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Editorial

Engineering Informatics and Intelligent Systems: Scope, Vision, and a Research Agenda for an AI-Enabled Engineering Future

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ABSTRACT Engineering is entering a period in which data abundance, pervasive sensing, high-performance computing, and rapidly advancing artificial intelligence are reshaping how physical systems are conceived, analysed, operated, and governed. Yet the practical integration of AI into engineering remains uneven. Many current deployments are still model-centric rather than decision-centric: they optimise benchmark performance but remain weakly connected to domain knowledge, physical law, regulation, lifecycle information, and the accountability structures required in safety-critical practice. This inaugural editorial introduces *Engineering Informatics and Intelligent Systems* (EIIS) as a forum for research at the intersection of engineering data architectures, knowledge representation, intelligent computation, and socio-technical decision support. It argues that the field now requires a coherent research agenda organised around four pillars: data-enriched engineering systems and semantic interoperability; knowledge-informed intelligence that embeds physical and regulatory constraints; trustworthy and explainable decision support; and human–AI collaboration in engineering workflows. The editorial further identifies hybrid AI, semantic digital twins, and federated intelligent infrastructures as emerging frontiers that will define the next phase of the discipline. The aim is to clarify what kinds of intelligence are genuinely usable, governable, and valuable in real engineering contexts.

Keywords: Trustworthy AI, Knowledge-based Systems, Semantic Interoperability, Digital Twins, Human–AI Collaboration

1. Introduction: an epistemic shift in engineering

Engineering practice has historically relied on deterministic physical models, codified design procedures, prototyping, and accumulated expert judgement. That foundation remains indispensable. However, engineering systems are now also embedded in dense informational environments: sensor streams, digital design artefacts, maintenance logs, image archives, operational telemetry, regulatory texts, and platform-generated behavioural traces. As a result, engineering is no longer only a discipline of artefacts and equations; it is increasingly a discipline of information architectures, machine-interpretable knowledge, and adaptive decision systems.

This transition has been accelerated by recent progress in AI. The 2025 AI Index reports strong growth in private investment, rapid diffusion of AI use across organisations, and continued industrial concentration in frontier model development [1]. At the infrastructure level, Deloitte's 2026 enterprise survey suggests that organisations are moving beyond isolated pilots toward more mature architectures centred on "AI factories", edge deployment, hybrid cloud, and multimodal workloads [2]. These developments matter for engineering because they change what is technically feasible across the lifecycle of built assets, infrastructure, manufacturing systems, transport networks, and software-intensive cyber-physical systems.

At the same time, the limits of naive AI adoption are increasingly visible. Engineering decisions are rarely judged only by predictive accuracy. They are judged by safety, traceability, robustness under distribution shift, regulatory compliance, interoperability with existing workflows, lifecycle maintainability, and the capacity for responsible human oversight. This means that the decisive question for the field is no longer whether AI can generate impressive outputs. It is whether AI can be integrated into engineering epistemology: can it reason with structured domain knowledge, remain bounded by physical and legal constraints, expose the basis of its recommendations, and fit within accountable human institutions?

It is in response to this question that *Engineering Informatics and Intelligent Systems* is launched. EIIS is envisioned as a cross-disciplinary venue for research on the data, knowledge, algorithmic, and organisational foundations of intelligent engineering systems. The journal is particularly interested in full lifecycle thinking, from conceptual design and analysis to operation, maintenance, retrofitting, compliance, and continuous decision support. In that spirit, this editorial outlines a research agenda for the field.

2. From AI capability to engineering deployment

The present wave of AI progress has created genuine momentum for engineering applications. According to the 2025 AI Index, U.S. private AI investment reached \$109.1 billion in 2024, generative AI attracted \$33.9 billion globally, and reported organisational AI use rose to 78% in 2024, up from 55% in 2023 [1]. These figures do not by themselves prove engineering value, but they do indicate that AI is moving from marginal experimentation to mainstream organisational infrastructure.

For engineering informatics, the more significant development is architectural rather than purely economic. Deloitte's 2026 survey reports that more than 70% of respondents expect to operate AI factories at scale by 2028, with AI-at-the-edge deployments showing a similar growth trajectory [2]. This suggests that engineering AI will increasingly be deployed in distributed, latency-sensitive, multimodal, and lifecycle-integrated environments rather than as isolated cloud-hosted analytics tools. Examples include building operations, structural health monitoring, industrial diagnostics, autonomous transport, utility systems, and software engineering toolchains.

This shift has two implications. First, engineering researchers can no longer treat infrastructure as a neutral background condition. Data locality, hardware heterogeneity, energy cost, cybersecurity, model orchestration, and lifecycle maintenance are now part of the design space of intelligent systems. Second, the centre of gravity in engineering AI research should move away from frontier-model novelty alone and toward adaptation, integration, governance, and evaluation in domain-constrained contexts. The most valuable contributions may not be the largest models, but the best engineered systems.

3. Pillar I: data-enriched engineering systems and semantic interoperability

The first pillar of engineering informatics is the transformation of fragmented engineering data into interoperable, semantically structured information environments. Modern engineering projects generate heterogeneous artefacts across design, construction, operation, and maintenance. These include CAD and BIM models, schedules, enterprise databases, sensor logs, computer vision outputs, inspection reports, code repositories, and natural-language documentation. In most organisations, these remain distributed across incompatible software ecosystems and weakly aligned information models.

Ontology-based semantic integration offers one route beyond this fragmentation. Work on semantic data integration methods based on ontologies has argued for protocol-level and metadata-driven approaches that can normalise heterogeneous structures into shared conceptual frameworks [3]. More recent work has demonstrated federated virtualised knowledge graph architectures in which heterogeneous data sources are exposed through shared semantic layers rather than physically consolidated into monolithic stores [4]. This is particularly important for engineering, where legacy systems, vendor lock-in, and evolving schemas make full standardisation difficult.

Large language models are now beginning to participate in this semantic layer as translation and enrichment tools. In civil engineering, LLMs have been used to transform relational infrastructure data into formal semantic representations, showing potential for accelerating RDF generation and semantic enrichment workflows [5]. In BIM workflows, lightweight schedule-level semantic mapping methods are also demonstrating how cross-model data integration can be made more scalable and usable across project stages [6]. These developments point toward a future in which engineering information systems are not merely digitised, but semantically navigable and machine-actionable.

However, data integration is not solely a technical problem. Data quality remains a persistent bottleneck. As engineering decision pipelines become increasingly data-dependent, poor-quality data can silently propagate failure downstream. Recent work on digital nudging for data quality review is therefore notable because it reframes quality assurance as a socio-technical process involving human motivation, context, and behavioural design, not only automated validation [7]. This insight is highly relevant for engineering informatics: semantic architectures require not just ontologies and mappings, but disciplined practices of curation, review, and stewardship.

Taken together, these studies suggest that the first research frontier for EIIS lies in open, extensible, and operationally useful semantic infrastructures. Future work should address federated ontologies for engineering domains, machine-assisted schema alignment, multimodal semantic enrichment, and continuous data validation pipelines that remain viable in real organisational settings.

4. Pillar II: knowledge-informed intelligence under physical and regulatory constraints

Data-rich environments do not automatically produce engineering-grade intelligence. In safety-critical or high-consequence contexts, purely correlation-driven learning is often insufficient because it can exploit spurious signals, fail under distributional change, and generate outputs that violate physical law, regulatory logic, or engineering common sense. For this reason, the second pillar of the field is knowledge-informed intelligence.

Recent research provides several strong examples of this direction. In rotating machinery diagnosis, rule-guided transformers have combined compact neural architectures with logic tensor networks so that engineering rules act as differentiable supervision during training, yielding interpretable and context-adaptive fault diagnosis without additional inference-time cost [8]. In transport control, residual reinforcement learning has been combined with traffic-domain expertise so that expert rules define a stable baseline policy while the learned controller improves performance through constrained residual correction rather than unconstrained exploration [9]. These approaches reflect a broader methodological shift: instead of asking models to rediscover everything from data, they treat prior knowledge as a computational asset.

The same issue arises in compliance checking, where engineering knowledge is encoded not only in physics but also in standards, codes, and regulations. A recent systematic review shows that machine learning is increasingly being explored in automated code checking, but that the field still faces major challenges related to representation, interpretability, and generalisability [10]. Ontology-based work on structural fire safety requirements has shown how regulatory reasoning can be formalised over semantically enriched building representations [11]. More recently, knowledge-driven approaches have extended this agenda to the operational phase, where compliance depends not only on design intent but also on the changing conditions of real buildings, visual evidence, and the accessibility of safety-critical assets [12].

These studies make a larger point. Engineering AI becomes more credible when it is explicitly bounded by structured external knowledge: constitutive equations, geometric constraints, domain heuristics, causal assumptions, operational envelopes, or legal rules. EIIS therefore welcomes contributions on neuro-symbolic systems, physics-informed machine learning, regulation-aware reasoning, constrained optimisation, and knowledge graph-based inference. The key test is not simply whether knowledge is mentioned, but whether it is operationalised in a way that changes model behaviour, improves verifiability, or strengthens out-of-distribution reliability.

5. Pillar III: trustworthy and explainable decision support

Engineering decisions require trust, but trust in this context cannot be reduced to user preference or interface smoothness. It must be grounded in evidence that a system is transparent enough to interrogate, reliable enough to depend upon, and governable enough to deploy responsibly. This is why trustworthy and explainable AI constitutes the third pillar of the field.

A growing body of literature argues that trustworthiness must be approached as a multi-dimensional systems property. A recent overview synthesises trustworthy AI around human agency and oversight, fairness and non-discrimination, transparency and explainability, robustness and accuracy, privacy and security, and accountability [13]. In engineering settings, these requirements are not abstract ethical aspirations; they are operational design constraints. A control system, diagnostic model, or digital twin that cannot be explained, audited, or bounded is difficult to certify and even harder to defend in practice.

Explainability is therefore most useful when it is treated as an engineering design objective rather than an afterthought. Recent work on explainability by design in AI-driven control systems argues for embedding interpretability and traceability into system architecture from the outset [14]. Complementing this, a systematic review in IEEE Access reports that XAI techniques can improve user confidence and decision support, while also highlighting unresolved issues around evaluation standards, user-centred assessment, and long-term trust effects [15]. These findings are relevant because engineering users rarely need explanation for its own sake; they need explanation as part of verification, validation, debugging, accountability, and safe intervention.

This leads to an important distinction for EIIS. The journal is interested not only in post hoc explanation methods, such as attention maps or feature attributions, but also in mechanisms that improve epistemic discipline in intelligent systems. Examples include calibrated uncertainty estimates, formal rule traces, causal explanations, counterfactual analysis, explanation interfaces for maintenance and inspection, and workflows that integrate XAI into compliance review or incident analysis. The field must move beyond asking whether a model can explain itself and toward asking whether its explanations support defensible engineering action.

6. Pillar IV: human–AI collaboration in engineering workflows

The fourth pillar concerns the socio-technical reorganisation of engineering work. Intelligent engineering systems are rarely deployed into empty spaces. They enter existing institutions, professional roles, liability structures, and tacit knowledge cultures. For that reason, the future of engineering AI depends as much on collaboration design as on algorithm design.

Recent evidence challenges the simplistic assumption that combining humans and AI automatically yields superior performance. A large meta-analysis in *Nature Human Behaviour*, spanning 106 experiments and 370 effect sizes, found that human–AI combinations were on average worse than the better of humans or AI alone, although important gains were observed in particular task types, especially when collaboration matched complementary strengths [16]. This result is highly relevant to engineering. It implies that collaborative advantage is contingent, not guaranteed.

Field evidence from engineering and design practice supports this more nuanced view. An ethnographic NASA study identified three recurrent strategies of generative AI use among engineering and design professionals: intimate co-design, selective delegation, and minimal use [17]. These patterns show that collaboration is not a binary choice between "use AI" and "do not use AI". It is a question of which cognitive tasks are delegated, which remain under human control, and how professionals manage uncertainty, responsibility, and workflow disruption. In software engineering, Treude and Gerosa similarly propose a taxonomy of human–AI interaction types, ranging from code completion to conversational assistance, with implications for productivity, control, and trust [18]. At the strategic level, synthesis work in engineering design is increasingly framing human–AI hybrid intelligence as a design space requiring explicit coordination of capabilities, roles, and governance mechanisms [19].

For engineering informatics, the challenge is therefore not to maximise automation indiscriminately. It is to design workflows in which AI meaningfully augments professional judgement without eroding responsibility, situational awareness, or domain expertise. This includes collaborative interfaces, escalation logic, role-aware explanation, organisational controls, and empirical studies of how practitioners actually interact with intelligent tools over time. EIIS encourages contributions that treat human–AI collaboration as a first-class engineering problem rather than a downstream adoption issue.

7. Emerging frontier: hybrid AI and next-generation digital twins

Digital twins provide perhaps the clearest integrative vision for the future of engineering informatics. At their best, they combine physical models, observational data, semantic context, simulation, reasoning, and decision support into continuously updated representations of assets or systems. Yet much of the digital twin literature still reflects a descriptive or monitoring-oriented paradigm. The next phase of the field is likely to involve a transition from passive data mirrors toward semantically grounded, reasoning-enabled, and distributed intelligent twins.

Domain studies are already moving in this direction. In bridge engineering, recent work on data- and knowledge-driven digital twin modelling explicitly combines sensing, structural information, and knowledge mechanisms for smart operation and maintenance [20]. In the construction domain more broadly, systematic reviews emphasise the need for stronger lifecycle integration and more coherent digital twin frameworks for building management [21]. In parallel, reviews of hybrid AI and federated learning suggest that future intelligent infrastructures may rely on distributed learning architectures that preserve privacy, reduce communication burdens, and allow local adaptation across networked assets and devices [22]. Beyond engineering, review work in personalised medicine shows how multi-scale digital twins are being conceptualised as semantically rich and causally informed systems that integrate heterogeneous evidence across levels of analysis [23]. That cross-domain trajectory is instructive for engineering as well.

The implication is that next-generation digital twins should not be defined only by fidelity of representation, but by the quality of their intelligence architecture. A meaningful research agenda includes semantic interoperability, causal reasoning, uncertainty management, federated learning, explainable intervention support, and alignment with organisational decision processes. EIIS is particularly interested in work that connects digital twin research to practical engineering functions such as maintenance planning, anomaly triage, inspection support, safety assurance, resilience analysis, and retrofit decision-making.

8. A research agenda for EIIS

The vision set out above implies a specific editorial orientation. EIIS aims to publish work that does at least one of the following:

1. develops robust engineering information architectures, especially semantic, multimodal, or lifecycle-spanning data frameworks;

2. advances knowledge-informed AI methods that materially improve the reliability, interpretability, or constraint compliance of intelligent engineering systems;

3. provides rigorous approaches to trustworthy decision support, including explainability, uncertainty, verification, and governance;

4. studies human–AI collaboration in real engineering contexts, with attention to workflow design, role allocation, and institutional accountability;

5. demonstrates integrative intelligent systems, such as digital twins or decision-support platforms, that are both technically sophisticated and operationally credible.

Just as importantly, EIIS seeks to avoid a false dichotomy between "technical AI" and "engineering application". In the most valuable submissions, the methodological contribution and the engineering problem should discipline one another. Engineering should not appear merely as a showcase for generic AI, and AI should not be reduced to an off-the-shelf utility layer. The journal's intellectual centre lies precisely in the hard interface between the two.

9. Conclusion

The future of intelligent engineering systems will not be secured by benchmark gains alone. It will depend on whether the field can produce systems that are semantically integrated, physically grounded, regulation-aware, explainable, and usable within real professional workflows. That challenge is inherently interdisciplinary. It requires contributions from civil, mechanical, electrical, software, transport, and industrial engineering, as well as computer science, information science, design, and the social sciences.

EIIS is founded on the belief that engineering informatics now needs a venue that treats this challenge with methodological seriousness and practical ambition. The journal welcomes work that is computationally innovative, but also disciplined by the realities of engineering judgement, safety, and lifecycle responsibility. The most important advances in the coming decade may not come from making AI more spectacular, but from making intelligent systems more legible, more bounded, and more genuinely useful in the worlds where engineers actually work.

Submission Pathways and Article Types

EIIS supports multiple article formats aligned with distinct forms of contribution. This is to ensure that foundational methods, validated engineering systems, benchmark resources, practice-driven evidence, and forward-looking community guidance each have an appropriate scholarly vehicle. In this way, the journal's article types are intended to operationalise the intellectual scope outlined in this editorial.

Original Research Articles

Original Research Articles constitute the principal publication category of the journal. They are intended to report complete studies that make substantial and original contributions to engineering informatics and intelligent systems. Such contributions may take the form of new theories, computational methods, knowledge frameworks, models, system architectures, workflows, or rigorously validated engineering applications.

The central requirement is not merely improvement on a single performance metric, but the presentation of a reproducible, interpretable, and testable chain of evidence demonstrating why the proposed method or system is effective, under what conditions it remains effective, and where its applicability boundaries or failure modes may lie in complex engineering environments. EIIS particularly welcomes studies that integrate engineering knowledge, standards and regulations, physical consistency, and multi-source heterogeneous data processes. Authors are expected to describe clearly the engineering problem setting, data and knowledge sources, evaluation protocol, baselines, robustness analyses, and practical deployment implications. Manuscripts primarily centred on dataset release, benchmark construction, opinion-led discussion, or brief milestone reporting may be more appropriately considered under the journal's Benchmark and Resource, Perspectives, or Communication formats.

Review and Foresight Articles

Review and Foresight Articles are intended to synthesise and critically structure the development of an important research theme, while also identifying future directions for the field. EIIS welcomes contributions that move beyond descriptive literature aggregation to provide conceptual clarification, methodological comparison, and agenda-setting insight. Particularly encouraged are articles addressing the limits of purely black-box paradigms, the emergence of knowledge-driven and constraint-computable approaches, the evolution of trustworthy evaluation frameworks, and the broader transformation of engineering work under intelligent systems.

These articles should help the community respond to technological opportunities and engineering constraints in a proactive and organised manner. They may be commissioned by the editorial team, but high-quality unsolicited submissions or proposals may also be considered where they demonstrate strong scholarly value and clear relevance to the journal's mission.

Benchmark and Resource Articles

Benchmark and Resource Articles are intended to establish reusable community assets that enable fair comparison, transparent evaluation, and cumulative progress. Rather than limiting this category to dataset publication alone, EIIS views benchmark contributions more broadly as including curated datasets, multimodal corpora, challenge problems, annotated engineering cases, reference ontologies, evaluation suites, simulation environments, baseline implementations, and reproducibility toolchains.

EIIS places particular emphasis on resources that reflect the realities of engineering practice, including heterogeneous and multimodal data, explicit engineering constraints, realistic acceptance criteria, reproducibility requirements, and trustworthiness-oriented evaluation dimensions such as robustness, compliance, traceability, or uncertainty awareness. A typical benchmark or resource contribution should clearly define the engineering problem, scenario assumptions, data provenance and licensing, uncertainty or quality characteristics, reference baselines, and the evaluation metrics through which future methods may be compared. Such articles may be submitted directly and may also be actively solicited from industrial partners, major engineering projects, and broader research communities where shared infrastructure is especially needed.

Short Communications and Industry Communications

Short Communications are designed for the rapid dissemination of concise but meaningful advances. These may include a well-defined theoretical result, a focused methodological innovation, a compact experimental finding, a tool or workflow milestone, or a carefully delimited engineering case with broader significance. The aim is not incompleteness, but precision: a Short Communication should make one clear contribution and support it convincingly.

EIIS also welcomes practice-oriented communication from industry, public-sector organisations, and engineering practitioners. Such contributions may report deployment lessons, implementation barriers, validation experiences, data challenges, or emerging engineering needs that can inform future research. For launch-stage policy, these communications may be handled under a unified format, subject to concise length limits and clear evidential standards, while preserving sufficient flexibility for the journal to refine this category as the field evolves.

Perspectives

The Perspectives section is intended for field-shaping arguments on the future direction of engineering intelligence. EIIS is especially interested in perspectives that examine the transition from isolated model-level performance to system-level engineering capability. In many high-risk engineering settings, the core limitation is no longer the absence of powerful models, but the absence of intelligent systems that can be verified, audited, governed, and responsibly deployed. End-to-end black-box decision pipelines often introduce unacceptable risks, including unfaithful outputs, hallucination, missing evidence chains, poor traceability, and weak enforcement of engineering standards or physical consistency.

Accordingly, this section welcomes rigorous, testable, and reproducible perspectives and roadmaps rather than purely opinion-based commentary. Contributions should define the system boundary of the problem under discussion, identify plausible failure modes, and propose concrete pathways for embedding engineering constraints, physical consistency, auditable evidence chains, and trustworthy evaluation mechanisms into future architectures and workflows. Strong Perspectives papers should help the field move from broad aspiration to disciplined research direction.

References

[1] University, S. The 2025 AI Index Report. Technical report, Stanford Institute for Human-Centered Artificial Intelligence, 2025.

[2] Deloitte Center for Integrated Research. Deloitte's Enterprise AI Infrastructure Survey: A 2028 Outlook, 2026.

[3] Vysotska, V.; Berko, A.; Chyrun, L.; Chyrun, S.; Panasyuk, V.; Budz, I.; Shakleina, I.; Garbich-Moshora, O.; Andrusyak, I. Semantic Data Integration Methods Based on Ontologies in Intelligent Business Analytics Systems. In Proceedings of the Proceedings of the 8th International Conference on Computational Linguistics and Intelligent Systems (COLINS), 2024, Vol. 3722, *CEUR Workshop Proceedings*, pp. 457–489. https://doi.org/10.31110/COLINS/2024-4/024.

[4] Fareedi, A.A.; Gagnon, S.; Ghazawneh, A.; Valverde, R. Semantic Fusion of Health Data: Implementing a Federated Virtualized Knowledge Graph Framework Leveraging Ontop System. *Future Internet* **2025**, *17*, 245. https://doi.org/10.3390/fi17060245.

[5] Höltgen, L.; Zentgraf, S.; Hagedorn, P.; König, M. Utilizing Large Language Models for Semantic Enrichment of Infrastructure Condition Data: A Comparative Study of GPT and Llama Models. *AI in Civil Engineering* **2025**, *4*, 14. https://doi.org/10.1007/s43503-025-00055-9.

[6] Zhao, T.; Na, R. Semantic Mapping and Cross-Model Data Integration in BIM: A Lightweight and Scalable Schedule-Level Workflow. *Buildings* **2026**, *16*, 1347. https://doi.org/10.3390/buildings16071347.

[7] Alkadhi, B.; Hendley, R.; Bahsoon, R. A Gentle Push in the Right Direction: A Nudge-Based Framework for Data Quality Review in Software Engineering. *Interacting with Computers* **2026**, p. iwag003. https://doi.org/10.1093/iwc/iwag003.

[8] Hogea, E.; Onchiș, D.M.; Yan, R.; Zhou, Z. Rule Guided Transformers for Dynamic Knowledge Adaptation in Rotating Machinery Fault Diagnosis. *Advanced Engineering Informatics* **2026**, *72*, 104444. https://doi.org/10.1016/j.aei.2026.104444.

[9] Sheng, Z.; Huang, Z.; Chen, S. Traffic Expertise Meets Residual RL: Knowledge-Informed Model-Based Residual Reinforcement Learning for CAV Trajectory Control. *Communications in Transportation Research* **2024**, *4*, 100142. https://doi.org/10.1016/j.commtr.2024.100142.

[10] Alnuzha, M.; Bloch, T. The Role of Machine Learning in Automated Code Checking – A Systematic Literature Review. *Journal of Information Technology in Construction* **2025**, *30*, 22–44. https://doi.org/10.36680/j.itcon.2025.002.

[11] Fitkau, I.; Hartmann, T. An Ontology-Based Approach of Automatic Compliance Checking for Structural Fire Safety Requirements. *Advanced Engineering Informatics* **2024**, *59*, 102314. https://doi.org/10.1016/j.aei.2023.102314.

[12] Chen, D.; Chen, L.; Yang, Y.; Lu, Q.; Hancock, C.; Lock, R.; Sølvsten, S. A Knowledge-Driven Approach for Automated Fire Safety Compliance Checking in Operational Buildings. *Knowledge-Based Systems* **2026**, *336*, 115156. https://doi.org/10.1016/j.knosys.2025.115156.

[13] Kowald, D.; Scher, S.; Pammer-Schindler, V.; Müllner, P.; Waxnegger, K.; Demelius, L.; Fessl, A.; Toller, M.; Estrada, I.G.M.; Simic, I.; et al. Establishing and Evaluating Trustworthy AI: Overview and Research Challenges. *Frontiers in Big Data* **2024**, *7*, 1467222. https://doi.org/10.3389/fdata.2024.1467222.

[14] Jaziri, W.; Sassi, N. Explainable by Design: Enhancing Trustworthiness in AI-Driven Control Systems. *Mathematics* **2025**, *13*, 3805. https://doi.org/10.3390/math13233805.

[15] Wiratsin, I.O.; Ragkhitwetsagul, C. Effectiveness of Explainable Artificial Intelligence (XAI) Techniques for Improving Human Trust in Machine Learning Models: A Systematic Literature Review. *IEEE Access* **2025**, *13*, 121326–121350. https://doi.org/10.1109/ACCESS.2025.3575022.

[16] Vaccaro, M.; Almaatouq, A.; Malone, T.W. When Combinations of Humans and AI Are Useful: A Systematic Review and Meta-Analysis. *Nature Human Behaviour* **2024**, *8*, 2293–2303. https://doi.org/10.1038/s41562-024-02024-1.

[17] Ma, K.; Moore, G.; Shyam, V.; Villarrubia, J.; Goucher-Lambert, K.; Brubaker, E.R. Human–AI Collaboration Among Engineering and Design Professionals: Three Strategies of Generative AI Use. In Proceedings of the Proceedings of the ASME 2024 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference, 2024. https://doi.org/10.1115/DETC2024-143560.

[18] Treude, C.; Gerosa, M.A. How Developers Interact with AI: A Taxonomy of Human–AI Collaboration in Software Engineering. In Proceedings of the Proceedings of the 2025 IEEE/ACM 2nd International Conference on AI Foundation Models and Software Engineering (FORGE), 2025. https://doi.org/10.1109/Forge66646.2025.00033.

[19] Trappey, A.J.C.; Lee, C.H.; Wang, Z.; Li, F. Exploring Advanced Human–AI Hybrid Intelligence Solutions Now and Beyond: A Synthesis of the Special Issue Portfolio. *Journal of Engineering Design* **2026**. https://doi.org/10.1080/09544828.2025.2610794.

[20] Sun, Z.; Liang, B.; Liu, S.; Liu, Z. Data and Knowledge-Driven Bridge Digital Twin Modeling for Smart Operation and Maintenance. *Applied Sciences* **2025**, *15*, 231. https://doi.org/10.3390/app15010231.

[21] Nguyen, T.D.; Adhikari, S. Advancing Digital Twins for Building Lifecycle Management in Construction: A Systematic Literature Review. *Buildings* **2026**, *16*, 1151. https://doi.org/10.3390/buildings16061151.

[22] Moussaoui, J.E.; Kmiti, M.; Gholami, K.E.; Maleh, Y. A Systematic Review on Hybrid AI Models Integrating Machine Learning and Federated Learning. *Journal of Cybersecurity and Privacy* **2025**, *5*, 41. https://doi.org/10.3390/jcp5030041.

[23] Vallée, A. Multi-Scale Digital Twins for Personalized Medicine. *Frontiers in Digital Health* **2026**, *8*, 1753906. https://doi.org/10.3389/fdgth.2026.1753906.