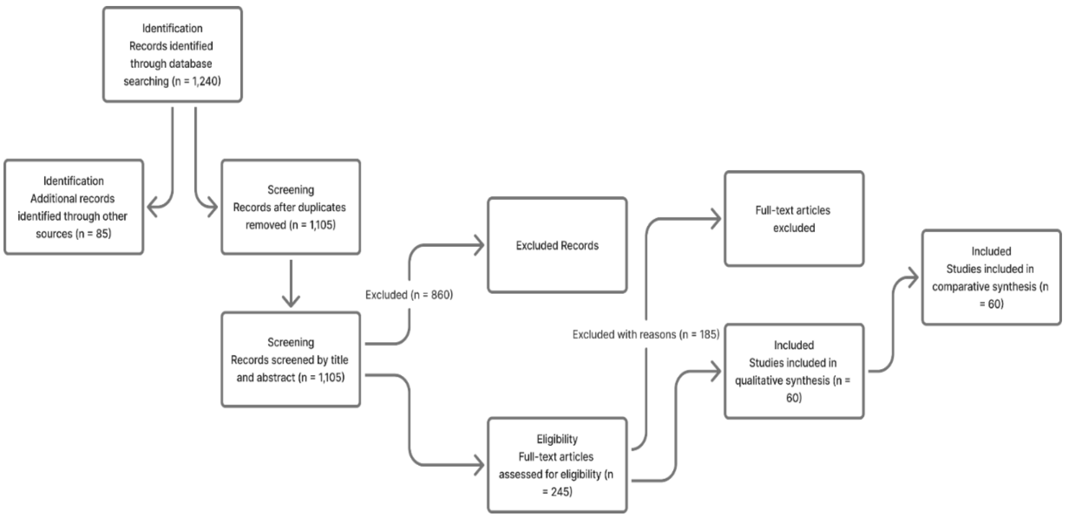

Figure 11 PRISMA Flowchart for Literature Screening and Selection

The Procedure of Comparative Synthesis of Scientific Papers

The synthesis was carried out on two levels:

- Synthesis within the phase: dominant practices, recurring techniques and key challenges are identified for each phase separately.
- Cross-stage synthesis: dependencies and influences between stages are analyzed (eg how preprocessing and feature selection affect model development/evaluation and decision quality).

The result of this synthesis supports the development of an integrated 6-phase framework for DDDM in IS, conceived as an iterative process with feedback loops.

Research Questions

The review is guided by the following research questions:

- RQ1. How is data quality, governance, and organizational readiness (eg, data quality, capacity, privacy/security) addressed in the collection and preprocessing phases, and what are the most commonly reported barriers/accelerators to DDDM adoption in IS?
- RQ2. What methodological approaches dominate for complexity reduction (eg, feature selection/model structuring) and for building analytical models that feed IS decision-making (including PAS/architecture and human–system integration), and how are tradeoffs between performance, interpretability, and organizational applicability justified?
- RQ3. How is the assessment of reliability of results reported and their conversion into action (decision support especially through Explainable AI, Human-in-the-Loop and ethical principles and which mechanisms increase "trust" and controllability of decisions in IS?

Evaluation of the Evidence Quality (Quality Appraisal)

The quality assessment focused on:

- methodological clarity (how well data, process and metrics are described),
- the realism of the assessment (real context vs simulation; reported limitations),
- transparency and reproducibility (details on methods, discussion of limitations).

This assessment served weighting of evidence in synthesis (which findings have a stronger basis), not strict exclusion.

Methodological Limitations and Scietific Effects

This review is limited by the heterogeneity of the studies (different contexts, sectors, data sources, metrics and reporting standards), therefore a direct “1:1” comparison of numerical performance and drawing generalized conclusions is limited. Furthermore, relying mainly on published literature may introduce “publication bias” (under-reporting of negative results), while some papers do not provide sufficient detail for reproducibility (eg, parameters, validation procedures, data). 6-stage coding, although based on protocol, also involves interpretive judgment and can create variation in categorization. Also, the study does not perform quantitative meta-analysis, but focuses on qualitative comparative synthesis of practices and mechanisms.

Despite these limitations, the scientific effect of the study lies in the reduction of conceptual fragmentation by providing a unified methodological lens from "data" to "decision support". The study systematizes cross-phase dependencies (eg, how governance and data quality affect interpretability and adoption) and makes clearer the "analytics-to-action gap" in IS. It also explicitly integrates mechanisms of trust and control (XAI, HITL, ethics, transparency/accountability) as methodological requirements and not as late additions. Finally, the documented protocol (research–screening–coding) increases transparency and reproducibility, creating a solid basis for empirical validation and extension of the framework in future work.

Analytical Synthesis Strategy

Following the coding process, the studies were comparatively analysed to identify recurring patterns, dominant approaches, and gaps across the six phases. The synthesis focused on three dimensions: phase coverage, trust and governance mechanisms, and decision-support integration. This approach enabled structured comparison of how studies address the full DDDM lifecycle and highlighted areas where integration between technical and organizational dimensions is limited. The analytical synthesis also examined cross-phase dependencies, such as how data quality influences model interpretability and how evaluation practices affect decision adoption. This structured interpretation supported the development of the integrated six-phase framework.

Methodological Limitations

This review has several limitations. First, the synthesis is based on published literature and does not include primary empirical validation of the proposed framework. Second, although structured coding was applied, interpretation of phase coverage may involve subjective judgment. Third, the review emphasizes conceptual and comparative analysis rather than quantitative meta-analysis. Despite these limitations, the structured phase-based approach provides a transparent and reproducible lens for analyzing DDDM in Information Systems.

RESULTS AND FINDINGS

The findings are organized according to the six-phase DDDM framework, allowing comparative interpretation of how studies address different stages of the data-to-decision pipeline. The synthesis focuses on phase coverage, integration of trust mechanisms, and the extent to which analytical outputs are translated into actionable decision support. This structure enables identification of recurring patterns and gaps across the reviewed literature. This chapter presented the results of the comparative literature review on Data-Driven Decision-Making (DDDM) in the field of Information Systems (IS), organized according to three research questions (RQ1–RQ3) and the integrated six-stage framework.

Findings were extracted from phase coding of studies (1–6) and synthesized by combining two levels of analysis: (i) within-phase synthesis (typical practices, techniques and challenges) and (ii) cross-phase synthesis (how early phases influence later phases). This approach made it possible to compare studies with different methodologies without being limited to numerical performance metrics, but also assessing data governance, organizational capacities, interpretability and trust mechanisms.

More specifically, RQ1 synthesized evidence on data quality, standardization, privacy/security and organizational readiness in the collection and preprocessing stages, identifying the most frequent barriers and accelerators. RQ2 presented results on complexity reduction and model development in phases 3–4, showing how IS literature relates model building to DSS/PAS architecture and human–system delegation design, and how performance–interpretability–applicability trade-offs are justified. RQ3 reported how credibility is assessed and how results are translated into action in stages 5–6, with a focus on Explainable AI, Human-in-the-Loop and ethical principles as mechanisms that increase controllability and accountability. To increase clarity, the chapter closes with a synthesis of the main cross-phase dependencies, showing where the "analytics-to-action gap" is created and which methodological interventions reduce it. Thus, the results were not treated simply as a list of practices, but as a map of cause–effect relationships linking governance, data quality, methodological choices and trust mechanisms to the actual adoption of data-based decision making in IS.

Analysis of the reviewed studies indicates that phase coverage is uneven across the DDDM lifecycle. Most studies emphasize model development and evaluation, while fewer address data governance, preprocessing quality, or decision-support implementation. Early-stage considerations such as data lifecycle management and governance are often treated conceptually, whereas technical modelling approaches receive more detailed treatment. This imbalance suggests that the literature prioritizes analytical performance over end-to-end decision integration. In particular, decision-support mechanisms and organizational adoption are less frequently discussed compared to model-centric phases. This pattern reinforces the existence of the analytics-to-action gap identified in the introduction.

RQ1. How is data quality, governance, and organizational readiness (eg, data quality, capacity, privacy/security) addressed in the collection and preprocessing phases, and what are the most commonly reported barriers/accelerators to DDDM adoption in IS?

The literature of recent years has addressed data quality and governance as direct prerequisites for DDDM, showing that problems at the source and in preprocessing have produced “inherited errors” throughout the pipeline. The study of Szukits & Móricz (2024) had shown that top management support and the perception of data quality had reinforced the analytical culture, while the centralization of data use itself had not automatically transformed into more "data-driven" decision-making. This suggested that data governance only became effective when it was accompanied by usage rates, routines and concrete responsibilities for quality.

In the same line, [19] categorized barriers to adoption into technical/data, organizational/managerial and socio-economic groups, and identified lack of planning and awareness, lack of management commitment, as well as privacy and cyber security concerns as critical. These barriers had directly affected phases 1–2: organizations had collected non-standardized data, with poor integration, and had limitations in the ability to clean, impute, harmonize and control operational drift.

From a health systems perspective, [16] had shown that even when the system had produced many indicators, incoherent governance had led to collection overlaps, lack of availability and operational inefficiencies. Their step-by-step approach (baseline assessment, list of candidate indicators, consensus meetings, procedure manuals) had demonstrated that governance and standardization of "what to collect" and "how to collect" had been among the strongest accelerators for improving data quality and their usability in decision-making. In this sense, the collection phase had become an institutional problem, not just a technical one.

They had added a cause-and-effect interpretation: they had established "data analytics literacy" and alignment with business strategy as causal factors, while data quality, infrastructure/technology and culture/governance had been identified as effect (dependent) factors. This had meant that quality improvement in stages 1–2 was not done by technical means alone (eg cleaning), but depended on the analytical competence of the organization and on the strategic direction that made sense of the investment in data [1].

In summary, the literature reported that the most frequent obstacles in phases 1–2 were: (i) poor quality and lack of standardization, (ii) limited capacity (human skills + infrastructure), (iii) privacy/security and regulatory uncertainty, and (iv) lack of planning and management support. The most frequent accelerators had been: (a) analytical culture supported by management, (b) governance mechanisms (ownership, standards, indicators, manuals), and (c) increased analytical literacy and linkage to organizational strategy. To standardize the findings of RQ1, barriers and accelerators were grouped into repeated categories (quality/standardization, capacities, privacy/security, management support; and analytical culture, governance mechanisms, literacy, and connection to strategy, respectively). This makes it clear that phases 1–2 are not only "technical", but have a direct dependence on governance and organizational skills.

RQ2. What methodological approaches dominate for complexity reduction (eg, feature selection/model structuring) and for building analytical models that feed IS decision-making (including PAS/architecture and human–system integration), and how are tradeoffs between performance, interpretability, and organizational applicability justified?

The literature had shown that in phases 3–4, two families of approaches to complexity reduction and model building dominated: (1) ML/analytical approaches (feature selection, dimensionality reduction, predictive/prescriptive models), and (2) architecture and system design-oriented IS approaches (DSS/BI/PAS), where the model was integrated into processes, roles, and human–system interactions.

They shown that prescriptive analytics systems (PAS) was conceived as an IS artifact with multiple sub-systems and components, and had derived archetypes (advisory, executive, adaptive, self-governing) that had determined the way the decision was delegated between the system and the decision maker. This literature made it clear that "model development" was not limited to the choice of algorithm, but included how the model was placed in the decision-making structure and what autonomy was given to the system [37-43]. On the architecture side, authors in [37] had proposed a layered structure for enterprise-level big data-driven decision-making, emphasizing performance, service composition, and resource optimization. These approaches had suggested that the construction of the model had become related to the design of the systems (service layer, reusable components, mechanisms for query performance), that is, to the "organizational applicability" and not only to the accuracy of the model.

For the reduction of complexity, the literature of IS and MCDM had shown that the selection of features and the structuring of the model was also done with a decision-making transparency approach [44-48]. Authors in [49] had reported the use of MCDM techniques (AHP, TOPSIS, fuzzy methods, ANP) in MIS for strategic/operational decisions, justifying this choice with the fact that these methods had produced higher traceability and explainability than "black-box" models in contexts where clear reasoning was required. This had shaped the main compromise: statistical performance was not considered sufficient if the decision was not explained and implemented [38].

The performance-interpretability-applicability trade-offs were justified in three ways:

1. When the decision was sensitive or controversial, the literature favored more interpretive models/structures (eg MCDM, PAS advisory) to maintain accountability and adoption.
2. When scaling and enterprise integration were required, the literature had pushed towards layered architectures and standardization of services, accepting technical complexity but increasing applicability [4].
3. When advanced automation was required, PAS literature had accepted higher autonomy (adaptive/self-governing), but had conditioned it with mechanisms of control, governance and human-system interaction [17].

The findings of RQ2 show that the methodological choice in stages 3-4 is not neutral: high-performance models often increase complexity and decrease interpretability, while MCDM/PAS advisory approaches increase transparency but may limit automation. Therefore, the literature justifies the trade-off as a necessary compromise between performance, interpretability and organizational applicability [39].

Trust-related mechanisms, including Explainable AI, Human-in-the-Loop, and ethical considerations, are increasingly discussed in recent studies. However, these mechanisms are typically introduced in the later stages of the pipeline, particularly during model evaluation or decision support. Few studies integrate explainability and human oversight across multiple phases of the DDDM lifecycle. This limited integration suggests that trust mechanisms are often treated as add-ons rather than embedded design principles. As a result, interpretability and controllability are not consistently linked to earlier decisions regarding data quality, feature selection, or model complexity [40, 41].

RQ3. How is the assessment of reliability of results reported and their conversion into action (decision support especially through Explainable AI, Human-in-the-Loop and ethical principles—and what mechanisms increase "trust" and controllability of decisions in IS?

The literature had reported that reliability assessment in phase 5 had expanded from classical performance metrics to the assessment of robustness, controllability and real impact on decision-making. In the context of PAS, authors in [17] had emphasized that the system was not only evaluated for "how well it predicted", but also for the way it interacted with people (synergy/delegation) and for its ability to produce feasible actions in organizational environments. Directly addressed the mechanism that increased trust: explainability in human-in-the-loop DDDAS/Digital Twins [2]. They had argued that reconfiguration decisions lost credibility when the rationale was not understood, leading to inappropriate updates and reduced model accuracy. Their approach used interpretable ML and goal modeling to explain decisions and analyze utility trade-offs between alternatives. This had caused the evaluation to not remain only in testing, but also to include an evaluation of the reasoning and the usefulness of the decision in the situation. The ethical dimension as part of decision support: the principles of fairness, accountability and transparency were integrated as guidelines for knowledge management and to avoid biased decisions in analytics, especially in the supply chain. In this sense, "trust" had increased when the system had rules and mechanisms that made the decision auditable and fair, not just technically correct [42, 43].

In health, [3] reported that the most recurring barriers to translating results into action were data quality and interpretability, despite benefits in personalizing and standardizing decisions. This strengthened the argument that decision support became effective only when the results were communicated in a comprehensible, reliable and related to real clinical/operational workflows.

In summary, the mechanisms that had increased the most "trust" and controllability were reported as:

- Explainable AI / interpretable ML (which made the reasoning of the model understandable)
- Human-in-the-Loop (which retained human control, review and correction)
- Goal modeling + trade-off/utility analysis (which explained why one alternative was chosen over another)
- Integrated ethical principles (fairness, accountability, transparency) for auditing and impartiality
- Clear human-system delegation design (PAS archetypes and boundaries of autonomy)

In RQ3, "trust" does not appear as the sole result of accuracy, but of a combination of: explainability (XAI), human control (HITL), ethical auditability and delegation design

PAS). These mechanisms expand the meaning of "evaluation" from numerical metrics to controllability and accountability.

Cross – Phase Dependencies

Cross-phase synthesis reveals five critical dependencies:

1. Governance and standardization (Phase 1) determine the quality of input and limit errors inherited in Phases 2–5.
2. Data processing (Stage 2) directly affects model interpretability and estimation stability in Stage 5.
3. Feature selection (Phase 3) is an important node for the performance-interpretability trade-off and affects fairness/ethics when features represent sensitive attributes.
4. Model development (Phase 4) requires adaptation to the organizational context: without an integrative architecture (eg PAS) the output of the model remains "analysis" without action.
5. Decision support (Phase 6) is sustainable only when XAI/HITL and ethics are designed as methodological requirements, not as additions to the model.

Overall, the findings highlight that DDDM research in Information Systems remains fragmented across phases, with stronger emphasis on modeling and evaluation than on governance and decision support. Trust mechanisms are increasingly present but rarely integrated across the full pipeline. These observations support the need for an integrated six-phase framework that explicitly connects technical and organizational dimensions of data-driven decision-making [44, 45].

Table 1. Comparative Foundations of Data-Driven Decision-Making in Information Systems

Ref.	Stream	Models	Evaluation – context	Key Metrics	Key Findings	Limitations	Decision	Output Architectural	Constraints Modeled	Pros / Cons (SOTA)
[33]	Sociotechnical “information-for-action”	Transparency + reskilling improved actionable data use	Data governance; sociotechnical design; reskilling	data-use rate; transparency; skill uptake	transparency + reskilling increased actionable data use	context-specific; limited quantitative validation	action-oriented decision support	sociotechnical governance + capability layer	cultural resistance; skill gaps	+ actionable focus; – limited technical benchmarking
[37]	End-to-end embedding of DDDM	DDDM worked when analytics were integrated into decision cycles	Decision integration; process alignment; DDDM lifecycle	decision-cycle integration; process alignment	DDDM worked when embedded in decision routines	weaker focus on XAI/HITL; heterogeneous cases	integrated operational decisions	end-to-end lifecycle embedded in processes	silos; process–analytics misfit	+ holistic lifecycle; – depends on org maturity
[8]	Strategic IS	IS strengthened agility and	DSS/BI; strategic alignment;	agility; strategic	IS strengthened agility and	mostly conceptual; limited	strategic decision support	DSS/ERP/BI integration	organizational complexity;	+ strategy linkage; – limited

Ref.	Stream	Models	Evaluation – context	Key Metrics	Key Findings	Limitations	Decision	Output Architectural	Constraints Modeled	Pros / Cons (SOTA)
	(DSS/ERP/BI)	strategic alignment	organizational agility	alignment; IS value	strategic alignment	empirical effect sizes			change adoption	empirical validation
[35]	SMEs & analytics maturity	SMEs mostly used descriptive analytics; predictive remained limited	Analytics maturity; predictive analytics; capability building	analytics maturity; predictive usage	SMEs stayed descriptive; predictive remained limited	SME-specific; uneven reporting	tactical/reporting decisions	basic BI/reporting setup	skills/infrastructure constraints	+ maturity lens; – weak prescriptive coverage
[32]	Smart cities & big data	Big data enabled planning via simulation/ monitoring	Big data planning; simulation; urban computing	planning efficiency; monitoring accuracy; scalability	big data enabled simulation/ monitoring for planning	high complexity/cost; governance/ privacy issues	urban planning decisions	smart-city big-data platform	volume/variety; privacy; integration	+ scalable; – heavy infrastructure burden
[17]	PAS design in IS	PAS archetypes clarified delegation and human–system synergy	Prescriptive analytics; PAS archetypes; human–system synergy	delegation level; usability; action feasibility	PAS archetypes clarified human–system roles and sustainability	archetype abstraction; limited cross-domain testing	prescriptive recommendations / automation choices	PAS architecture (advisory→self-governing)	autonomy boundaries; governance needs	+ links analytics-to-action; – implementation effort/complexity
[49]	MCDM in MIS	MCDM supported transparent trade-offs in decisions	MCDM; AHP/TOPSIS/ANP; decision transparency	traceability; explainability; decision consistency	MCDM improved transparent trade-offs in MIS decisions	subjectivity in weights; limited scalability	multi-criteria ranking/selection	MCDM workflow integrated in MIS	uncertainty; stakeholder preference conflicts	+ interpretable; – may reduce automation/performance ceiling
[59]	Visual DSS & consensus	Visual analytics + MCDM accelerated agreement	Visual analytics; MCDM; consensus building	consensus speed; user comprehension; decision quality	visual analytics + MCDM accelerated agreement	depends on facilitation; limited generalization	group consensus decisions	visual DSS + MCDM layer	stakeholder disagreement; cognitive load	+ fast alignment; – UI/design dependence
[58]	Data-driven optimization	Optimization reduced cost without degrading outcomes	Optimization; decision support; efficiency	cost; efficiency; outcome stability	optimization reduced cost without degrading outcomes	strong assumptions; transferability limits	optimized action plans	optimization + decision support pipeline	constraints feasibility; operational variability	+ measurable gains; – sensitive to assumptions/data quality
[2]	Explainable HITL Digital Twins	XAI + goal modelling increased trust in reconfiguration	Digital twins; XAI; HITL; utility trade-offs	trust; interpretability; utility trade-offs	XAI + goal modeling increased trust in reconfiguration	domain specificity; model complexity	reconfiguration/adaptation decisions	HITL digital twin + interpretable ML	dynamic drift; explanation adequacy	+ controllable decisions; – added complexity/overhead

Ref.	Stream	Models	Evaluation – context	Key Metrics	Key Findings	Limitations	Decision	Output Architectural	Constraints Modeled	Pros / Cons (SOTA)
[7]	Analytical culture	Culture mattered more than centralization for DDDM	Analytical culture; leadership support; decentralization	analytical culture; perceived data quality; leadership support	culture/leadership mattered more than centralization	survey/context limits; causality constraints	managerial data-use behaviors	governance + culture routines	adoption resistance; accountability gaps	+ highlights socio-technical drivers; – limited technical pipeline detail
[11]	Analytics vs intuition	Analytics coexisted with managerial judgment	Managerial judgment; digital orientation; sensemaking	reliance on analytics vs intuition; sensemaking	analytics coexisted with managerial judgment	interpretive; limited measurable outcomes	judgment-supported decisions	hybrid human decision process	ambiguity; bounded rationality	+ realistic decision behavior; – less prescriptive guidance
[38]	Blockchain–IoT architecture	Blockchain–IoT improved transparency and agility	Blockchain; IoT; privacy/security; agility	transparency; traceability; security posture	blockchain–IoT improved transparency/agility	scalability/energy; integration cost	trusted operational decisions	blockchain + IoT architecture	latency; interoperability; privacy	+ auditability; – complexity/cost
[4]	Enterprise big-data architecture	Layered design improved scalable decision support	Enterprise architecture; service-oriented IS; scalability	scalability; query performance; service efficiency	layered enterprise architecture improved scalable decision support	architecture-level; limited outcome evaluation	enterprise-level decisions	layered/service-oriented big-data architecture	resource constraints; performance bottlenecks	+ scalable design; – high implementation complexity
[16]	HIS governance & indicators	Standardized indicators improved data-driven governance	Data governance; standardization; KPIs/metadata	indicator availability; standardization; governance quality	standardizing indicators improved data-driven governance	domain-specific; resource intensive	governance/management decisions	HIS governance + indicator framework	overlap; missingness; coordination issues	+ strong governance method; – slow adoption/coordination burden
[19]	Adoption barriers	Barriers clustered in technical/data + managerial + socio-economic	Organizational readiness; adoption barriers; privacy/security	adoption barriers frequency; readiness dimensions	barriers clustered: technical/data, managerial, socio-economic	categorization subjectivity; context variation	adoption/implementation decisions	organizational readiness view	privacy/security; low planning/commitment	+ clear barrier taxonomy; – less phase-by-phase operational detail
[1]	Causal drivers (DEMATEL)	Literacy + strategy alignment drove DDDM effectiveness	Analytics literacy; strategy alignment; causal factors	causal weights; literacy; strategy alignment	analytics literacy + strategy alignment drove DDDM effectiveness	method-dependent (e.g., DEMATEL); input bias	capability investment decisions	causal factor model for DDDM	skill gaps; misalignment	+ causal structure; – depends on expert judgments/data
[40]	Clinical AI pipelines	Secure ML supported sensitive	Privacy-preserving AI; federated	privacy risk; model utility;	privacy-preserving ML supported	performance trade-offs; deployment complexity	clinical decision support	secure ML / federated pipeline	privacy; regulation; data sharing limits	+ safer deployment; – overhead and

Ref.	Stream	Models	Evaluation – context	Key Metrics	Key Findings	Limitations	Decision	Output Architectural	Constraints Modeled	Pros / Cons (SOTA)
		decision contexts	learning; ML pipeline	security robustness	sensitive decisions		under constraints			possible accuracy loss
[3]	DDDM in patient management	AI/DSS enabled personalization; interpretability remained challenge	AI-enabled DSS; interpretability; data quality	interpretability; data quality; workflow fit	personalization benefits existed, but interpretability stayed a barrier	healthcare specificity; data heterogeneity	patient management decisions	AI-enabled DSS + workflows	missing/biased data; explainability limits	+ real-world relevance; − persistent trust barriers
[36]	Precision decision support	ML improved precision decisions in complex diagnosis	Precision analytics; ML decision support; feature extraction	diagnostic precision; feature relevance	ML improved precision decision support in complex diagnosis	generalization limits; explainability variability	diagnostic support decisions	ML pipeline + feature extraction	class imbalance; noisy signals	+ performance gains; − interpretability/transferability risks
[60]	Predictive early-warning	Predictive models supported early intervention	Predictive analytics; early-warning; risk detection	early-warning accuracy; lead time; false alarms	predictive models supported earlier intervention	drift/maintenance needs; context dependence	early intervention triggers	predictive early-warning system	drift; threshold calibration	+ proactive value; − false alarms/drift sensitivity
[?]	Personalized support systems	Personalization improved outcomes via data-informed interventions	Personalization; dashboards; performance improvement	personalization impact; KPI improvement; engagement	personalized support improved outcomes via interventions	requires rich data; privacy concerns	personalized recommendations	dashboards + personalization engine	privacy; segmentation bias	+ targeted action; − data/ethics requirements
[46]	Large-scale group decisions	Fuzzy/LSGDM methods managed multi-stakeholder uncertainty	LSGDM; fuzzy MCDM; uncertainty; consensus	consistency; consensus quality; uncertainty handling	fuzzy/LSGDM managed multi-stakeholder uncertainty	complexity; parameter/weight sensitivity	group decision aggregation	large-scale group decision framework	uncertainty; conflicting preferences	+ handles uncertainty well; − complexity/interpretation load
[9]	Ethics in analytics systems	Ethics improved fairness, accountability and transparency	Ethical AI; fairness; accountability; transparency	fairness; accountability; transparency	ethical principles improved auditable decision support	operationalization difficulty; limited metrics	ethically constrained decisions	ethics layer in analytics/knowledge mgmt	bias; compliance constraints	+ trust/auditability; − harder implementation/measurement

Comparative Synthesis and Conceptual Framework

This comparison also indicates that the emphasis on model-centric phases often overshadows the importance of governance and decision-support integration. As a result, many studies optimize analytical performance without explicitly addressing how results are interpreted, validated, and operationalized within organizational contexts. This imbalance reinforces the need for a holistic perspective that connects data lifecycle management with actionable decision support [46].

The comparative synthesis integrates findings across the six phases of the DDDM pipeline to identify dominant patterns and recurring gaps. The analysis shows that studies tend to concentrate on analytical model development and evaluation, while earlier stages such as data governance and preprocessing receive less systematic attention. Similarly, decision-support mechanisms are often discussed separately from model development, indicating a weak connection between analytical outputs and organizational action [47].

Comparative literature synthesis showed that DDDM in IS had developed in four main streams:

a. governance and analytical culture [7], ii) system architecture and integration [4].
b. (iii) analytical models and MCDM/optimization [36] and
c. (iv) trust mechanisms and HITL/XAI [2].

These streams did not operate in isolation, but were interdependent across the six stages of the pipeline. In phases 1–2, the literature had shown that data quality and standardization conditioned the entire subsequent process. Studies such as [4] had emphasized that management support, analytical culture and institutional planning were prerequisites for effective use of data. In the health sector, [16] demonstrated that standardization of indicators and procedural manuals increased the usability of data for decision-making [48]. These streams collectively illustrate that DDDM in Information Systems is inherently socio-technical, combining data governance, analytical modelling, system architecture, and decision support. However, the literature rarely integrates these dimensions within a single end-to-end pipeline. Instead, studies tend to prioritize individual streams, which contributes to fragmented implementation of DDDM practices. Researchers in [1] had added that "analytics literacy" and compliance with the strategy had acted as causal factors for the improvement of quality and governance [49]. In phases 3–4, two dominant paradigms were identified: ML/optimization approaches and IS-oriented architectural approaches. Authors in [36] had reported improved performance through ML and optimization, while [49] had argued that MCDM had increased transparency and traceability of decisions. Authors in [17] had structured PAS as an IS artifact with delegation archetypes (advisory–self-governing), showing that the development of the model also included the design of autonomy. Had emphasized layered architecture as a condition for scalability and organizational applicability.

Thus, the performance–interpretability–applicability trade-off was treated as a conscious methodological choice. In stages 5–6, reliability assessment had expanded beyond classical metrics. Had shown that XAI and HITL increased confidence in Digital Twins through explainability and utility analysis. They had integrated the principles of fairness, accountability and transparency as methodological requirements [50]. They confirmed that the interpretability and quality of the data were crucial for translating the results into clinical practice.

The cross-phase synthesis had revealed five critical dependencies:

1. governance in phase 1 had limited legacy errors;
2. preprocessing had affected stability and interpretability;
3. feature selection was the key to the performance-ethics compromise;
4. model development required architectural integration (eg, PAS); and
5. decision support was stable only when XAI/HITL and ethics were designed from the beginning.

These dependencies highlight that decisions made in early phases propagate across the entire pipeline. Weak governance or inadequate preprocessing can reduce model reliability, while limited interpretability can hinder decision adoption. Therefore, effective DDDM requires coordinated design across all phases rather than isolated optimization. Based on this synthesis, the proposed conceptual framework presented DDDM as an iterative socio-technical system with six interconnected phases, where governance and analytical culture acted as foundations, delegation architecture and design as integration mechanisms, while XAI, HITL and ethics acted as guarantors of trust. This framework reduced the "analytics-to-action gap" by linking technical performance with controllability and organizational adoption in IS [51].

The comparative synthesis therefore supports the need for a structured framework that explicitly connects technical and organizational dimensions of DDDM. Such a framework should integrate governance, analytical modelling, evaluation, and decision support within a single iterative structure, ensuring that trust and controllability mechanisms are embedded across phases [52].

Scenario Based System Context

It has been presented the scenario-based system context (Scenario-Based System Context), within which the six-stage integrated framework of DDDM in IS was placed. This concept treated DDDM not as a linear technical process, but as a socio-technical system located in a concrete organizational environment, influenced by strategy, governance, culture and institutional constraints. The scenario-based approach positioned the decision-making system within a real operational context (public organization, health system, industrial enterprise or digital enterprise), where data flow, analytical models and trust mechanisms functioned as part of an integrated architecture. This allowed the stages of DDDM to be interpreted as components of an interconnected ecosystem rather than as isolated activities, see Figure 12. This scenario-based perspective reflects the comparative findings, which indicate that DDDM effectiveness depends on the interaction between technical and organizational dimensions. By embedding the six phases within a concrete operational environment, the framework emphasizes that data-driven decision-making is shaped by governance structures, resource availability, and decision authority. This contextualization supports interpretation of DDDM as a controllable socio-technical system rather than a purely analytical pipeline [53].

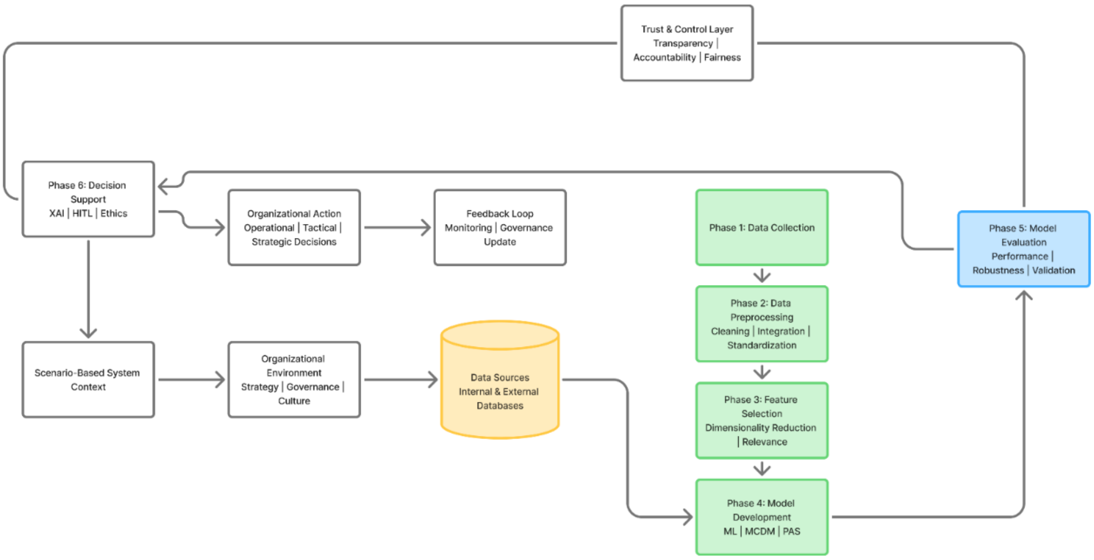

Figure 12. Scenario-Based System Context for an Integrated Six-Phase Data-Driven Decision-Making Framework in Information Systems

Key points of the concept

- The organizational context (strategy, governance, analytical culture) was presented as a fundamental layer that influenced all phases.
- Data sources (internal and external databases) were modelled as structural input of the system.

The integration of these elements highlights that decision-making is influenced not only by analytical performance but also by organizational readiness and trust mechanisms. The scenario-based context ensures that governance and culture shape data preparation and model design, while trust and control mechanisms support interpretability and adoption in later phases. This layered structure reflects the cross-phase dependencies identified in the comparative synthesis [54].

The six stages of DDDM were presented as interrelated processes:

- 1. Data Collection
- 2. Data Preprocessing
- 3. Feature Selection
- 4. Model Development
- 5. Model Evaluation
- 6. Decision Support
- A separate layer of "Trust & Control" (Transparency, Accountability, Fairness) was horizontally integrated over phases 4–6.

- A feedback loop from Decision Support to Data Collection was included, emphasizing the iterative nature of the system.
- Output was conceptualized as organizational action (operational, tactical, strategic).

The figure above presented a flow chart where on the left side was placed the organizational context based on the scenario, which included strategy, governance and culture. Below it, the data sources were modelled with the database symbol (cylindrical shape), indicating the structural input of the system. In the centre of the picture, the six phases of DDDM were presented as process blocks arranged linearly from Data Collection to Decision Support. Arrows were drawn between them that showed the logical flow of data and their progressive transformation into a decision. Above the stages of development, evaluation and decision-making, a horizontal layer "Trust & Control Layer" was integrated, which connected Model Development, Model Evaluation and Decision Support, emphasizing the role of XAI, HITL and ethics [55].

At the end of the flow, Organizational Action was presented as the final result, while a feedback loop was connected from Decision Support to Data Collection, indicating monitoring, updating governance and continuous improvement of the system. The scenario-based system context therefore operationalizes the conceptual framework by situating the six phases within an organizational environment that supports iterative learning and continuous improvement. By combining governance, analytical modeling, and decision support in a single architecture, the framework emphasizes that effective DDDM requires alignment between technical outputs and organizational decision processes. This integration strengthens the connection between analytics and actionable outcomes in Information Systems [56].

CONTRIBUTION OF THE CONCEPTUAL FRAMEWORK

The proposed conceptual framework articulates DDDM in the field of Information Systems as an integrated process with six phases (Data Collection, Preprocessing, Feature Selection, Model Development, Model Evaluation, Decision Support) where the technical and socio-organizational dimensions are treated inseparable. The framework reduces the analytics-to-action gap by making the Decision Support phase explicit through Explainable AI (XAI) and Human-in-the-Loop (HITL) mechanisms, conceptualizing decision-making as a continuous cycle with governance, auditing and controllability. In this way, it serves as (i) a theoretical basis for comparative literature synthesis, (ii) an analytical tool to compare SOTA pipelines/frameworks, and (iii) a practical reference point for more reproducible and applicable design of DDDM systems in an organizational context. More specifically, the framework contributes by making explicit the links between early-stage data governance, intermediate analytical design choices, and late-stage decision adoption. In this way, it does not treat data preparation, modeling, evaluation, and decision support as isolated technical tasks, but as interdependent components of an auditable socio-technical system. This strengthens the comparative value of the framework and clarifies its relevance for Information Systems research, where organizational context and controllability are as important as analytical performance [57, 58].

- Theoretical contribution: formalizes inter-phase dependencies and the role of governance/XAI/HITL as methodological requirements.
- Methodological contribution: creates a standard lens for coding and phase-by-phase comparison of studies.
- Practical contribution: provides operational structure (inputs-processes-outputs-controls-actors) for design and implementation.

Taken together, these contributions position the framework as a bridging model between traditional analytical pipelines and more recent socio-technical approaches to decision-making. Its main value lies in showing that DDDM effectiveness depends not only on model accuracy, but also on how governance, interpretability, and human oversight are embedded throughout the pipeline [59, 60].

IMPLICATIONSS AND FUTURE RESEARCH

The findings of this paper have important theoretical and practical implications for the research and implementation of Data-Driven Decision-Making (DDDM) in Information Systems (IS). These theoretical implications suggest that future research should treat data-driven decision-making as an end-to-end socio-technical process rather than a sequence of isolated analytical tasks. In particular, integrating governance, interpretability, and human oversight across phases can improve both the transparency and organizational usability of analytical outcomes.

Theoretically, the paper contributes by conceptualizing DDDM as an integrated socio-technical process with six stages, addressing the fragmentation of existing treatments in the literature. The proposed framework shows that the performance of analytical models cannot be evaluated in isolation from organizational factors such as data governance, analytical culture and "analytics literacy" because these factors condition the quality of data, the interpretability of results, and the applicability of decisions in practice. Also, by establishing reliability and controllability (eg through XAI and HITL) as methodological requirements, the paper shifts the focus from "accuracy" to "auditable and acceptable decisions" in the context of IS. On a practical level, the findings suggest that organizations aiming to take advantage of analytics and AI should first strengthen organizational readiness (eg data standardization, roles/responsibilities, analytics capabilities, privacy/security policies), before investing in advanced models. The paper also highlights that the trade-off between performance, interpretability and controllability is inevitable; therefore, the integration of approaches such as Prescriptive Analytics Systems (PAS), Multi-Criteria Decision Making (MCDM), Explainable AI (XAI) and Human-in-the-Loop (HITL) is necessary to increase trust and decision adoption. From a governance perspective, it is emphasized that data governance should extend beyond technical policies, including decision-making responsibility, audit trail and ethical principles. For future research, empirical validation of the 6-phase framework in real organizational contexts through longitudinal studies and field experiments is recommended, as well as the development of clearer measures of the trustworthiness, explainability, and long-term impact of DDDM on organizational performance, especially in increasingly autonomous and complex systems .

Future studies may also explore comparative evaluation of the proposed framework against established pipelines such as CRISP-DM or KDD in different organizational settings. Additionally, research is needed to develop operational indicators for measuring trust, controllability, and decision adoption across the DDDM lifecycle. Such empirical and comparative work would strengthen the practical applicability of the framework and support its validation in real-world Information Systems environments.

SUMMARY OF CONCLUSIONS

This paper aimed to address the fragmentation of treatments in the literature of Data-Driven Decision-Making (DDDM) in the context of Information Systems (IS), where studies often address only one segment of the chain (eg modeling, or analytical culture), without clearly linking the flow from data to decision. Carrying out a comparative review of the literature of the period 2016-2025, the paper proposed an integrated lens with six phases (Data Collection, Data Preprocessing, Feature Selection, Model Development, Model Evaluation, Decision Support) to systematize the evidence and make consistent comparisons between technical and socio-organizational approaches.

The findings of RQ1 showed that the early stages (data collection and processing) are decisive for the success of DDDM, not only for technical reasons, but also for organizational and institutional reasons. The most frequent barriers are related to poor data quality and standardization, limited capacity (skills and infrastructure), as well as privacy/security and lack of managerial commitment. In contrast, the most mentioned accelerators are analytical culture, governance mechanisms (ownership, standards, indicators, documentation), analytics literacy and the connection with the organizational strategy. The findings of RQ2 highlighted that the phases of complexity reduction and model development (feature selection and model development) are dominated by two families of approaches: (i) analytical/ML approaches for performance and automation, and (ii) IS design-oriented approaches (eg PAS/architecture) that aim at integration into processes, roles and responsibilities. The literature justifies the performance–interpretability–applicability tradeoff as inevitable: in contexts where accountability is required, transparency and decision rationale often carry equal weight with numerical accuracy. The findings of RQ3 confirmed that the evaluation of models is not limited to metrics (accuracy, RMSE, etc.), but extends to reliability, controllability and real impact on decision-making. Mechanisms that increase trust and adoption are reported as XAI (explainability), HITL (human control, review and correction), trade-off/utility analysis and integration of ethical principles (fairness, accountability, transparency). Taken together, these findings show that the effectiveness of DDDM in Information Systems depends on alignment across the full pipeline rather than excellence in isolated phases. The review demonstrates that governance, preprocessing quality, interpretability, and decision-support design are mutually reinforcing elements that shape whether analytical outputs become usable organizational actions.

This places "Decision Support" as a critical phase where the analytical result must become understandable, auditable and acceptable action. In conclusion, the six-phase integrated framework conceives DDDM in IS as a continuous socio-technical process, where interphase dependencies are key: governance and data quality in phases 1–2 condition the interpretability and usability of decisions in phases 5–6. To strengthen the position against SOTA frameworks, the paper compares the proposed framework with known pipelines and demonstrates the phase-by-phase flow through an empirical-demonstration illustration, emphasizing that practical value increases when XAI/HITL and governance mechanisms are treated as design requirements. The main limitations are related to the heterogeneity of the studies and the fact that the review does not aim at complete numerical meta-analysis; however, the framework provides a reproducible basis for comparison and design. Future research should focus on empirical validation in real organizations (longitudinal studies, cases, experiments), operationalizing measures of trust/controllability, and analyzing human–system dynamics in increasingly autonomous and complex systems. Overall, the study argues that data-driven decision-making in Information Systems creates sustainable value only when data, models, governance, and human oversight are designed as parts of one integrated and controllable decision system.

AUTHOR CONTRIBUTIONS

Conceptualization, L.L.N and A.D.; Methodology, L.L.N; Validation, L.L., and A.I.; Investigation, A.D; Resources, B.A.; Data Curation, L.LN.; Writing –Original Draft Preparation, L.L.N.; Writing –Review & Editing, L.LN.; Visualization, B.A.; Supervision, A.I.; Project Administration, L.L.N.

CONFLICT OF INTERESTS

The authors declare no conflicts of interest.

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