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Editorial

Artificial Intelligence and Decision Support Systems: Contributions, Emerging Patterns, and Future Directions

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1. Introduction

Decision-making is one of the most fundamental activities in many human, organizational, scientific, and societal contexts. The increasing complexity of decision processes, the availability of large-scale data, the interdependence of socio-technical systems, and the need to act under uncertainty have made Decision Support Systems (DSSs) a strategic research area [1–3]. Since the early formulations of management decision systems and DSS frameworks, the field has progressively evolved from model-driven analytical tools toward interactive, data-driven, knowledge-based, and, more recently, AI-enabled decision environments.

Traditional DSSs were often conceived as interactive computer-based systems designed to assist decision-makers in semi-structured or unstructured decision problems. Their main components typically included data management modules, analytical models, and user interfaces [4,5]. Over time, DSSs have evolved from static tools for data retrieval and model execution into intelligent systems capable of learning from data, representing knowledge, generating recommendations, and explaining their behavior [6,7].

Artificial Intelligence (AI) has accelerated this evolution [8]. Machine learning algorithms allow DSSs to detect patterns and build predictive models from historical data. Deep learning architectures support complex tasks such as time-series forecasting, image analysis, natural language processing, and representation learning. Knowledge-based AI, including Bayesian networks, ontologies, rule-based systems, and fuzzy cognitive maps, provides explicit structures for reasoning, explanation, and scenario analysis. Multi-criteria decision-making methods enable the comparison of alternatives under multiple and sometimes conflicting criteria.

Furthermore, there is a growing emphasis on the explainability of DSSs [9]. Specifically, in decision-support contexts, system quality cannot be assessed solely in terms of predictive performance. Therefore, a DSS must also support understanding, justification, transparency and human oversight. This is particularly important in domains such as healthcare, finance, environmental policy, energy planning, and project management, where decisions can have significant social, economic, or organizational consequences. Explainable AI (XAI) methods applied to DSSs help users understand why specific recommendations are produced, thereby supporting trust, accountability, and adoption.

The Special Issue "Artificial Intelligence and Decision Support Systems" [10] was launched to collect high-quality research contributions addressing the interplay between AI and DSSs. The aim was to bring together theoretical, methodological, and applied

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studies showing how AI techniques can improve decision support in practical domains. The Special Issue comprises a group of articles published in *Information* between 2024 and 2026 that address decision-support problems in renewable energy, finance, environmental management, biomedical research, software engineering, healthcare, and institutional AI governance [11–17]. Although they cover different domains and methodologies, they share a common concern: transforming AI models into useful, interpretable, actionable and accountable decision-support tools. Collectively, they illustrate current efforts to make AI-based DSSs more accurate, adaptive, explainable, and responsive to domain-specific requirements. At the same time, they also reveal persistent challenges concerning scalability, generalizability, data quality, human trust, ethical use, governance and operational accountability.

Related Special Issues have addressed complementary aspects of the relationship between AI and decision support, including multi-criteria decision-making and AI-based handling of uncertainty, explainable AI, decision intelligence, and emerging AI solutions for DSSs [18–21]. Against this background, the distinctive positioning of the present Special Issue lies in its deliberately cross-method and cross-domain perspective. Rather than focusing on a single AI paradigm or decision-support methodology, the collected contributions span transparent multi-criteria ranking, deep-learning forecasting with temporal explanations, expert-driven causal scenario analysis, intrinsically interpretable models, case-based reasoning with feature attribution and data augmentation, metaheuristic optimization, and traceable AI governance [11–17]. Taken together, they emphasize not only analytical performance but also the broader transition from model outputs to interpretable, actionable, and accountable decision-support workflows.

This Editorial presents the papers published in the Special Issue and complements them with a discussion on how current AI-based DSS research is evolving across domains and what challenges still need to be addressed.

The rest of this paper is structured as follows. In Section 2, we discuss the scope and editorial synthesis approach we used to analyze the Special Issue contributions. In Section 3, we present and discuss the papers published in the Special Issue. In Section 4, we identify cross-cutting themes emerging from the collection. In Section 5, we discuss open challenges and future research directions. Finally, Section 6 concludes the paper.

2. Methodology

The purpose of this paper is to critically synthesize the Special Issue contributions, compare their methodological and application-oriented characteristics, identify recurring themes and limitations, and use the resulting observations to create a bounded set of future research directions. The editorial synthesis was guided by the following research questions:

1. Which application domains, AI and analytical techniques, decision-support functions, and explainability mechanisms are represented in the Special Issue?
2. What methodological strengths, limitations, and cross-cutting patterns emerge from the comparison of the contributions?
3. Which recurring gaps identified across the contributions motivate plausible future research directions for AI-based DSSs?

Each contribution was examined according to a common analytical scheme comprising application domain, decision problem, AI or analytical techniques, data sources, validation strategy, evaluation measures, explainability mechanism, governance or human-oversight mechanism, decision-support output, and main strengths and limitations. Specifically, we followed a structured comparative procedure. First, each article was analyzed according to the common dimensions defined above; the corresponding evidence is summarized in Tables 1 and 2. Second, the contributions were compared across these dimensions to

identify similarities, differences, recurring methodological patterns, and shared limitations. Third, the recurring patterns emerging from this comparison were synthesized into the four cross-cutting themes discussed in Section 4. Finally, the gaps identified across the contributions were used as the starting point for the future research directions presented in Section 5, where they were interpreted in light of selected recent studies. This procedure was intended to provide a transparent and consistent editorial synthesis rather than a formal systematic review or qualitative meta-synthesis. Selected foundational and recent research is used to contextualize the observations, but the manuscript does not claim exhaustive coverage of the broader field.

Table 1. Conceptual and functional overview of the Special Issue contributions.

Contribution	Application Domain	Decision Problem	Main AI/DSS Techniques	Decision-Support Function	Explainability Approach
Serrano-Gomez et al. [11]	Renewable energy	Selection of PV modules and batteries according to technical and economic criteria.	AHP- and Entropy-based criterion weighting combined with TOPSIS.	Ranking and selection of PV-module and battery configurations.	Procedural transparency through explicit AHP/Entropy weighting and TOPSIS ranking; no separate XAI method.
Moustati et al. [12]	Finance	Forecasting of stock returns and support for portfolio decision-making.	BERT-based sentiment analysis, LSTM forecasting, TimeSHAP and TIME.	Stock return forecasting, trading-signal generation, and simulated portfolio actions.	Temporal explanation of LSTM predictions through TimeSHAP and TIME.
Kokkinos et al. [13]	Environmental management	Assessment of interventions for mitigating marine-species extinction risk.	BESTEL, expert elicitation, PCA, and FCM.	Simulation and comparison of environmental policy scenarios.	Structural interpretability through expert-elicited FCM relationships and scenario simulation.
Martinotti et al. [14]	Biomedical research	Classification of the wound-healing properties of honey.	Bayesian networks and decision trees.	Classification of honey samples and exploration of biologically relevant relationships.	Intrinsic interpretability complemented by a domain-oriented interface.
Li et al. [15]	Software engineering	Estimation of software-development effort.	CBR, SHAP, and Mixup.	Effort estimation and retrieval of relevant historical projects.	SHAP-informed feature weighting used in the CBR similarity and retrieval process.
Ziane et al. [16]	Healthcare	Diabetes prediction using reduced feature subsets.	Hybrid PSO-GWO feature selection and machine learning classifiers (random forest, SVM, KNN, and logistic regression).	Diabetes classification and identification of parsimonious feature subsets.	No dedicated XAI method; interpretability is supported indirectly through feature reduction and model parsimony.
Alhalangy [17]	Institutional decision support and AI governance	Accountable eligibility, prioritization, or resource-allocation decisions under fairness and traceability requirements.	Logistic regression, case-level explanation, selective human review, fairness auditing, and structured audit trail.	Prediction, explanation-guided escalation, human review, final-decision recording, and audit reconstruction.	Case-level feature contributions linked to explicit review rules and persistent decision records.
Salem et al. [22]	AI illiteracy in knowledge workers	Assessment and impact of organizational AI illiteracy on decision quality in public organizations.	NLP-based semantic analytics and Partial Least Squares Structural Equation Modeling (PLS-SEM).	Explaining human–AI decision vulnerability by showing how AI illiteracy is associated with strategic decision quality.	Integration of Adaptive Structuration Theory, Dual-Process Theory, and a Technology–Organization–Environment framework to explore technology use, human cognition, and organizational readiness.
Tselepatiotis et al. [23]	Human resources and organizational management	Identification and interpretation of organizational issues.	LLM-based semantic classification and interpretation.	Organizational monitoring and managerial recommendations.	McKinsey 7S and Deming-grounded, evidence-linked explanations.

Table 2. Comparative appraisal of the Special Issue contributions.

Contribution	Dataset	Validation Protocol	Evaluation Metrics	Main Reported Outcome	Critical Appraisal
Serrano-Gomez et al. [11]	An 8 × 8 MCDM decision matrix built from eight PV modules/batteries alternatives and eight technical and economic criteria derived from a real off-grid photovoltaic case study.	Comparison of AHP-derived and Entropy-derived weighting schemes.	Ranking of alternatives and consistency of the preferred configurations.	The two weighting procedures produce substantially different criterion weights but converge on similar top-ranked configurations.	*Strengths:* transparent comparison of subjective and data-derived weighting procedures. *Limitations:* conclusions depend on the selected alternatives, criteria, weighting assumptions, and case-study context; transferability to other settings is not empirically established.
Moustati et al. [12]	Stock market data gathered from Yahoo Finance and a tweet corpus associated with the stocks.	Predictive and simulated portfolio evaluation.	RMSE, MAE, MSE, directional accuracy, and portfolio outcome.	The study reports strong forecasting results, including a directional accuracy of 95.24%, and translates the forecasts into simulated trading actions.	*Strengths:* the evaluation connects predictive performance with an actionable portfolio component. *Limitations:* the evidence is restricted to a specific asset, period, and simulated setting. The unusually high directional accuracy requires cautious interpretation and independent temporal replication across assets and market regimes.
Kokkinos et al. [13]	Expert knowledge from 34 domain experts; identification of 30 BESTEL factors, followed by PCA-guided reduction and expert validation for FCM construction.	Two stages: (1) PCA dimensionality reduction combined with domain-expert contextual re-evaluation during the construction of the FCM, and (2) scenario (what-if) simulation over four policy scenarios to assess the behavior of the FCM under alternative policy scenarios.	Kaiser–Meyer–Olkin measure of sampling adequacy and Bartlett's test of sphericity to evaluate PCA suitability. Structural metrics (e.g., in-degree, out-degree, and centrality) to evaluate FCM network topology. Changes in extinction-risk variables under alternative scenarios.	The simulations identify the relative effects of different combinations of climate-change mitigation and dam-related interventions.	*Strengths:* systematic integration of expert knowledge, causal representation, and scenario analysis. *Limitations:* outcomes depend on the participating experts, elicited causal relationships, and FCM parameterization. They should be interpreted as model-based scenario insights rather than as empirically validated forecasts.
Martinotti et al. [14]	Focused dataset involving three honey types from a single local source collected in summer 2024.	Stratified 10-fold cross-validation, per-class evaluation and confusion-matrix analysis.	Accuracy, precision, recall, F-measure, Matthews correlation coefficient, ROC area, PRC area and confusion matrices.	Bayesian networks and decision trees provide encouraging classification results and interpretable relationships among honey properties and wound-healing categories.	*Strengths:* detailed classification evaluation using intrinsically interpretable models. *Limitations:* the narrow and retrospective evidence base limits generalizability. Independent samples, broader geographical coverage, formal end-user studies, and prospective validation remain necessary.
Li et al. [15]	Seven public software-effort datasets obtained from the PROMISE and ISBSG data repositories.	Five-fold cross-validation and comparisons with baseline CBR and other prediction approaches.	MMRE, MdMRE, MAE, MSE and Pred(0.25).	The proposed framework reports lower estimation errors than baseline CBR configurations across the benchmark datasets.	*Strengths:* multi-dataset and multi-metric evaluation of a hybrid estimation framework. *Limitations:* validation is based on public benchmarks rather than prospective industrial use. Cross-organizational generalizability and the computational costs of SHAP and data augmentation require further assessment.
Ziane et al. [16]	Three public clinical datasets.	Stratified five-fold cross-validation and fold-level comparisons using Wilcoxon signed-rank and paired *t*-tests.	Accuracy, precision, recall, weighted F1-score, feature reduction, runtime and statistical comparisons.	The optimized random forest reaches a reported mean accuracy of 84.74%, with an average feature-count reduction of approximately 26%.	*Strengths:* multi-dataset evaluation combines predictive performance, feature reduction, runtime, and statistical analysis. *Limitations:* the results remain retrospective and dataset-dependent. Statistical superiority is not uniform across the reported comparisons, and external prospective clinical validation is absent.

Table 2. *Cont.*

Contribution	Dataset	Validation Protocol	Evaluation Metrics	Main Reported Outcome	Critical Appraisal
Alhalangy [17]	A controlled proof-of-concept dataset comprising 8000 synthetic institutional cases with historically biased labels and a protected-group attribute used for fairness evaluation and review-policy simulation.	Design-science evaluation comparing three conditions: (1) baseline prediction, (2) prediction with case-level explanation, and (3) the full architecture combining explanation, selective human review and audit recording. The study also reports sensitivity analysis and bootstrap confidence intervals within the simulation setting.	Accuracy, F1 score, AUC, demographic-parity gap, equal-opportunity gap, false-positive-rate gap, escalation rate, override precision and Audit Completeness Index.	Compared with the baseline, the full architecture increases F1 from 0.781 to 0.795, reduces the demographic-parity gap from 0.070 to 0.010 and the equal-opportunity gap from 0.116 to 0.036, and raises audit completeness from 0.33 to 1.00 while escalating 4.8% of cases for human review.	*Strengths:* integrates prediction, explanation, selective review, fairness evaluation and structured traceability within a single operational decision pathway; evaluates governance utility alongside predictive performance. *Limitations:* the evaluation is based on synthetic data and simulated reviewer behavior. The reported improvements constitute proof-of-concept evidence and require validation with real institutional data, workflows, stakeholders and domain-specific governance requirements.
Salem et al. [22]	Structured questionnaire responses administered to 200 public sector knowledge workers in Saudi Arabia.	Cross-sectional mixed-method validation, using 5000-resample bootstrapping, repeated topic modeling, and independent human annotation.	PLS-SEM reliability/validity indices, path coefficients, R^2, Q^2, topic coherence/diversity/stability, Cohen's κ, accuracy, macro-precision, macro-recall, and macro-F1.	AI illiteracy significantly reduced decision quality. Aspect-Based Sentiment Analysis results show that employees generally viewed AI positively in relation to productivity, access to knowledge, learning, and decision support, while they indicate concerns about biased recommendations, opaque AI processes, limited explainability, and AI-related risks.	*Strengths:* The framework triangulates structural modeling with multiple NLP methods and computational and expert validation. *Limitations:* The cross-sectional, self-reported, single-country sample and small textual corpus limit causal inference and generalizability.
Tselepatiotis et al. [23]	Three literature-grounded synthetic organizational scenarios with 15 indicators; component-level evaluations used 20 general-domain DynaSent examples and ratings from 16 participants.	Scenario-based testing combined with repeated classifications, prompt reformulations, external reference labels, and a blinded within-subject comparison of three interpretation approaches.	Exact agreement, Fleiss'/Cohen's κ, macro-F1, five-point human ratings, Friedman tests, Wilcoxon tests, and Kendall's W.	Classification achieved 95.0% accuracy and 0.947 macro-F1, while the proposed interpretation outperformed the baseline but not the generic LLM.	*Strengths:* The multi-stage evaluation examines system behavior, classification robustness, and perceived decision-support quality. *Limitations:* Reliance on synthetic scenarios, 20 general-domain sentiment examples, one LLM configuration, and 16 evaluators prevents organization-specific or real-world validation.

3. Overview of the Special Issue Contributions

The Special Issue includes contributions addressing both methodological innovation and domain-specific decision support. Tables 1 and 2 provide complementary views of such contributions. Specifically, Table 1 summarizes their conceptual and functional characteristics, including the application domain (column "Application domain"), the decision problem (column "Decision problem"), the methodological architecture (column "Main AI/DSS techniques"), the decision-support function (column "Decision-support function"), and the explainability or interpretability approach (column "Explainability approach"). Table 2 focuses instead on their empirical evaluation, reporting the dataset used for the evaluation (column "Dataset"), the validation strategy (column "Validation protocol"), the evaluation measures (column "Evaluation metrics"), the main reported outcomes (column "Main reported outcome") and a critical appraisal of the strengths and limitations of each study (column "Critical appraisal").

The separation between conceptual characteristics and empirical appraisal avoids conflating the design of a DSS with the strength of the evidence supporting it. In particular, the numerical results reported by the contributions should not be directly compared, because the studies address different decision problems, use heterogeneous evidence bases and validation protocols, and adopt non-equivalent evaluation measures.

These tables show that AI-enabled DSSs are not confined to a single field or methodological family. Instead, they provide a transversal research paradigm that can be adapted to multiple domains, from technical planning to clinical prediction, and from environmental conservation to financial decision-making.

In the rest of this section, we discuss each contribution published in this Special Issue.

3.1. Renewable Energy Decision Support

In [11], the authors address the selection of photovoltaic (PV) modules and batteries for off-grid PV installations. This is a typical decision-support problem: multiple alternatives must be evaluated in terms of technical and economic dimensions.The authors propose a DSS based on two multi-criteria decision-making strategies: the *Analytic Hierarchy Process* (AHP) method combined with the *Technique for Order of Preference by Similarity to Ideal Solution* (TOPSIS), and the *Entropy* method combined with TOPSIS. AHP [24] and Entropy [25] are used to compute criterion weights: AHP incorporates expert judgment, while Entropy derives weights from data variability. Instead, TOPSIS [26] is used to rank the alternatives. The study finds that AHP and Entropy can generate substantially different weights, yet TOPSIS converges toward similar top-ranked solutions; in the analyzed case, the combination of lithium-ion batteries with copper indium gallium selenide PV modules emerges as the most suitable option.

This contribution is particularly relevant as it provides a rigorous framework, as well as a valuable decision-support tool, for evaluating complex PV systems based on both technical and economic criteria. Moreover, the work demonstrates that classical multi-criteria decision-making approaches remain highly relevant in AI-based DSS research. In many practical contexts, transparent and structured decision methodologies are preferable to black-box approaches (e.g., those based on deep learning [27]) because they allow stakeholders to understand how alternatives are evaluated. Finally, the paper highlights a key issue in decision support: the relationship between subjective and objective weighting. The comparison between these approaches illustrates the need to balance expert knowledge (which may prioritize intuitive criteria such as costs and energy yield) and data-driven objectivity (which may disproportionately weight criteria with limited data variability). However, the results presented in the case study should be interpreted within the boundaries of the criteria, alternatives, and weighting assumptions considered in the case study

itself. The convergence of the top-ranked solutions across the two weighting approaches is encouraging, but it does not imply that the same configuration will remain preferable under different geographic, economic, technological, or stakeholder conditions.

In the broader context of the Special Issue, this paper represents the Multi-Criteria Decision-Making (MCDM)-oriented branch of DSS research. It reminds us that decision support is not only about prediction, but also about ranking, prioritization, and transparent evaluation of alternatives.

3.2. Financial Decision Support

In [12], the authors propose an Internet of Behaviors (IoB) ecosystem for enhanced financial decision-making. Financial markets are characterized by volatility, noise, and behavioral factors. By incorporating sentiment and behavioral information, the proposed IoB ecosystem moves beyond purely technical or historical-price-based forecasting. Specifically, the proposed system integrates market data, social-media-derived behavioral signals, sentiment analysis based on the Bidirectional Encoder Representations from Transformers (BERT) model, technical indicators (such as moving average, z-score and momentum), a multi-layer Long Short-Term Memory (LSTM) forecasting model and dynamic portfolio management mechanisms to support decisions in dynamic environments.

The role of explainability is also central. Financial DSSs must support trust because users need to understand why a recommendation or forecast is produced. The paper explicitly addresses this issue by introducing temporal XAI techniques (such as TimeSHAP and TIME) to interpret the contribution of features over time. This is particularly relevant for time-series DSSs, where explanations must account not only for feature importance but also for temporal dependencies.

The empirical results show strong predictive performance on Tesla, Inc. stock returns, including a reported directional accuracy of 95.24%, and the portfolio management component translates forecasts into trading strategies and simulated financial outcomes.

This paper provides two important contributions. First, the proposed framework combines temporal forecasting with global and local interpretability mechanisms that may support user understanding and appropriately calibrated trust. Second, the paper shows that successfully capturing short-term noise is challenging. A possible improvement would be incorporating additional market contexts, such as order book depth or macroeconomic indicators, to refine local trend forecasting. However, the reported directional accuracy is remarkably high and should therefore be interpreted cautiously. The evaluation focuses on a specific stock, data period, and experimental pipeline, and the reported result cannot be directly generalized to other assets or market regimes. Moreover, unusually strong financial forecasting results require particularly careful protection against temporal leakage, look-ahead bias, and overfitting. Although the study describes a temporally structured forecasting workflow, independent replication and walk-forward evaluation across multiple assets and market conditions would be necessary to establish the robustness of the reported performance.

Within the Special Issue, this paper illustrates the convergence of deep learning, natural language processing, behavioral analytics, explainability, and decision automation. It suggests that future DSSs may increasingly operate as adaptive pipelines, continuously collecting data, forecasting future states, generating actions, and learning from feedback.

3.3. Environmental and Policy Decision Support

In [13], the authors propose a DSS to mitigate the extinction of marine species in the Mediterranean Sea. Environmental systems are complex, nonlinear, and characterized by multiple interacting factors. In such contexts, purely data-driven models may be insuffi-

cient, especially when data are incomplete or when policy decisions require causal and systemic interpretation. To address these challenges, the proposed DSS integrates BESTEL (a modified PESTEL framework [28] where the political dimension is replaced with a biological dimension) with the Principal Component Analysis (PCA) [29] and Fuzzy Cognitive Map (FCM) [30] techniques. Expert knowledge from 34 specialists is used to identify key factors influencing extinction risk, while PCA supports dimensionality reduction. The use of FCMs is particularly appropriate because they allow experts to represent causal relationships among concepts and simulate possible system evolutions. The resulting FCM model simulates policy scenarios related to climate change and dam proliferation, identifying climate stressors and infrastructure-related pressures as dominant drivers.

The relevance of this contribution lies primarily in its ability to combine qualitative expertise and quantitative modeling within a single environmental decision-support framework. In addition, the use of FCMs enables scenario-based reasoning, making the system suitable not only for prediction but also for scenario analysis and policy prioritization. However, the insights generated by the FCM model depend on the experts involved, the elicited causal relationships, and the model parameterization. The reported outcomes should therefore be interpreted as model-based scenario analyses rather than as empirically validated forecasts of ecological change.

In the context of the Special Issue, this contribution expands the scope of AI-based DSS research toward socio-ecological systems. It highlights the importance of supporting decisions that involve environmental sustainability, uncertainty, and long-term consequences.

3.4. Biomedical Decision Support

In [14], the authors present SCRATCH-AI, a tool for predicting medical-grade honey wound-healing properties. The system uses interpretable machine learning methods, namely Bayesian networks [31] and decision trees [32], to classify honey-treated samples into wound closure categories, distinguishing treatments on the basis of the botanical origin and chemical–biological characteristics (such as antioxidant activity) of the applied honey dressing. The tool also includes a user-friendly graphical interface designed to support biologists and clinicians. The authors emphasize that the models provide non-trivial insights into causal dependencies among honey features and wound-healing properties, while remaining inherently interpretable.

This contribution is particularly relevant as it demonstrates the value of white-box AI in biomedical decision support. Indeed, in many biomedical applications, predictive accuracy alone is not enough. Researchers and clinicians need explanations that can be inspected, discussed, and linked to biological mechanisms. Bayesian networks and decision trees provide this interpretability by representing dependencies and decision rules explicitly. Moreover, the paper also addresses usability, which is often neglected in AI research [33]. A DSS is useful only if it can be adopted by its intended users. By providing a graphical interface aligned with laboratory workflows, SCRATCH-AI illustrates how AI models can be embedded into practical decision-support tools. Nevertheless, the reported results remain dependent on the available dataset and retrospective modeling process. Prospective assessment with intended users, independent samples, and clinically meaningful decision outcomes would be required before inferring operational or therapeutic effectiveness.

This contribution fits into a broader theme of the Special Issue: interpretable AI as a bridge between computational models and domain expertise. Rather than replacing expert reasoning, the system helps experts explore relationships among variables and generate biologically meaningful hypotheses.

3.5. Software Engineering Decision Support

In [15], the authors address software effort estimation using a SHAP-value-weighted case-based reasoning (CBR) model with improved Mixup data augmentation. Software effort estimation is a critical project-management task, and inaccurate estimates can lead to cost overruns, schedule delays, or poor resource allocation. The proposed framework combines CBR [34] (an approach to solving new problems based on the solution of similar past problems), stability-aware *SHapley Additive exPlanations* (SHAP) feature weighting [35] (a unified game-theoretic approach to interpreting model predictions), and a novel density-based Mixup augmentation [36] (a data-augmentation strategy used to enhance a model's adaptability, especially in case of training data scarcity, that expands the set of cases with new ones obtained by means of nearest-neighbor density information within the feature space). The framework is evaluated on seven benchmark datasets and is reported to reduce Mean Absolute Error (MAE) and Mean Squared Error (MSE) by up to 20.2% on average compared with baseline CBR models, while improving interpretability for project managers.

This contribution is notable as it combines three key ideas: learning from past cases through CBR, improving data quality through the density-aware Mixup, and explaining feature relevance through SHAP. Specifically, CBR is a natural approach for decision support because it mirrors human reasoning by analogy: new problems are solved by retrieving and adapting similar historical cases. However, traditional similarity metrics often fail to account for the actual predictive relevance of different features. By incorporating SHAP-based weighting, the authors make case retrieval both more accurate and more interpretable. The use of density-aware Mixup addresses another common problem in DSS applications: data scarcity. Many real-world decision domains do not have large, clean datasets. The proposed augmentation strategy attempts to generate more reliable synthetic samples by respecting the local data structure. The reported improvements are supported by experiments on multiple benchmark datasets, which strengthens the internal comparison with baseline CBR approaches. However, public benchmark datasets may not fully capture organizational differences, evolving development practices, or the data-quality constraints of industrial projects. Cross-company and prospective industrial validation would therefore be important to establish the practical generalizability of the approach.

This paper represents an example of hybrid decision intelligence, combining analogical reasoning, explainable AI, and data augmentation. It also points to a future in which DSSs will not simply apply AI models, but will integrate multiple mechanisms to improve data, reasoning, and explanation simultaneously.

3.6. Clinical Decision Support

In [16], the authors propose an intelligent diabetes prediction system based on hybrid Particle Swarm Optimization (PSO) [37] and Grey Wolf Optimizer (GWO) [38] feature selection and optimized machine learning. Their pipeline combines metaheuristic feature selection with several classifiers, including random forests [39], Support Vector Machines (SVMs) [40], K-Nearest Neighbors (KNN) [41], and logistic regression. The hybrid PSO-GWO algorithm uses alternating collaboration and an adaptive fitness function that adjusts to class balance, sample size, and dimensionality. The method is evaluated on three clinical datasets using stratified five-fold cross-validation. The authors report an average cross-validation accuracy of 83.36% at the feature-selection stage, an optimized random forest accuracy of 84.74%, and an average feature-count reduction of approximately 26%.

The importance of this contribution lies in its ability to address a central challenge in clinical DSSs: the need to build predictive models that are accurate, parsimonious, and potentially usable in practice. Feature selection is especially important in healthcare because irrelevant or redundant variables can reduce model performance, increase data

collection costs, and make interpretation more difficult. The hybrid PSO-GWO approach combines complementary search behaviors, aiming to improve the robustness of the feature-selection process. The paper also emphasizes validation. The authors explicitly discuss the importance of stratified cross-validation and bounded interpretation, avoiding exaggerated claims of universal generalizability. This is an important methodological stance for AI-based DSS research, where results are often sensitive to datasets, validation protocols, and preprocessing choices. The use of three heterogeneous datasets and stratified cross-validation provides a broader evaluation than a single-dataset experiment. Nevertheless, the reported results remain retrospective and dataset-dependent. External validation on larger clinical populations, calibration analysis, comparison with clinical baselines, and prospective assessment would be needed before considering deployment in clinical decision-making.

Within the Special Issue, this contribution represents the optimization-driven machine learning branch of intelligent DSSs. It shows how metaheuristics can support model construction, not merely final decision optimization.

3.7. Institutional and Accountable Decision Support

In [17], the author addresses accountable AI in institutional decision-support processes, such as eligibility assessment, case prioritization and resource allocation. The proposed *traceable bias auditing framework* follows a design-science approach and integrates four operational layers: prediction, case-level explanation, selective human review and structured audit recording. A logistic-regression classifier generates an initial recommendation, while explanation signals, proximity to the decision boundary and review-priority rules determine whether a case should be escalated for human assessment. The final decision, the reviewer's action and justification, and the relevant model information are then preserved in a persistent audit trail.

The framework is evaluated through a controlled (simulation-based) proof of concept involving 8000 synthetic institutional cases and historically biased labels. Three experimental conditions are compared: (1) baseline prediction, (2) prediction supplemented with explanation and (3) the complete architecture combining explanation, selective review and audit recording. Adding explanations alone improves reviewability and record completeness but does not substantially change predictive or fairness outcomes. By contrast, the complete architecture increases the reported F1 score from 0.781 to 0.795, reduces the demographic-parity gap from 0.070 to 0.010 and the equal-opportunity gap from 0.116 to 0.036, and increases audit completeness from 0.33 to 1.00 while escalating 4.8% of cases for human review.

This contribution is particularly relevant because it treats explainability not as an isolated interface feature but as one component of an accountable institutional workflow. Its main insight is that explanations acquire operational significance when they are connected to explicit review triggers, human responsibilities and records that allow for individual decisions to be reconstructed and contested. The study also broadens DSS evaluation beyond predictive performance by including fairness disparities, administrative review burden, override usefulness and audit completeness.

The reported findings should nevertheless be interpreted within the boundaries of the simulation. The cases, historically biased labels, review rules and reviewer behavior are synthetic, and the resulting improvements do not constitute evidence of effectiveness in a real public or organizational setting. Field validation would be required to examine institutional feasibility, reviewer consistency, affected-person contestability, organizational incentives, legal compliance and the possible re-emergence of bias after deployment.

Within the Special Issue, this paper represents the governance-oriented branch of AI-based DSS research. It complements the other contributions by showing that actionable decision support involves not only generating predictions, rankings, or scenarios, but also defining who reviews consequential recommendations, under which conditions, and how the complete decision process is documented.

3.8. Impact of AI Illiteracy on Decision Support

The study in [22] proposes an explainable Management Information Systems framework combining Partial Least Squares Structural Equation Modeling (PLS-SEM) with Natural Language Processing (NLP) to investigate how employees' AI illiteracy is associated with the quality of AI-supported strategic decisions. AI illiteracy is conceptualized as a multidimensional organizational vulnerability involving limited technical understanding, critical evaluation skills, and awareness of the limitations and risks of AI systems. Drawing on Adaptive Structuration Theory, Dual-Process Theory, and the Technology–Organization–Environment framework, the authors examine both the direct relationship between AI illiteracy and strategic decision quality and the mediating roles of automation bias, uncritical trust in AI, and cognitive offloading. Digital proficiency and AI-governance awareness are also considered as potential moderators.

The work adopts a cross-sectional mixed-method design based on 200 knowledge workers employed in Saudi Arabian public-sector organizations. Survey data are analyzed through PLS-SEM, whereas a corpus of 224 textual units, consisting of participants' open-ended responses and supplementary organizational documents, is examined using Sentence-BERT embeddings, BERTopic, semantic network analysis, and Aspect-Based Sentiment Analysis (ABSA). The measurement model is assessed through indicator loadings, Cronbach's alpha, composite reliability, average variance extracted, the Fornell–Larcker criterion, and the heterotrait–monotrait ratio. Structural relationships, mediation effects, and moderation effects are evaluated using 5000 bootstrap resamples. The NLP component is validated through topic coherence, diversity and stability analyses, independent expert assessment, inter-coder agreement, and comparison of automated sentiment predictions with a human-coded reference set.

This contribution is particularly relevant as it integrates structured survey evidence with multiple forms of semantic analysis, providing a richer interpretation than either PLS-SEM or NLP alone. Its theoretical integration of technological appropriation, cognitive reliance, and organizational governance offers a useful framework for analyzing vulnerabilities in human–AI decision-making. Moreover, the distinction between AI as a tool for augmenting human judgment and AI as a substitute for independent reasoning has clear practical relevance.

Nevertheless, the cross-sectional observational design cannot establish temporal order or causal relationships, despite the mediation terminology used in the model. The reliance on self-reported measures collected from the same respondents may introduce common-method and social-desirability biases. Generalizability is limited by the relatively small sample drawn exclusively from Saudi Arabian public-sector organizations. The textual corpus is also modest, and the inclusion of only 24 organizational documents limits the breadth of the semantic evidence. Finally, the sentiment model was originally trained on Twitter data and may not fully capture the language and contextual nuances of organizational discourse; although manual validation produced strong results, comparisons with domain-specific or multilingual models would provide a more robust assessment.

Within the Special Issue, this paper represents an example of a hybrid decision support system, and an interesting reflection on the impact of AI illiteracy, digital proficiency and AI-governance awareness on the quality of human decision-making.

3.9. Identification and Interpretation of Organizational Issues

The paper in [23] presents IntellicaHR, a LLM-assisted Organizational Decision Support System designed to integrate heterogeneous evidence generated through routine organizational activities. The system combines structured indicators—such as employee competencies, project performance, assessments, and participation—with unstructured information derived from reports, feedback, and workplace communication. Its objective is to transform fragmented organizational data into interpretable evidence that can support decisions. The McKinsey 7S Framework is used to organize evidence across interconnected organizational dimensions, while Deming's System of Profound Knowledge (SoPK) guides executive interpretation by emphasizing systemic relationships, variation, epistemic limitations, and human factors. Importantly, the system is intended to augment rather than automate managerial judgment, leaving decision authority and responsibility with human users.

The architecture integrates role-specific workflows, business-intelligence indicators, LLM-based semantic classification, fuzzy logic, organizational dashboards, and theory-grounded executive interpretations. Its operation is demonstrated through three literature-based synthetic scenarios. The resulting profiles show that IntellicaHR can distinguish different organizational conditions and generate role-specific analyses and recommendations consistent with the underlying evidence.

The evaluation combines a system-in-the-loop scenario demonstration with three supplementary analyses. First, the reliability of the semantic-classification component is examined using 20 independently human-labeled examples from the DynaSent benchmark. Across five repeated classification passes, the component achieves substantial repeatability (Fleiss' $\kappa = 0.802$), while testing with two equivalent prompt formulations demonstrates strong robustness to prompt variation (pooled weighted $\kappa = 0.921$). Comparison with the external labels yields 95.0% accuracy and a macro-F1 score of 0.947. Second, a controlled prompt ablation compares descriptive Business Intelligence (BI), generic LLM, and SoPK-grounded interpretations while holding the input evidence and generation settings constant. Third, 16 participants blindly evaluate the three alternatives for two organizational scenarios according to accuracy, relevance, evidence integration, recommendation usefulness, and decision-support value.

The SoPK-grounded interpretation receives the highest overall human-evaluation score ($M = 3.81$), followed by the generic LLM ($M = 3.54$) and BI-style baseline ($M = 3.52$). The overall difference is statistically significant, and the proposed interpretation significantly outperforms the BI baseline. It also receives the highest mean score for every individual criterion and is preferred in 17 of 32 scenario-level selections. However, its advantage over the generic LLM is not statistically significant after correction for multiple comparisons. The results therefore support the system's functional and interpretive coherence but do not demonstrate its superiority over general-purpose LLM analysis.

A principal strength of the paper is its integration of organizational theory, structured analytics, semantic processing, and human oversight within an implemented and transparent decision-support architecture. The multi-stage evaluation examines complementary properties, including scenario sensitivity, classification consistency, prompt robustness, and perceived usefulness. The controlled ablation is particularly valuable because it attempts to isolate the contribution of management-theory grounding, rather than attributing all improvements to the LLM itself. The emphasis on evidence attribution and human decision authority also provides an appropriate governance model for organizational applications.

Nevertheless, the evidence remains preliminary. The system-level evaluation relies on three deliberately constructed synthetic scenarios rather than real organizational data and therefore demonstrates pipeline coherence rather than diagnostic validity or organizational

effectiveness. The external classification experiment includes only 20 general-domain examples and a single model configuration, while the blinded evaluation involves only 16 participants and two scenarios. Furthermore, the fuzzy rules, thresholds, and indicator mappings are design choices that require domain-expert validation and adaptation before deployment.

Within the Special Issue, the paper represents the importance of organizational data as a data source for decision support, and provides evidence-linked, theoretically grounded explanations using the McKinsey 7S and Deming frameworks.

4. Discussion

Building on the descriptive and comparative analysis reported in Tables 1 and 2, this section addresses the first two research questions presented in Section 2 by synthesizing the methodological characteristics, strengths, limitations, and recurring patterns emerging across the seven contributions. In particular, the comparison of explainability mechanisms, AI/DSS techniques, domain requirements and decision-support outputs led to four cross-cutting themes: *explainability as a foundational requirement*, *hybrid intelligent architectures*, *domain-specific DSS design* and the *transition from prediction to actionable decision support*.

- *Explainability as a foundational requirement.* Explainability appears throughout the Special Issue in different forms. In [11], MCDM methods offer transparent ranking procedures in renewable energy planning. In [12], TimeSHAP and TIME are applied in financial forecasting. In [13], FCMs provide causal and scenario-based interpretability in environmental decision support. In [14], Bayesian networks and decision trees support biomedical interpretation. In [15], SHAP is used to weight features in software effort estimation. In [16], interpretability is supported indirectly through feature reduction and model parsimony, although no dedicated XAI method is applied. Finally, in [17], case-level explanations are connected to selective human review and structured audit records, showing that explainability can also function as an operational governance mechanism rather than merely as a means of communicating model behavior. This diversity confirms that XAI should be considered as a design principle that can be implemented through feature attribution, symbolic models, causal maps, decision rules, transparent criteria, or user-centered interfaces [42]. The appropriate form of explanation depends on the decision domain, the user, the type of model and the institutional procedures through which the recommendation may be reviewed or contested.
- *Hybrid intelligent architectures.* A second theme is hybridization. None of the contributions relies on a simplistic "one-model fits all" perspective. Instead, the papers combine multiple methods or system components: AHP and TOPSIS [11]; BERT, LSTM, and XAI [12]; BESTEL, PCA, and FCM [13]; Bayesian networks and decision trees [14]; SHAP, Mixup, and CBR [15]; PSO and GWO [16]; and prediction, case-level explanation, selective human review, and audit recording [17]. This confirms a broader trend in AI-based DSS research: real-world decision problems often require multiple forms of intelligence [8]. Hybrid DSSs therefore appear increasingly common in contemporary AI-based decision-support research.
- *Domain-specific DSS design.* The papers also show that effective DSSs must be tailored to domain needs. A renewable-energy DSS must compare alternatives under multiple technical and economic criteria [11]. A financial DSS must handle temporal data, sentiment, volatility, and risk [12]. An environmental DSS must support scenario analysis and expert reasoning [13]. A biomedical DSS must provide explanations meaningful to laboratory and clinical users [14]. A clinical DSS must consider validation, parsimony, and interpretability [16]. An institutional DSS must support fairness

assessment, contestability, selective human intervention, traceability and case-level reconstruction [17]. Thus, effective AI-based DSSs cannot be designed as generic predictive engines. Rather, they must reflect the structure, constraints, and decision practices of the target domain.

- *Transition from prediction to actionable decision support.* Several contributions go beyond prediction. Specifically, the work in [11] ranks design alternatives. The work in [12] translates forecasts into portfolio strategies. The work in [13] simulates policy scenarios. The work in [14] supports biological interpretation and potential therapeutic planning. The work in [15] provides project managers with feature-based insights. The work in [16] reduces variables for more parsimonious clinical prediction. Finally, the work in [17] transforms model outputs into reviewable institutional decisions supported by escalation rules, human justification and an auditable record. This shift from prediction to actionable and accountable support is essential, because strong predictive performance alone is insufficient when decisions must also be understood, justified, reviewed, contested and reconstructed.

These four themes should not be interpreted as independent characteristics. Rather, the comparison suggests that they are closely interconnected. Domain-specific requirements influence both the architecture of a DSS and the type of explanation that is meaningful: temporal explanations are relevant to financial forecasting [12], causal scenario representations to environmental policy [13], intrinsically interpretable models to biomedical analysis [14], and reviewable explanations with persistent records to institutional governance [17]. Hybridization provides the architectural mechanism through which these requirements are addressed, by combining prediction with ranking, knowledge representation, optimization, explanation, or human intervention [11–17]. Explainability, in turn, contributes to the transition from analytical output to actionable support by making rankings, predictions, scenarios, and recommendations more inspectable and accountable. The contributions can therefore be read not simply as seven domain-specific applications, but as different realizations of a common progression from isolated analytical models toward integrated socio-technical decision-support workflows.

Comparative Methodological Insights

The seven contributions address different decision-support objectives and consequently rely on heterogeneous evaluation strategies. Serrano-Gomez et al. [11] assess rankings obtained through alternative weighting and MCDM procedures; Moustati et al. [12] evaluate financial forecasting through error measures, directional accuracy, and simulated portfolio outcomes; Kokkinos et al. [13] examine the responses of an expert-driven FCM under alternative environmental policy scenarios; Martinotti et al. [14] evaluate classification performance and interpretability; Li et al. [15] compare software-effort estimates across benchmark datasets; Ziane et al. [16] assess classification performance, feature reduction, runtime, and statistical significance; and Alhalangy [17] evaluates predictive performance, group-fairness gaps, review burden, override precision, and audit completeness under simulated operating conditions. Because the studies address different decision tasks, use heterogeneous data and validation protocols, and report non-equivalent evaluation measures, their numerical results should be interpreted within the context of each individual contribution rather than compared directly.

A broader distinction emerges between model- or task-level evaluation and decision-support evaluation. Most contributions assess analytical performance, ranking consistency, scenario responses, or predictive accuracy. The institutional governance study [17] constitutes a partial exception because it also considers fairness, escalation burden, override precision, and audit completeness; however, its evaluation remains simulation-based and does

not involve real institutional users or field deployment. Overall, none of the seven studies reports a real-world controlled evaluation of sustained effects on human decision quality, decision time, calibrated trust, or organizational outcomes. Future AI-based DSS research should therefore complement model-performance measures with user-centered, decision-centered, and deployment-oriented evaluation. The comparison therefore suggests an important asymmetry: the architectural and methodological sophistication of AI-based DSSs has advanced more rapidly than their validation at the level of real-world decision processes and outcomes.

5. Open Challenges and Future Research Directions

In this section, we discuss open challenges and possible future directions in AI-based DSS research. This section addresses the third research question presented in Section 2 by examining which recurring gaps identified across the Special Issue contributions motivate plausible future directions for AI-based DSSs. These directions represent forward-looking interpretations derived from three complementary axes: (a) the cross-cutting themes emerging from the published papers (see Section 4), (b) recurring open issues suggested by these contributions (e.g., user-centered explanation and usability [12,14,15,17]), and (c) recent developments in the broader AI and DSS literature (e.g., explainable AI for DSSs [9,43]).

Table 3 summarizes the open challenges and future research directions we identified through editorial synthesis.

In particular, for each gap observed across the Special Issue contributions (column "Gap"), the table reports the evidence provided by the relevant contributions (column "Evidence"), the authors' interpretation explaining why this evidence motivates a broader research opportunity (column "Interpretation"), the corresponding future research direction (column "Direction"), and the main challenges that should be addressed to advance that direction (column "Challenges"). The "Interpretation" column does not report conclusions explicitly stated in the individual papers; rather, it makes transparent the inferential step connecting the observed evidence to the proposed future research direction. The strength of the connection between the observed gaps and the proposed future directions varies across the table. Specifically, neuro-symbolic DSSs and collaborative DSSs remain relatively close to methodological combinations, human involvement and multi-stakeholder requirements reflected in the Special Issue contributions [11,13–17]. The governance mechanisms proposed in [17] also provide a more direct foundation for the human-oversight, traceability, and accountability requirements associated with agentic and LLM-based DSSs. Nevertheless, Generative AI, LLM-based DSSs, agentic DSSs and digital twins remain broader forward-looking extrapolations, because these technologies were not themselves directly investigated in the seven studies.

The following discussion complements Table 3 by outlining the broader opportunities and research challenges associated with each proposed direction.

Table 3. Summary of open challenges and future directions in AI-based DSS research.

Gap	Evidence	Interpretation	Direction	Challenges
Limited generation of new alternatives.	The renewable-energy DSS ranks predefined photovoltaic configurations [11]; the environmental DSS simulates predefined policy scenarios [13]; and the software-engineering DSS estimates effort for new cases [15].	These systems evaluate or predict within an existing decision space. Generative methods could extend them by proposing novel alternatives, provided that the generated outputs are constrained and validated using domain knowledge.	Generative AI	Hallucination, feasibility checking, and domain-grounded validation.
Limited conversational and adaptive explanation.	The financial system provides temporal explanations [12]; SCRATCH-AI combines interpretable models with a graphical interface [14]; the software-engineering DSS uses SHAP-weighted retrieval [15]; and the institutional DSS demonstrates that explanations become operationally meaningful when linked to review rules and traceable records [17].	Existing explanations remain tied to specific models or interfaces. Grounded LLMs could support interactive questioning and user-adapted explanations, but their outputs should be connected to validated models, explicit review procedures and traceable records rather than treated as self-sufficient justifications.	LLM-based DSS	Reliability, traceability, privacy, hallucination, and grounding.
Limited workflow autonomy.	The financial system integrates data acquisition, prediction, explanation, and portfolio actions [12]; the clinical system integrates feature selection, classification and optimization [16]; the institutional governance architecture coordinates prediction, explanation, selective escalation, human review and audit recording [17].	These multi-stage pipelines suggest opportunities for greater task autonomy, while the governance contribution shows that consequential actions require explicit authorization, escalation rules, human intervention and persistent auditability.	Agentic DSS	Human oversight, accountability, and safe delegation.
Limited synchronization with operational systems.	The renewable-energy DSS evaluates technical configurations [11], while the environmental DSS performs scenario-based simulation [13].	Both applications could benefit from continuously updated virtual representations linking analytical models to operational or environmental data.	Digital Twins	Data integration, synchronization, model validity, and computational cost.
Limited integration of learning and explicit reasoning.	The contributions combine CBR and SHAP [15], Bayesian networks and decision trees [14], BESTEL, PCA, and FCM [13], and PSO-GWO with machine learning [16].	These combinations are largely modular. Neuro-symbolic approaches could provide tighter integration between learned representations, explicit domain knowledge, and reasoning processes.	Neuro-symbolic DSS	Scalability, semantic consistency, integration complexity, and explainability preservation.
Limited support for collaborative decision processes.	Energy planning [11], environmental conservation [13], biomedical interpretation [14], and clinical decision support [16] involve decisions affecting multiple stakeholder groups, but stakeholder interaction is not explicitly modeled. The institutional study explicitly models interaction between automated recommendations and designated human reviewers [17], although broader negotiation among affected stakeholders is not represented.	Collaborative DSSs could make preferences, disagreement, negotiation, and consensus-building explicit components of the decision process.	Collaborative DSS	Conflict resolution, participatory design, and evaluation of group decision quality.

- *Generative AI for alternative generation.* Generative AI can be used not only to produce text, but also to generate design alternatives, policy scenarios, intervention strategies, and simulation inputs [44,45]. In AI-based DSSs, this capability could extend the decision space considered by human users. However, generated alternatives must be evaluated using rigorous criteria, constraints, and domain knowledge. Future research should therefore investigate how generative models can be combined with optimization methods, knowledge bases, simulation environments, constraint-checking mechanisms, and human validation. Such integration would help distinguish plausible and admissible decision alternatives from outputs that are merely syntactically coherent or statistically likely. This direction is motivated by the fact that several contributions in the Special Issue already move beyond prediction toward the generation or evaluation of actionable decision alternatives, such as PV technology selection [11], environmental policy scenarios [13], and software effort estimation support [15].
- *Large Language Models for decision support.* Large Language Models (LLMs) are likely to transform DSS interfaces. They can support natural language querying, explanation generation, report writing, scenario discussion, and conversational interaction with decision-makers [46]. However, their use in DSSs raises issues of hallucination, reliability, traceability, privacy, and accountability [47]. Future research should therefore examine how LLMs can be grounded in verified data sources, linked to structured decision models, constrained by domain knowledge, and integrated with traceable reasoning and citation mechanisms. Their role should be conceived primarily as an interaction and explanation layer around validated analytical components, rather than as an unverified replacement for them. This direction is connected to the usability and explainability requirements emerging from the SCRATCH-AI tool [14], the financial XAI-based DSS [12], and the SHAP-weighted CBR model for software engineering [15]. The governance-oriented contribution [17] further suggests that conversational explanations should be linked to explicit review responsibilities and persistent records, rather than treated as self-sufficient institutional justifications.
- *Agentic DSSs.* Agentic AI systems can autonomously collect information, monitor environments, execute subtasks, and coordinate with other agents [48,49]. In future DSSs, specialized agents could support different stages of the decision process, including data acquisition, risk assessment, explanation, optimization, and stakeholder communication. This may enable more autonomous or semi-autonomous decision-support workflows, particularly in dynamic environments where data and constraints evolve continuously. The challenge will be to maintain human oversight and accountability. Future agentic DSSs should therefore operate within explicit authorization boundaries and support monitoring, auditability, interruption, and human intervention. Research is also needed to determine which decisions can be safely delegated, which require prior approval, and how responsibility should be allocated when multiple autonomous components contribute to an outcome. This direction extrapolates from the adaptive and pipeline-oriented nature of the financial Internet of Behaviors ecosystem [12] and from the optimization-driven workflow proposed for clinical prediction [16]. The selective-escalation and audit architecture proposed in [17] provides a concrete example of the authorization, human-intervention, and traceability mechanisms that more autonomous DSS workflows would require.
- *Digital twins and real-time decision intelligence.* Digital twins (DTs) provide dynamic virtual representations of physical or organizational systems [50]. When combined with AI, they can support real-time monitoring, what-if analysis, predictive maintenance, scenario simulation and adaptive optimization [51,52]. Several domains represented in this Special Issue (e.g., energy, environment, finance, and healthcare)

could benefit from DT-enhanced DSSs. Future research should investigate how synchronization quality, model drift, incomplete observations, and computational costs affect the reliability of the resulting recommendations. This direction is particularly related to the environmental DSS [13] (where policy scenarios are simulated) and to the renewable-energy DSS [11] (where technical configurations are evaluated under multiple criteria).

- *Neuro-symbolic DSSs.* Neuro-symbolic AI combines neural learning with symbolic reasoning [53,54]. This direction is particularly promising for DSSs because it may combine the predictive power of machine learning with the interpretability and structure of knowledge-based systems. However, this integration does not automatically guarantee interpretability or robustness. Thus, future research should examine how learned and symbolic components can be validated both separately and jointly, how inconsistencies between data and encoded knowledge can be resolved, and how semantic coherence, scalability, and explanation quality can be preserved as system complexity increases. The hybrid architectures presented in this Special Issue (including CBR with SHAP [15], Bayesian networks with decision trees [14], FCM with PCA and BESTEL [13], and PSO-GWO with machine learning [16]) suggest that neuro-symbolic DSSs may become increasingly relevant.
- *Human-centered and collaborative DSSs.* Future DSSs should place human users at the center. This means designing systems that provide understandable explanations, support interactive exploration, adapt to user expertise and facilitate group decision-making [43]. Collaborative DSSs will be especially important when decisions involve multiple stakeholders with conflicting objectives. Future research should investigate how stakeholder preferences can be elicited and revised, how unequal expertise or decision power affects collaboration, and how group decision quality can be evaluated. Relevant measures should include not only computational performance but also fairness of participation, transparency of compromise, acceptance of outcomes, and the long-term effects of collaborative decisions. This direction is especially relevant for domains represented in the Special Issue, such as energy planning [11], environmental conservation [13], biomedical interpretation [14], and clinical decision support [16].

Beyond the above future directions, several challenges still remain open in AI-based DSS research:

- *Human factors and user-centered explainability.* Many XAI techniques provide technical explanations, but these are not always meaningful to decision-makers [55]. Future research should evaluate explanation quality from the perspective of domain experts and end users. The institutional contribution further shows that explanations alone may improve reviewability without changing fairness outcomes unless they are connected to explicit human responsibilities and decision procedures [17].
- *Robustness and generalizability.* Several AI-based DSS models perform well on specific datasets or scenarios, but real-world deployment requires robustness under distribution shifts, evolving environments, and incomplete data [56].
- *Ethical, legal, regulatory and governance considerations.* AI-based DSSs can influence high-stakes decisions. Bias, fairness, privacy, transparency, contestability, accountability and traceability should therefore be integrated into DSS design from the beginning [57]. The architecture proposed in [17] provides proof-of-concept evidence that fairness monitoring, selective review and structured audit trails can be operationalized within a decision workflow, although field validation remains necessary.
- *Operational deployment and organizational integration.* Practical DSSs must integrate with existing (and potentially heterogeneous) data sources, workflows, legacy systems, se-

curity requirements and accountability structures. This requires software engineering, user experience design, governance, and domain expertise.

- *Evaluation beyond model performance.* Accuracy, error measures and ranking consistency assess analytical components but do not fully establish the value of a DSS. DSSs should therefore be assessed in terms of decision quality, user trust, usability, organizational impact and long-term consequences. The institutional study illustrates this broader approach by jointly reporting predictive utility, group-fairness gaps, review burden, override precision and audit completeness [17]. Its simulation-based setting, however, also highlights the need to extend such evaluation to real users, affected individuals and organizational environments.
- *Data quality and representativeness.* The reliability of a DSS depends on the completeness, provenance, accuracy, and representativeness of its data. Future research should therefore include explicit data-quality assessment, provenance tracking, bias analysis, and clear communication of data limitations.
- *Reproducibility of hybrid decision pipelines.* Hybrid DSSs combine multiple components, from data preprocessing and ML models to optimization and interfaces. Consequently, reproducibility requires more than sharing the final predictive model. It demands full transparency regarding data transformations, component configurations, software dependencies, and evaluation protocols. Where feasible, both component-level and end-to-end validations should be reported separately.
- *Scalability and computational sustainability.* Combining AI, optimization, simulation, and explanation methods while maintaining computational complexity and cost within acceptable limits introduces significant challenges [58]. Future work should consider the trade-offs between analytical sophistication, scalability, responsiveness, and practical usability, particularly in real-time or resource-constrained settings.

Taken together, these challenges indicate that progress in AI-based DSSs will depend not only on more advanced models, but also on stronger validation, reproducibility, governance, deployment practices, and human-centered evaluation. The future directions outlined above should therefore be pursued as part of an integrated decision-support research agenda rather than as isolated technological developments.

6. Conclusions

The Special Issue "Artificial Intelligence and Decision Support Systems" provides a broad and timely overview of how AI is transforming decision support across domains.

The analysis conducted in response to the three research questions presented in Section 2 yields four principal insights. First, explainability is implemented through heterogeneous mechanisms (including temporal explanation methods, feature attribution, interpretable models, causal maps, transparent ranking procedures, and case-level explanations linked to institutional review and audit) and should therefore be evaluated in relation to specific users, decision tasks, and governance processes, rather than treated as a uniform system property. Second, hybridization emerges across all contributions as a practical response to the multidimensional requirements of decision support (encompassing not only combinations of analytical models but also the integration of prediction, explanation, human intervention and structured recording), although it also increases integration, reproducibility, and validation challenges. Third, the collection demonstrates a shift beyond isolated prediction toward ranking, scenario analysis, optimization, interpretation, action and accountable decision workflows. However, evidence regarding end-user impact and sustained deployment in operational environments remains limited. Fourth, the heterogeneity of decision objectives, datasets, validation protocols and evaluation measures

prevents direct quantitative comparison and calls for stronger external validation and decision-centered evaluation.

Although the papers published in the Special Issue cannot provide a representative or exhaustive account of the complete AI-based DSS field, they offer a heterogeneous cross-section of how different analytical, knowledge-based, optimization, and explainability methods can be combined to address domain-specific decision problems.

Looking forward, LLMs, generative AI, agentic systems, digital twins, and neuro-symbolic reasoning may further expand the capabilities of DSSs. However, these technologies must be integrated responsibly, with attention to trust, transparency, ethics, and human oversight. These future directions follow from explicit gaps identified in the Special Issue contributions (rather than as empirical conclusions of the Special Issue itself) and are further supported by the recent literature.

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