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Πρότυπα αλληλεπίδρασης ανθρώπου – ΤΝ σε Συνεργατικά Συστήματα Υποστήριξης Αποφάσεων: Μια συστηματική ανασκόπηση και διεπιστημονικές εφαρμογές

Patterns of human – AI interaction in Collaborative Decision Support Systems: A systematic review and cross-domain applications

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Abstract

Artificial intelligence (AI) is rapidly being integrated into collaborative decision support systems (CDSS), transforming decision-making in sectors such as health, education, industry, and public administration. The aim of this paper is to systematically review research on human–AI interaction in CDSS, following the PRISMA 2020 methodology. A total of 137 publications were examined and, after thematic analysis, classified into five fundamental collaboration patterns: (a) advisory/consultative, (b) co-creation, (c) dialogical/iterative, (d) multi-agent/group-based, and (e) autonomous/supervised. For each category, illustrative applications are described, along with challenges related to trust, transparency, and explainability. The findings indicate that CDSSs are evolving into dynamic, collaborative environments in which humans and AI assume fluid, complementary roles, underscoring the importance of active user participation and the provision of understandable explanations to enhance acceptance and credibility.

Keywords

Artificial Intelligence, Collaborative Decision Support Systems, Human–AI Interaction

Περίληψη

Η Τεχνητή Νοημοσύνη (ΤΝ) ενσωματώνεται ραγδαία στα Συνεργατικά Συστήματα Υποστήριξης Αποφάσεων (Collaborative Decision Support Systems - CDSS), μεταμορφώνοντας τη λήψη αποφάσεων σε τομείς, όπως η υγεία, η εκπαίδευση, η βιομηχανία και η δημόσια διοίκηση. Στόχος της παρούσας εργασίας είναι η συστηματική ανασκόπηση ερευνητικών προσεγγίσεων για την αλληλεπίδραση ανθρώπου–ΤΝ στα CDSS, με βάση τη μεθοδολογία PRISMA-2020. Συνολικά, εξετάστηκαν 137 δημοσιεύσεις, οι οποίες ταξινομήθηκαν μετά από θεματική τους ανάλυση, σε πέντε βασικά πρότυπα συνεργασίας: (α) συμβουλευτικό/υποστηρικτικό, (β) συν-δημιουργίας, (γ) διαλογικό/επαναληπτικό, (δ) πολυπρακτορικό/ομαδικό και (ε) αυτόνομο/εποπτευόμενο. Για κάθε κατηγορία, παρουσιάζονται ενδεικτικές εφαρμογές και προκλήσεις που σχετίζονται με την εμπιστοσύνη, τη διαφάνεια και την επεξηγησιμότητα. Τα ευρήματα δείχνουν ότι τα CDSS εξελίσσονται σε δυναμικά περιβάλλοντα συνεργασίας, με ρευστούς και συμπληρωματικούς ρόλους μεταξύ ανθρώπου και ΤΝ, υπογραμμίζοντας τη σημασία της ενεργής συμμετοχής των χρηστών και της παροχής κατανοητών εξηγήσεων για την ενίσχυση της αποδοχής και της αξιοπιστίας τους.

Λέξεις-κλειδιά

Τεχνητή Νοημοσύνη, Συνεργατικά Συστήματα Υποστήριξης Αποφάσεων, Αλληλεπίδραση Ανθρώπου – Τεχνητής Νοημοσύνης

Introduction

Artificial Intelligence (AI) increasingly augments Decision Support Systems (DSS), expanding the boundaries of human judgment and enabling faster, more reliable, and more transparent decision-making in critical domains. Within this landscape, Collaborative DSS (CDSS) are distinctive because humans and AI interact in real time, combining complementary capabilities within a bidirectional framework of cooperation. Recent work on human–AI interaction and hybrid-intelligence teaming underscores the promise—and design challenges—of such tight coupling (Amershi et al., 2019; Dellermann et al., 2021).

In CDSS, decision-making is dynamic: roles shift as tasks unfold, initiative can pass between human experts and AI agents, and responsibility is negotiated rather than fixed. Foundational perspectives highlight these issues via levels of automation—who does what, at which stage—and mixed-initiative principles—when and how initiative should transfer between human and system (Parasuraman et al., 2000).

Despite rapid progress, published studies on CDSS interactions remain fragmented across domains and vocabularies, complicating cross-field comparison and the distillation of actionable design lessons. Recent systematic work emphasizes that interaction protocols are often one-shot and inconsistently described, reinforcing the need for a data-grounded, cross-domain typology centered on agency (distribution of control/initiative) and mode of operation (how collaboration unfolds) (Gomez et al., 2025).

Responding to this gap, the present study empirically derives a classification of human–AI interaction in CDSS from the published evidence. We address two research questions:

RQ1. Which distinct forms of interaction emerge in CDSS, when studies are thematically coded by degree of agency and mode of operation?

RQ2. Across which application domains, do these interaction forms occur and how are studies distributed across domains?

To address RQ1–RQ2, we conducted a PRISMA-guided systematic search (Page et al., 2021), followed by thematic analysis with the support of ChatGPT (Turobov et al., 2024). Building on this approach, Section 2 reviews the background and related work, Section 3 details the methodological procedures, and Section 4 presents the emergent collaboration patterns together with their distribution across domains. These findings are then discussed in Section 5, which highlights key implications and challenges, while Section 6 offers the concluding remarks of the study.

Literature Background

The literature on CDSS has repeatedly sought to classify how humans and AI share agency and coordinate their mode of operation. Early work grounded classification in conceptual lenses—notably Levels of Automation and mixed-initiative principles—

which specify who performs each phase of decision making and when initiative should transfer between human and system (Horvitz, 1999; Parasuraman et al., 2000). Although not CDSS-exclusive, these lenses have been used to code decision-support setups by control allocation, initiative hand-offs, and oversight, providing a coarse taxonomy of interaction.

Subsequent research classified primary CDSS studies through systematic/scoping syntheses that extracted categories from how interaction unfolds in practice. Cross-domain reviews of AI-assisted decision making, for example, coded studies by ordering and depth of interaction—AI-first, AI-follow/second-opinion, request-driven, and dialogic/multi-step—and concluded that much current practice remains one-shot rather than genuinely collaborative (Gomez et al., 2025). In parallel, the hybrid-intelligence strand proposed design taxonomies for human–AI teaming (goal alignment, division of labor, learning flows, control/accountability), which have been applied to group-based CDSS to classify studies by team structure and knowledge flow (Dellermann et al., 2021; Smirnov et al., 2023).

A complementary line experimentally compared collaboration protocols within clinical CDSS (e.g., radiology, ECG reading)—AI as independent second reader, triage/pre-screening, human-first vs. AI-first review, and parallel/continuous support—treating the protocol itself as the taxonomic unit. These studies show that the same human–AI pairing can vary in accuracy, workload, and trust/reliance depending on ordering, synchrony, explanation level, and override rights (Cabitza et al., 2023; Chen et al., 2024; van Winkel et al., 2025). Taken together, prior efforts converge on a small set of cross-cutting axes—initiative/ordering, interaction flow, explanation and control rights, and single- vs. multi-actor decision populations—while still using heterogeneous terminology.

These converging insights set the stage for our systematic review, which applies thematic analysis to synthesize interaction patterns across domains.

Research Methodology

This study followed the PRISMA-2020 guidelines to ensure reliability and transparency. A systematic literature search was conducted in three internationally recognized databases—Scopus, Web of Science, and IEEE Xplore— using complex queries that combined terms for collaborative decision support systems with ethics-related dimensions (e.g., transparency, accountability, fairness, privacy), as these aspects are closely tied to how human–AI collaboration is governed and evaluated. Queries were adapted to the syntactic requirements of each database. The search was carried out on June 3, 2025, yielding a total of 1,711 records (1,052 from Scopus, 365 from WoS, and 294 from IEEE Xplore).

After removing 405 duplicates via Zotero, 1,306 unique articles remained. To be included, a study had to (i) examine collaborative decision-making systems or environments with an explicit focus on ethical operation, and (ii) incorporate AI or algorithmic methods. In the first screening phase, 585 articles were excluded based on titles and abstracts, and a further 157 were excluded for not contributing substantially to the ethical debate, leaving 564 articles. Full texts could not be retrieved for 127 of these.

From the remaining 437 articles, a thematic analysis was conducted to verify compliance with the two selection criteria. This process combined GPT-assisted screening with detailed reviews by two independent human evaluators. Disagreements were resolved through independent re-review and short consensus meetings, with only a small minority of cases requiring input from a third reviewer. Although no formal inter-rater reliability coefficient was computed, agreement between evaluators was consistently high across the screening and coding stages. ChatGPT was used solely as a supportive tool for inductive coding (e.g., suggesting candidate codes and drafting neutral summaries), while all final coding decisions were taken by the human reviewers.

On this basis, each article was assigned to the predominant interaction pattern that best reflected its agency allocation and mode of operation. In total, 137 studies met the criteria, and from these, data were extracted to evaluate the different forms and modes of interaction between users and AI in CDSS, as well as to derive representative examples from different domains.

For clarity, the following Figure 1 illustrates the flow of the PRISMA method, as presented through the online tool by Haddaway et al. (2022).

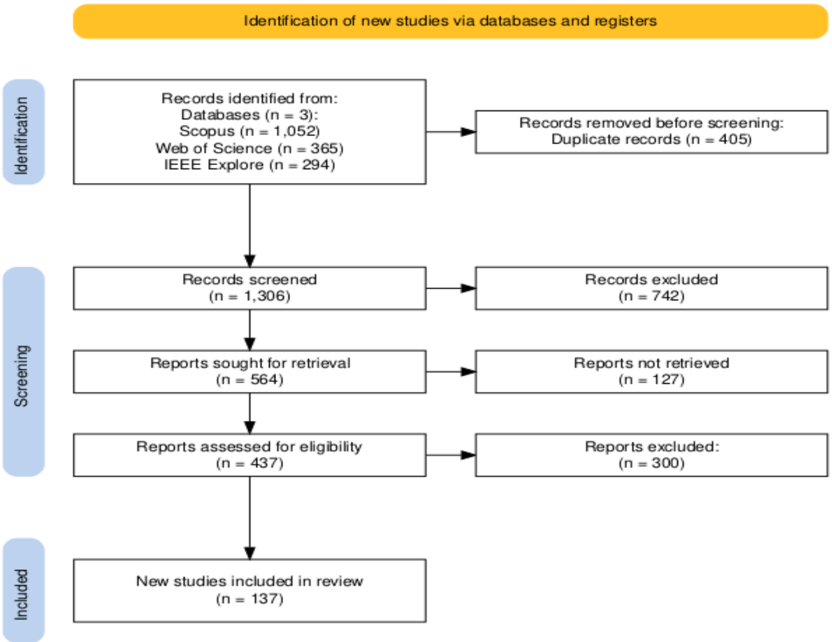

Figure 1: PRISMA Flow Diagram of the Article Selection Process

Identified Patterns of Human - AI Interaction in CDSS

Based on the thematic analysis of the 137 included studies, we identified five functional patterns of human–AI interaction in CDSS:

- **Advisory/Consultative:** AI provides recommendations or risk estimates; the human retains decision authority and validation/override.
- **Co-creation/Parameterization:** humans shape AI behavior (e.g., tuning parameters, constraints, training signals), influencing downstream recommendations.
- **Dialogical/Iterative:** human and AI engage in multi-step exchanges (clarifications, counter-proposals, explanations) until convergence.
- **Multi-agent/Group-based:** multiple humans and/or multiple AI agents contribute; judgments are combined via explicit aggregation or team processes.
- **Autonomous/Supervised:** AI initiates or executes decisions with high autonomy under human-on-the-loop or human-in-command safeguards.

The distribution of studies across these five patterns is summarized in the following Table 1.

Table 1. *Distribution of studies across interaction patterns in CDSS (n = 137)*

Interaction Pattern	Number of Studies	% of Total
Advisory / Consultative	53	38,7%
Co-creation / Parameterization	11	8,0%
Dialogical / Iterative	17	12,4%
Multi-agent / Group-based	53	38,7%
Autonomous / Supervised	3	2,2%
Total	**137**	**100%**

Advisory and Consultative CDSS

Advisory and consultative CDSS are among the most prevalent forms of human–AI collaboration, identified in 53 of the 137 studies analyzed (see Table 1). In this model, AI acts as a supportive mechanism that provides recommendations, predictions, or classifications, while humans retain final decision-making authority. Such systems are widely applied in diverse domains, from healthcare to law and industry, reflecting their adaptability and broad impact.

In healthcare, such systems are applied across multiple specialties. For instance, in pulmonology, the qXR system enables earlier detection of tuberculosis by analyzing chest X-rays and highlighting suspicious regions, reducing radiologist reading times by 4.4 minutes in normal cases without diminishing their interpretive authority (Hua et al., 2025). Similarly, in gastroenterology, real-time computer vision tools support endoscopists by marking potential neoplasms on the mucosa, improving detection and reducing missed lesions while remaining integrated into clinical workflows (Introzzi et al., 2024). In psychiatry, a different application emerges, where CDSS for autism spectrum disorder integrate video recordings, questionnaires, and developmental indicators to generate preliminary assessments, which clinicians contextualize with family and social information, thereby reducing assessment time and improving consistency (Zhu et al., 2025). Neurology provides another example, where AI systems aid prognosis in stroke recovery and cognitive decline, supported by explainability tools such as SHAP and counterfactual plots, which highlight key prognostic factors and facilitate communication among care teams (Lombardi et al., 2024). Finally, in oncology, CDSS dashboards provide predictions of treatment response and side effects, with explainability and uncertainty displays supporting clinician oversight. Beyond specific domains, evidence from a user study with 147 participants showed that, among those with negative attitudes toward AI (n = 43), trust in AI increased for 25/43 (58.1%) when uncertainty was visualized; 13/43 (30.2%) also found the visualization useful (Reyes et al., 2025).

Similar advisory and consultative models are applied in healthcare administration. Chen et al. (2024) developed a CDSS for categorizing incident reports using contextual embeddings with LIME, improving performance (F1-score from 0.631 to 0.753; accuracy from 84/126 (66.7%) to 95/126 (75.4%)) while enhancing transparency by highlighting key features influencing predictions. Likewise, Ammeling et al. (2025) describe a system for hospital admission prioritization and bed allocation, which combines algorithmic recommendations with interactive visualizations, while allowing administrators to adapt outputs to organizational needs.

Beyond medicine, advisory CDSS have also been explored in law and criminology, where they support judges, prosecutors, and law enforcement by analyzing case law, forensic evidence, or crime data. These systems provide advisory insights while leaving responsibility for final decisions to human actors, ensuring accountability in highly sensitive contexts (e.g., Portela et al., 2024; Farber, 2025).

Finally, in industry and services, advisory CDSS are employed to optimize production processes, logistics, and customer service. They integrate predictive analytics to improve efficiency, risk assessment, and allocation of resources. Representative studies (e.g., Vössing et al., 2022; Zhang and Hiekata, 2024) demonstrate their effectiveness in streamlining operations while maintaining human oversight in strategic decision-making.

CDSS with Co-creation and Parameterization

The co-configuration mode involves active human participation in shaping how AI systems operate. Rather than passively receiving recommendations, users define rules, set parameters, and may even contribute to training processes, aligning the system with their specific needs and values. This results in a dynamic, adaptive interaction often described as co-training. Within this review, 11 studies adopt co-

configuration as the primary interaction model, where users directly influence system behavior and outputs across healthcare, social domains, organizations, and education. In healthcare, customization is particularly critical, as outcomes directly affect patient well-being. Bhattacharya (2024) demonstrates the value of interactive XAI dashboards for chronic disease management, where tailored explanations enhanced trust and comprehension among professionals and patients. The participatory C-XAI framework developed by Naiseh et al. (2024) likewise showed that interdisciplinary co-configuration—bringing together doctors, pharmacists, and psychologists—improves trust calibration and reduces error risks by aligning explanations with professional needs. Similarly, in mental health, the Counselor-AI Collaborative Transcription and Editing System (Lee et al., 2025) enabled child psychologists to refine AI-generated transcripts of counseling sessions, reducing documentation burden and improving efficiency. Among 48 participants, 45/48 (93.75%) expressed a strong intent to continue using the system.

Comparable dynamics are observed in social and humanitarian fields. In social work, Tan et al. (2025) developed a participatory CDSS that adapts AI responses to cultural contexts and practitioner expertise, supporting documentation, intervention planning, and supervision, especially for younger professionals. In the humanitarian sector, Andres et al. (2020) presented an "expert-in-the-loop" CDSS for displaced populations, allowing practitioners to embed domain knowledge, adjust parameters, and adapt data and models to specific scenarios. This approach improved trust, transparency, and responsiveness, underscoring the value of active professional involvement in designing equitable interventions.

Finally, organizational and educational contexts provide further evidence of co-creation's benefits. Blaurock et al. (2024) studied collaborative intelligence systems in finance and HR, showing that employee feedback and control over AI processes enhanced transparency, perceived service quality, responsibility, and workplace engagement. In education, Duan et al. (2024) designed a CDSS for student performance prediction using SHAP-based explainability, where teachers identified key features, evaluated explanations, and corrected bias. Replacing the problematic *ExerciseScore* variable with *ExerciseScorePerMin* improved model performance (RMSE from 12.51 to 11.79; MAE from 8.37 to 7.50 on a test set of 280 students) and strengthened perceived trust and usability among end users.

Dialogical/Iterative CDSS

Dialogic interaction involves continuous, two-way communication between humans and AI, where decision-making unfolds iteratively through feedback, clarifications, and mutual adaptation. Identified in 17 studies (see Table 1), this interaction model is applied across domains such as social phenomena detection, healthcare, organizational management, and education, illustrating its versatility in enhancing collaboration and trust.

In the social domain, Ferguson et al. (2024) showed how AI-generated verbal explanations for ambiguous scenarios helped users assess implicit sexism by evaluating persuasiveness, relevance, and credibility, though participants often struggled to distinguish human- from AI-produced arguments. Iterative feedback is also central to AdaTest++ (Rastogi et al., 2023), where humans and AI jointly uncover model weaknesses, significantly improving error detection. Similarly, Bertaglia et al. (2023) developed a GPT-3.5–based CDSS for detecting sponsored social media content. Adding AI-generated explanations increased inter-annotator agreement (Krippendorff's Alpha from 54.98 to 63.58; +15.65%), absolute agreement (+17.2%), detection accuracy (+9.46%), and user confidence (7/8 participants, 87.5%).

Furthermore, in healthcare, dialogic CDSS support life-critical decisions by fostering interactive collaboration. The ALFABETO platform (Bergomi, 2024) generates personalized explanations and visualizations for physicians and patients, who can request clarifications or add feedback, thereby improving transparency and trust. Van Voorst (2025) conceptualizes such systems as "dialogic hybrid entities": ethnographic studies in Dutch and Estonian hospitals revealed that decision quality depended not only on AI accuracy but also on the depth of human–AI dialogue, with Dutch physicians critically verifying AI advice and Estonian clinicians often over-trusting it. In specialized diagnostics, SepsisLab (Zhang et al., 2024) exemplifies joint reasoning: clinicians interact with AI predictions of sepsis risk, exploring counterfactuals or rejecting outputs. This interactive process improved predictive performance (AUC from 0.79 to

0.89) while increasing test orders by only 9.6% (116.1 to 127.2 tests per patient) and led to lower uncertainty and higher clinical acceptance.

In workplace and HR management, dialogic CDSS facilitate hiring and performance evaluation. Ling et al. (2024) compared three AI involvement modes in cardiovascular screening—human-led, AI-led, and balanced collaboration—finding that balanced collaboration improved perceived fairness, especially for negative decisions (mean rating 3.32 vs. 2.95 under AI leadership; n = 268, 5-point scale). Beyond recruitment, Park et al. (2021) analyzed performance review systems combining algorithmic analysis with human oversight, where managers and employees engaged interactively with the outputs. Although these systems reduced bias and increased accountability, they also created six reported burdens (emotional, cognitive, bias, manipulation, privacy, and social), underscoring the importance of transparency and human intervention.

Finally, in education and scientific research, dialogical CDSS foster collaborative learning. Zhu et al. (2024) studied how 79 students collaborated with ChatGPT during problem solving, identifying three modes: human-led (44.3%), balanced (32.9%), and AI-led (15.2%). Although most preferred to lead, balanced collaboration yielded more positive outcomes, while lower perceived control (i.e., higher negative agency) predicted weaker performance ($b = –0.34$, $p = 0.006$). In scientific inquiry, Morrison et al. (2024) examined group decision-making with interactive XAI systems, showing that explanation quality directly affected both accuracy and trust: transparent, complete explanations improved outcomes, while incomplete ones undermined them.

Multi-agent and Group-based CDSS

Group-based or multi-agent interaction involves multiple users collaborating with AI in shared decision-making, where the system facilitates coordination, integration of perspectives, and collective intelligence. This model—identified in 53/137 (38.7%) studies according to Table 1 and tied with Advisory/Consultative as the most common form of human–AI collaboration—appears across healthcare, public governance, industry, crisis management, and transport.

In healthcare, multi-agent CDSS enhance multidisciplinary collaboration in diagnosis, treatment planning, and public health information management. Chatzisaak et al.

(2025) introduced a system where ChatGPT-4 served as a "digital advisor" in oncology boards, aligning with team decisions in up to 82.8% of cases (n = 100 patients), though performance declined in psychosocially complex scenarios. Similarly, MdtDSS (Zhu & Cao, 2020) supported physicians' voting on AI-recommended treatment plans, with over 70% consulting the system's suggestions, while routine case discussions were shortened to an average of 4.36 minutes. More advanced designs include the CARE system (Li et al., 2025), which integrates knowledge graphs and retrieval-augmented generation within a multi-agent framework, achieving 0.90 accuracy on BioASQ and receiving broadly positive evaluations in a user study with 150 healthcare professionals. At the systemic level, TriIntel (Zhang et al., 2024) integrated deep learning, GPT-4, and human crowdsourcing for health-related social media analysis, improving accuracy from 66.1% to 72.1% (+6.0 percentage points) compared to the best baseline. For procedural consensus, Zhang et al. (2025) developed the LSGDM model, which dynamically allocates AI as decisive, equal, or auxiliary agent; in COPD diagnosis with 20 experts, the global consensus index improved from 0.74 to 0.91 while requiring fewer iterations to reach agreement.

In public governance and administration, multi-agent CDSS expand participation and counter bias in large-scale consultation. D-Agree (Haqbeen et al., 2021) supported 733 citizens in urban planning by structuring nearly 1,900 arguments through AI facilitation. In recruitment, Ensembling (Keppeler et al., 2025) balanced AI suitability scores with civil servant judgments, reducing bias and improving equity across 538 managers. In participatory budgeting, MARL-PB (Majumdar & Pournaras, 2023) modeled citizens as reinforcement learning agents, achieving consensus bundles with overlap rates of 0.62–0.72 compared to established voting methods. Finally, COLLAGREE (Yang et al., 2021) facilitated large-scale consultations, guiding participants through divergence, convergence, and consensus phases with 98% accuracy in offline validation of facilitation recommendations.

In industry and logistics, Lai & Rau (2025) studied dual leadership in quality control teams, showing that high structural input from AI combined with human care improved trust, satisfaction, and strategy diversity (30% of workers diverged from AI recommendations). Neurobiological evidence confirmed increased motivation when human guidance compensated for low AI structure. In supply chains, Vann Yaroson et al. (2025) showed that human–AI collaboration alone had no significant effect on sustainable performance or well-being, but when mediated by responsible AI principles, the effects became strong and positive (SCWB: $\beta = 0.492$, $p < 0.001$; SBP: $\beta = 0.419$, $p < 0.001$).

In emergency response and transport, multi-agent CDSS enable coordinated, high-stakes decision-making. HAC-ER (Ramchurn et al., 2016) combined humans and UAVs in crisis scenarios, achieving 65% prediction accuracy within 0.1 of optimal values and accelerating response times in simulations with 100+ participants. CERTT-RPAS-STE (Duan et al., 2024) distributed UAV roles (operator, navigator, photographer) between humans and AI, showing that long-term trust depended on communication and error correction rather than initial confidence (89% trusted AI more at first). In transport, Frasheri et al. (2022) simulated AI-controlled vehicles negotiating priority rights, exposing risks of unethical behaviors that worsened congestion. For urban planning, S-MCDA (Manzolli et al., 2025) brought citizens, experts, and agencies into hybrid simulations of cycling infrastructure expansion, improving transparency and bias mitigation. Lastly, Qin et al. (2024) applied cooperative game theory to traffic lights, reducing bus travel time by 24.6% overall (37.4% in city centers) without delaying cars, demonstrating fairness in agent–AI negotiation.

Autonomous/Supervised CDSS

Autonomous or supervised interaction describes cases where AI takes a high degree of initiative in decision-making, while humans mainly supervise, oversee, or intervene in critical situations. CDSS in this mode typically act automatically with minimal human input but preserve the possibility of oversight, feedback, or approval—especially in high-responsibility contexts. This review identified only three studies focusing primarily on this interaction pattern.

A first example is the autonomous drone pavement inspection system by Okamura and Yamada (2020). Here, drones follow preprogrammed routes and use AI with sensor and vision data to detect potholes, while operators supervise and may intervene. To manage misaligned trust, the system provides adaptive trust calibration cues, which improved correct user behavior by up to 20% and increased sensitivity to trust-related errors compared to traditional supervision.

Tolmeijer et al. (2022) investigated autonomy in ethically sensitive UAV scenarios for search-and-rescue and defense. They contrasted human-in-the-loop with human-on-the-loop settings, where AI could prioritize rescues or missions under uncertainty and only alert humans when oversight was required. Participants consistently trusted AI more for competence but humans more for moral judgment, attributed primary responsibility to human operators (with programmers and vendors also implicated in AI conditions), and nonetheless relied on AI recommendations at least as often as on human experts, showing no evidence of algorithm aversion.

Finally, Alm et al. (2020) introduce “Invisible AI-driven HCI” systems as an example of autonomous collaborative DSS, where AI unobtrusively adapts environments and automates micro-decisions based on behavioral and contextual data. Users retain override capacity for critical cases, while in everyday use such systems aim to reduce cognitive load and human error. The authors highlight potential applications in safety-critical and industrial contexts, showing how autonomy can be combined with human override to preserve accountability.

Discussion

This systematic review developed a structured typology of human–AI interaction in CDSS, identifying five recurring patterns: advisory/consultative, co-creation, dialogical/iterative, multi-agent/group-based, and autonomous/supervised. These patterns illustrate a shift from recommendation-driven systems toward more interactive and adaptive models of collaboration.

The analysis showed that advisory and group-based systems are most prevalent, reflecting the continued emphasis on supporting rather than replacing human judgment. At the same time, the emergence of dialogical and co-creative approaches signals a shift toward personalization, interactivity, and shared responsibility in decision-making. This trend suggests that CDSS are gradually evolving into adaptive environments where roles between humans and AI are fluid and complementary.

Across domains—including healthcare, education, governance, industry, and transport—this evolution is closely tied to explainability and user agency. Systems that provide clear, comprehensible justifications are more likely to foster trust and adoption, while human oversight ensures accountability. Yet tensions persist, such as explanation depth vs. cognitive load and trust calibration vs. over-reliance, indicating that no pattern is universally optimal.

At the same time, certain limitations must be acknowledged. The review was based on three major databases (Scopus, Web of Science, IEEE Xplore), potentially excluding relevant work from other sources or grey literature. The focus on CDSS with explicit ethical framing may also have left out hybrid or unconventional systems. Finally, the typology itself is interpretive: although the five categories capture dominant patterns, many real-world systems combine elements from multiple models, which constrains the generalizability of some conclusions.

Looking forward, future research should examine hybrid and adaptive forms of interaction that transcend fixed typologies, leveraging contextual awareness and real-time feedback. There is also a need for evaluation frameworks that assess not only technical performance but also human-centered factors such as agency, perception, and long-term trust. For practice, advisory/consultative CDSS suit routine oversight, dialogic and co-creative modes are preferable where personalization is critical, and group-based approaches fit multi-stakeholder domains. Implementation challenges include workflow integration, accountability governance, and training to calibrate user trust. Ultimately, advancing CDSS will require interdisciplinary collaboration, integrating technical innovation with ethical and social perspectives to ensure that such systems are transparent, equitable, and broadly accepted in practice.

Conclusions

This study synthesized evidence from 137 publications to map five key patterns of human–AI interaction in CDSS across domains. The findings highlight both the functional diversity of these systems—from advisory to autonomous—and the ethical and social dimensions that shape their use. Explainability, transparency, and user agency consistently emerged as central conditions for trust and acceptance. As CDSS continue to evolve, user-centered and ethically aligned design will be essential to ensure that these systems complement rather than replace human judgment.

References

Alm, C. O., Alvarez, A., Font, J., Liapis, A., Pederson, T., & Salo, J. (2020, October). Invisible AI-driven HCI Systems–When, Why and How. In *Proceedings of the 11th Nordic Conference on Human-Computer Interaction: Shaping Experiences, Shaping Society* (pp. 1-3). https://doi.org/10.1145/3419249.3420099

Amershi, S., Weld, D., Vorvoreanu, M., Fourney, A., Nushi, B., Collisson, P., ... & Horvitz, E. (2019, May). Guidelines for human-AI interaction. In *Proceedings of the 2019 chi conference on human factors in computing systems* (pp. 1-13). https://doi.org/10.1145/3290605.3300233

Ammeling, J., Aubreville, M., Fritz, A., Kießig, A., Krügel, S., & Uhl, M. (2025). An interdisciplinary perspective on AI-supported decision making in medicine. *Technology in Society*, *81*, 102791. https://doi.org/10.1016/j.techsoc.2024.102791

Andres, J., Wolf, C. T., Cabrero Barros, S., Oduor, E., Nair, R., Kjærum, A., ... & Madsen, B. S. (2020, April). Scenario-based XAI for humanitarian aid forecasting. In *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems* (pp. 1-8). https://doi.org/10.1145/3334480.3382903

Bergomi, L. (2024). Fostering Human-AI interaction: development of a Clinical Decision Support System enhanced by eXplainable AI and Natural Language Processing. Available at: https://ceur-ws.org/Vol-3793/paper_41.pdf

Bertaglia, T., Huber, S., Goanta, C., Spanakis, G., & Iamnitchi, A. (2023, July). Closing the loop: Testing chatgpt to generate model explanations to improve human labelling of sponsored content on social media. In *World Conference on Explainable Artificial Intelligence* (pp. 198-213). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-44067-0_11

Bhattacharya, A. (2024, May). Towards Directive Explanations: Crafting Explainable AI Systems for Actionable Human-AI Interactions. In *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems* (pp. 1-6). https://doi.org/10.1145/3613905.3638177

Blaurock, M., Büttgen, M., & Schepers, J. (2024). Designing collaborative intelligence systems for employee-AI service co-production. *Journal of Service Research*, 10946705241238751. https://doi.org/10.1177/10946705241238751

Cabitza, F., Campagner, A., Ronzio, L., Cameli, M., Mandoli, G. E., Pastore, M. C., ... & Gamboa, H. (2023). Rams, hounds and white boxes: Investigating human–AI collaboration protocols in medical diagnosis. *Artificial Intelligence in Medicine*, *138*, 102506. https://doi.org/10.1016/j.artmed.2023.102506

Chatziisaak, D., Burri, P., Sparn, M., Hahnloser, D., Steffen, T., & Bischofberger, S. (2025). Concordance of ChatGPT artificial intelligence decision-making in colorectal cancer multidisciplinary meetings: retrospective study. *BJS open*, *9*(3), zraf040. https://doi.org/10.1093/bjsopen/zraf040

Chen, H., Cohen, E., Wilson, D., & Alfred, M. (2024). A machine learning approach with human-AI collaboration for automated classification of patient safety event reports: algorithm development and validation study. *JMIR Human Factors*, *11*(1), e53378. https://doi.org/10.2196/53378

Chen, M., Wang, Y., Wang, Q., Shi, J., Wang, H., Ye, Z., ... & Qiao, Y. (2024). Impact of human and artificial intelligence collaboration on workload reduction in medical image interpretation. *NPJ Digital Medicine*, *7*(1), 349. https://doi.org/10.1038/s41746-024-01328-w

Dellermann, D., Calma, A., Lipusch, N., Weber, T., Weigel, S., & Ebel, P. (2021). The future of human-AI collaboration: a taxonomy of design knowledge for hybrid intelligence systems. *arXiv preprint arXiv:2105.03354*. https://doi.org/10.48550/arXiv.2105.03354

Duan, W., Zhou, S., Scalia, M. J., Yin, X., Weng, N., Zhang, R., ... & Tolston, M. (2024). Understanding the evolvement of trust over time within Human-AI teams. *Proceedings of the ACM on Human-Computer Interaction*, *8*(CSCW2), 1-31. https://doi.org/10.1145/3687060

Duan, X., Pei, B., Ambrose, G. A., Hershkovitz, A., Cheng, Y., & Wang, C. (2024). Towards transparent and trustworthy prediction of student learning achievement by including instructors as co-designers: A case study. *Education and Information Technologies*, *29*(3), 3075-3096. https://doi.org/10.1007/s10639-023-11954-8

Farber, S. (2025). AI as a decision support tool in forensic image analysis: A pilot study on integrating large language models into crime scene investigation workflows. *Journal of Forensic Sciences*, *70*(3), 932-943. https://doi.org/10.1111/1556-4029.70035

Ferguson, S., Aoyagui, P. A., Rizvi, R., Kim, Y. H., & Kuzminykh, A. (2024). The Explanation That Hits Home: The Characteristics of Verbal Explanations That Affect Human Perception in Subjective Decision-Making. *Proceedings of the ACM on Human-Computer Interaction*, *8*(CSCW2), 1-37. https://doi.org/10.1145/3687056

Frasheri, M., Struhar, V., Papadopoulos, A. V., & Causevic, A. (2022). Ethics of autonomous collective decision-making: the CAESAR framework. *Science and Engineering Ethics*, *28*(6), 61. https://doi.org/10.1007/s11948-022-00414-0

Gomez, C., Cho, S. M., Ke, S., Huang, C. M., & Unberath, M. (2025). Human-AI collaboration is not very collaborative yet: a taxonomy of interaction patterns in AI-assisted decision making from a systematic review. *Frontiers in Computer Science*, *6*, 1521066. https://doi.org/10.3389/fcomp.2024.1521066

Haddaway, N. R., Page, M. J., Pritchard, C. C., & McGuinness, L. A. (2022). PRISMA2020: An R package and Shiny app for producing PRISMA 2020-compliant flow diagrams, with interactivity for optimised digital transparency and Open Synthesis Campbell Systematic Reviews, 18, e1230. https://doi.org/10.1002/cl2.1230

Haqbeen, J., Sahab, S., Ito, T., & Rizzi, P. (2021). Using decision support system to enable crowd identify neighborhood issues and its solutions for policy makers: An online experiment at Kabul municipal level. *Sustainability*, *13*(10), 5453. doi: https://doi.org/10.3390/su13105453

Horvitz, E. (1999, May). Principles of mixed-initiative user interfaces. In *Proceedings of the SIGCHI conference on Human Factors in Computing Systems* (pp. 159-166). https://doi.org/10.1145/302979.303030

Hua, D., Petrina, N., Sacks, A. J., Young, N., Cho, J. G., Smith, R., & Poon, S. K. (2025). Towards human-AI collaboration in radiology: a multidimensional evaluation of the acceptability of AI for chest radiograph analysis in supporting pulmonary tuberculosis diagnosis. *JAMIA open*, *8*(1), ooae151. https://doi.org/10.1093/jamiaopen/ooae151

Introzzi, L., Zonca, J., Cabitza, F., Cherubini, P., & Reverberi, C. (2024). Enhancing human-AI collaboration: The case of colonoscopy. *Digestive and Liver Disease*, *56*(7), 1131-1139. https://doi.org/10.1016/j.dld.2023.10.018

Keppeler, F., Borchert, J., Pedersen, M. J., & Nielsen, V. L. (2025). How ensembling AI and public managers improves decision-making. *Journal of Public Administration Research and Theory*, muaf009. Available at: https://osf.io/download/67d7e12ad2cd30ce8000ee8f/

Lai, X., & Rau, P. L. P. (2025). AI as co-leader: Effects of human consideration and AI structure behaviors on leadership effectiveness and neural activation. *International Journal of Human–Computer Interaction*, *41*(9), 5694-5712. https://doi.org/10.1080/10447318.2024.2365029

Lee, H., Lee, J., Yang, M., Lee, D., Song, H., Han, Y., & Han, J. (2025, March). Counselor-AI Collaborative Transcription and Editing System for Child Counseling Analysis. In *Proceedings of the 30th International Conference on Intelligent User Interfaces* (pp. 425-445). https://doi.org/10.1145/3708359.3712081

Li, H., Cheng, X., & Zhang, X. (2025, April). Accurate Insights, Trustworthy Interactions: Designing a Collaborative AI-Human Multi-Agent System with Knowledge Graph for Diagnosis Prediction. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems* (pp. 1-15). https://doi.org/10.1145/3706598.3713526

Ling, B., Dong, B., & Cai, F. (2024). Applicants' fairness perception of human and AI collaboration in resume screening. *International Journal of Human–Computer Interaction*, 1-12. https://doi.org/10.1080/10447318.2024.2437235

Lombardi, A., Marzo, S., Di Noia, T., Di Sciascio, E., & Ardito, C. (2024, June). Exploring the usability and trustworthiness of AI-driven user interfaces for neurological diagnosis. In *Adjunct Proceedings of the 32nd ACM Conference on User Modeling, Adaptation and Personalization* (pp. 627-634). https://doi.org/10.1145/3631700.3665192

Majumdar, S., & Pournaras, E. (2023, September). Consensus-Based Participatory Budgeting for Legitimacy: Decision Support via Multi-agent Reinforcement Learning. In *International Conference on Machine Learning, Optimization, and Data Science* (pp. 1-14). Cham: Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-53969-5_1

Manzolli, J. A., Yu, J., & Miranda-Moreno, L. (2025). Synthetic multi-criteria decision analysis (S-MCDA): A new framework for participatory transportation planning. *Transportation Research Interdisciplinary Perspectives*, *31*, 101463. https://doi.org/10.1016/j.trip.2025.101463

Morrison, K., Spitzer, P., Turri, V., Feng, M., Kühl, N., & Perer, A. (2024). The impact of imperfect XAI on human-AI decision-making. *Proceedings of the ACM on Human-Computer Interaction*, *8*(CSCW1), 1-39. https://doi.org/10.1145/3641022

Naiseh, M., Simkute, A., Zieni, B., Jiang, N., & Ali, R. (2024). C-XAI: A conceptual framework for designing XAI tools that support trust calibration. *Journal of Responsible Technology*, *17*, 100076. https://doi.org/10.1016/j.jrt.2024.100076

Okamura, K., & Yamada, S. (2020). Adaptive trust calibration for human-AI collaboration. *Plos one*, *15*(2), e0229132. https://doi.org/10.1371/journal.pone.0229132

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., ... & Moher, D. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *bmj*, *372*. https://doi.org/10.1136/bmj.n71

Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model for types and levels of human interaction with automation. *IEEE Transactions on systems, man, and cybernetics-Part A: Systems and Humans*, *30*(3), 286-297. https://doi.org/10.1109/3468.844354

Park, H., Ahn, D., Hosanagar, K., & Lee, J. (2021, May). Human-AI interaction in human resource management: Understanding why employees resist algorithmic evaluation at workplaces and how to mitigate burdens. In *Proceedings of the 2021 CHI conference on human factors in computing systems* (pp. 1-15). https://doi.org/10.1145/3411764.3445304

Portela, M., Castillo, C., Tolan, S., Karimi-Haghighi, M., & Pueyo, A. A. (2024). A comparative user study of human predictions in algorithm-supported recidivism risk assessment. *Artificial Intelligence and Law*, 1-47. https://doi.org/10.1007/s10506-024-09393-y

Qin, H., Zhang, W., & Tian, R. (2024, May). Collaborative Control Method of Transit Signal Priority Based on Cooperative Game and Reinforcement Learning. In *2024 IEEE 4th International Conference on Electronic Technology, Communication and Information (ICETCI)* (pp. 537-542). IEEE. https://doi.org/10.1109/ICETCI61221.2024.10594507

Ramchurn, S. D., Huynh, T. D., Wu, F., Ikuno, Y., Flann, J., Moreau, L., ... & Jennings, N. R. (2016). A disaster response system based on human-agent collectives. *Journal of Artificial Intelligence Research*, *57*, 661-708. https://doi.org/10.1613/jair.5098

Rastogi, C., Tulio Ribeiro, M., King, N., Nori, H., & Amershi, S. (2023, August). Supporting human-ai collaboration in auditing llms with llms. In *Proceedings of the 2023 AAAI/ACM Conference on AI, Ethics, and Society* (pp. 913-926). https://doi.org/10.1145/3600211.3604712

Reyes, J., Batmaz, A. U., & Kersten-Oertel, M. (2025). Trusting AI: does uncertainty visualization affect decision-making?. *Frontiers in Computer Science*, *7*, 1464348. https://doi.org/10.3389/fcomp.2025.1464348

Smirnov, A. V., Levashova, T., & Shilov, N. (2023). Human-AI Collaboration Types and Standard Tasks for Decision Support: Production System Configuration Use Case. In *ICEIS (1)* (pp. 599-606). Available at: https://www.scitepress.org/Papers/2023/119874/119874.pdf

Tan, Y., Soh, K. X., Zhang, R., Lee, J., Meng, H., Sen, B., & Lee, Y. C. (2025, April). Empowering Social Service with AI: Insights from a Participatory Design Study with Practitioners. In *Proceedings of the Extended Abstracts of the CHI Conference on Human Factors in Computing Systems* (pp. 1-10). https://doi.org/10.1145/3706599.3719736

Tolmeijer, S., Christen, M., Kandul, S., Kneer, M., & Bernstein, A. (2022, April). Capable but amoral? Comparing AI and human expert collaboration in ethical decision making. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (pp. 1-17). https://doi.org/10.1145/3491102.3517732

Turobov, A., Coyle, D., & Harding, V. (2024). Using ChatGPT for thematic analysis. *arXiv preprint arXiv:2405.08828*. https://doi.org/10.48550/arXiv.2405.08828

van Voorst, R. (2025). Redefining intelligence: collaborative tinkering of healthcare professionals and algorithms as hybrid entity in public healthcare decision-making. *AI & SOCIETY*, 1-12. https://doi.org/10.1007/s00146-024-02177-7

van Winkel, S. L., Peters, J., Janssen, N., Kroes, J., Loehrer, E. A., Gommers, J., ... & Mann, R. M. (2025). AI as an independent second reader in detection of clinically relevant breast cancers within a population-based screening programme in the Netherlands: a retrospective cohort study. *The Lancet Digital Health*. https://doi.org/10.1016/j.landig.2025.100882

Vann Yaroson, E., Abadie, A., & Roux, M. (2025). Human-artificial intelligence collaboration in supply chain outcomes: the mediating role of responsible artificial intelligence. *Annals of Operations Research*, 1-35. https://doi.org/10.1007/s10479-025-06534-7

Vössing, M., Kühl, N., Lind, M., & Satzger, G. (2022). Designing transparency for effective human-AI collaboration. *Information Systems Frontiers*, *24*(3), 877-895. https://doi.org/10.1007/s10796-022-10284-3

Yang, C., Gu, W., Ito, T., & Yang, X. (2021). Machine learning-based consensus decision-making support for crowd-scale deliberation. *Applied Intelligence*, *51*, 4762-4773. https://doi.org/10.1007/s10489-020-02118-z

Zhang, S., Yu, J., Xu, X., Yin, C., Lu, Y., Yao, B., ... & Wang, D. (2024). Rethinking human-AI collaboration in complex medical decision making: a case study in sepsis diagnosis. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems* (pp. 1-18). https://doi.org/10.1145/3613904.3642343

Zhang, Y., & Hiekata, K. (2024). Human Decision Making Assisted by Artificial Intelligence: Electricity Demand Forecasting in Japan. http://doi.org/10.3233/ATDE240936

Zhang, J., Wang, N., & Tang, M. (2025). Human-AI coordination for large-scale group decision making with heterogeneous feedback strategies. *Journal of the Operational Research Society*, 1-21. https://doi.org/10.1080/01605682.2025.2466677

Zhu, G., Sudarshan, V., Kow, J. F., & Ong, Y. S. (2024, June). Human-Generative AI Collaborative Problem Solving: Who Leads and How Students Perceive the Interactions. In *2024 IEEE Conference on Artificial Intelligence (CAI)* (pp. 680-686). IEEE. https://doi.org/10.1109/CAI59869.2024.00133

Zhu, Y., Zhang, M., Fang, C., Fang, L., Liu, M., Long, Y., ... & Wang, S. J. (2025). AI Doctor for ASD: Physician Perceptions and Adoption Challenges in Autism Clinical Practice. *Proceedings of the ACM on Human-Computer Interaction*, *9*(2), 1-28. https://doi.org/10.1145/3710925

Zhu, N., Cao, J., Shen, K., Chen, X., & Zhu, S. (2020). A decision support system with intelligent recommendation for multi-disciplinary medical treatment. *ACM Transactions on Multimedia*

Computing, Communications, and Applications (TOMM), *16*(1s), 1-23. https://doi.org/10.1145/3352573

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