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| REVIEW ARTICLE

Artificial Intelligence for High-Stakes Decision Support: Architectures, Applications, and Deployment Challenges

Shahadat Molla[1], and S M Zobayed[2]
[1] Department of Information Systems, California State University, Los Angeles, CA 90032, USA
[2] Department of Engineering Management, Westcliff University, 17877 Von Karman Avenue, 4th Floor, Irvine, CA 92614, USA
Corresponding Author: Shahadat Molla, **E-mail**: shadat.cse@gmail.com

| ABSTRACT

Artificial intelligence (AI) is increasingly embedded in consequential decision-making processes across healthcare, assistive technologies, smart infrastructure, agriculture, business analytics, cybersecurity, and sustainability. Unlike general-purpose AI deployments, high-stakes decision support demands not only predictive accuracy but also explainability, robustness, privacy, scalability, human oversight, and governance readiness. This structured critical review synthesizes to map the current landscape of AI for high-stakes decision support using a four-axis taxonomy: application domain, data modality, architecture family, and deployment concern. The review identifies six application domains, healthcare and biomedical decision support, human-centered and assistive AI, smart infrastructure and cyber-physical systems, agriculture and sustainability, business and enterprise decision support, and cybersecurity and distributed intelligence, and eight architecture families ranging from conventional machine learning and convolutional neural networks to vision transformers, graph neural networks, Bayesian models, generative AI, and federated learning systems. The synthesis reveals that while significant architectural advances have been made, deployment-critical properties such as uncertainty quantification, privacy-preserving inference, real-time feasibility on edge devices, and governance-aligned reporting remain inconsistently addressed. Future research must prioritize cross-domain benchmarking, trustworthy and auditable AI pipelines, human-in-the-loop frameworks, and evidence maturity standards appropriate for high-stakes contexts. This review provides an evidence-grounded taxonomy and actionable research agenda for researchers and practitioners to build the next generation of responsible AI decision-support systems.

| KEYWORDS

Artificial intelligence; High-stakes decision support; Trustworthy AI; Explainable AI; Human-in-the-loop AI; Federated learning; Graph neural networks; Vision transformers; Uncertainty quantification; AI governance

| ARTICLE INFORMATION

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1. Introduction

The deployment of artificial intelligence in consequential decision environments, those where an erroneous prediction or recommendation carries significant human, financial, or societal cost, has accelerated substantially over the past decade. Healthcare diagnosis, patient monitoring, infrastructure fault detection, agricultural disease management, credit risk assessment, and cybersecurity threat response all constitute high-stakes domains in which AI is increasingly positioned not as an experimental tool, but as an operational support system. The breadth of this deployment presents both an opportunity and a methodological challenge: no single architecture, modality, or evaluation framework can address the full spectrum of requirements encountered across these domains.

Existing reviews of AI in decision support tend to focus narrowly on a single domain, most commonly medical imaging or clinical prediction, while the cross-domain structural similarities and shared deployment challenges remain under-examined. A review that spans healthcare [49, 20, 26], assistive and neuro-affective AI [1, 2, 13], smart infrastructure and IoT [3, 9, 18], agriculture and sustainability [25, 70, 77], business analytics and enterprise AI [40, 42, 74], and cybersecurity [73, 78, 79] reveals recurring architectural patterns, deployment tensions, and governance gaps that are invisible when each domain is examined in isolation.

This review is motivated by three observations. First, the architecture families are most frequently employed in high-stakes applications, CNNs, vision transformers, ensemble methods, graph neural networks, and federated systems, each carry distinct tradeoffs between accuracy, interpretability, and deployment feasibility. Second, the dominant evaluation criterion of predictive accuracy is necessary but insufficient: robustness to distribution shift, resistance to adversarial inputs, uncertainty quantification, and privacy compliance are equally consequential in deployment environments. Third, the literature reveals growing recognition that human oversight is not an optional add-on but a structural requirement in high-stakes AI, particularly in domains such as autonomous robotics [16], clinical decision support [49, 71], and automated risk assessment [69]. This review addresses these gaps by constructing a structured cross-domain taxonomy, synthesizing architecture and deploying evidence, and identifying the research directions most critical for responsible AI decision support at scale. Figure 1 demonstrates the end-to-end pathway through which AI systems move from heterogeneous data sources to model-generated recommendations, human review, deployment monitoring, and governance feedback.

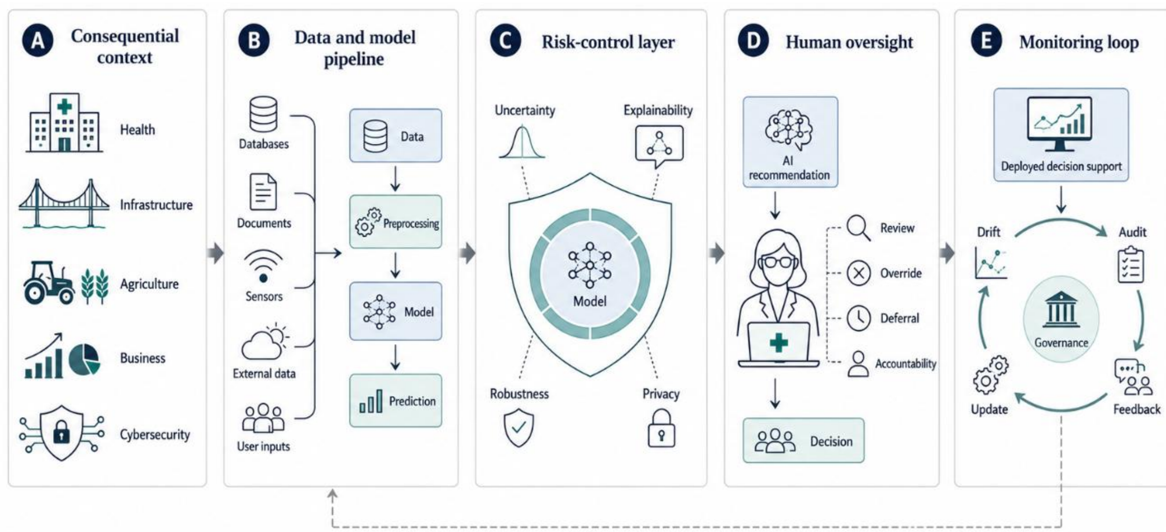

Figure 1. High-stakes AI decision-support lifecycle.

2. Review Scope and Taxonomic Framework

The corpus was assembled to span the principal application domains, architecture families, data modalities, and deployment concerns relevant to high-stakes AI decision support. Papers were selected to ensure representational balance across domains and to enable a structured evidence map rather than an exhaustive literature census. A four-axis taxonomy organizes the corpus. Axis 1 classifies papers by application domain: (i) healthcare and biomedical decision support, (ii) human-centered, neuro-affective, and assistive AI, (iii) smart infrastructure, IoT, robotics, and cyber-physical systems, (iv) agriculture, environment, and sustainability, (v) business, enterprise, and organizational decision support, and (vi) cybersecurity, privacy, and distributed intelligence. Axis 2 classifies by data modality—medical images, facial and affective signals, EEG and physiological signals, IoT and sensor streams, acoustic-emission and industrial signals, text and natural language, graph and knowledge-structured data, business and tabular data, and multimodal data. Axis 3 identifies the architecture family: conventional machine learning, CNN-based deep learning and transfer learning, vision transformers and attention-based models, graph neural networks and knowledge graphs, hybrid and ensemble systems, Bayesian and physics-guided models, generative and agentic AI, and federated/edge/privacy-preserving systems. Axis 4 catalogues the deployment concern: explainability, robustness, privacy, scalability, real-time feasibility, human oversight, governance, security, and safety/accountability. The taxonomy enables two forms of analysis: vertical analysis within a domain (tracking how architecture choices affect deployment readiness) and horizontal analysis across domains (identifying universal deployment tensions that transcend domain-specific context).

3. Architecture Families for High-Stakes Decision Support

3.1. Conventional Machine Learning and Structured Decision Models

Conventional machine learning encompasses logistic regression, decision trees, random forests, gradient boosting, and support vector machines applied to structured tabular data, remains highly relevant in high-stakes decision support, particularly in clinical, business, and financial settings where data are structured and interpretability is paramount. Work focusing on clinical decision support for heart disease prediction using structured patient data [49] illustrates the continued utility of classical ML pipelines when feature engineering and validation are handled rigorously. In business contexts, research on credit scoring for financially underserved populations [40], predictive analytics for project risk [42], retail demand forecasting [57], and small-business management including customer retention and financial forecasting [58] demonstrates that gradient-boosted ensembles and LSTM networks constitute practical, deployment-ready tools when the decision environment is data-rich but annotation-constrained. Multi-class sentiment classification [38] and data-driven sentiment extraction from drug reviews [39] further illustrate ML's relevance in text-based decision support. Market basket analysis for healthcare service bundling [43] and studies on customer satisfaction and business transactions in hospitality [59] represent the application of association and regression methods to organizational decision support at scale. Enhanced market trend forecasting with external factor integration [60] and ML-driven e-commerce pricing optimization [55] extend this cluster to demand-side business intelligence. Collectively, these works suggest that structured ML remains a foundational layer of high-stakes decision support, often more interpretable and computationally efficient than deep learning alternatives, though issues of fairness, feature reliability, and governance remain underspecified.

3.2. CNN-Based Deep Learning and Transfer Learning

Convolutional neural networks and their transfer-learned variants constitute the dominant architecture family in image-based high-stakes AI. The application range spans medical imaging, including multichannel lung cancer classification from CT data [20], early leukemia diagnostics via transfer learning [36], and aquaculture disease diagnosis using lightweight ResNeXt architectures [46] to agricultural disease detection and industrial inspection. Transfer learning is particularly prominent in domains characterized by limited labelled training data: the use of transfer learning for sleep stage classification under data-constrained conditions [47] illustrates how pre-trained feature extractors can be repurposed to clinically sensitive classification tasks. Facial emotion recognition systems, including a bidirectional Elman neural network approach [7] and a hybrid deep belief optimization system [8], similarly leverage learned feature representations from large facial datasets. The lightweight deep learning framework applied to concrete crack characterization using acoustic-emission signals [21] extends the CNN paradigm to industrial sensing, where real-time feasibility and sensor-data compatibility are critical. Across all these applications, the transfer learning strategy addresses data scarcity but introduces the risk of negative transfer and domain mismatch, both of which are deployment concerns requiring systematic evaluation.

3.3. Vision Transformers and Attention-Based Architectures

Vision transformers (ViTs) and their attention-based variants have emerged as a high-performing architecture family for image classification in high-stakes domains, progressively displacing purely convolutional approaches in medical imaging and precision agriculture. The dual-branch visual transformation framework developed for ASD classification [4, 1] illustrates how transformer architectures can model spatially distributed facial features more flexibly than fixed-receptive-field CNNs. In medical imaging, the hybrid vision transformer for prostate cancer classification in MRI images [48] and the LMVT hybrid vision transformer for lung cancer diagnosis [30] demonstrate that combining convolutional feature extraction with self-attention can improve both accuracy and explainability. The hierarchical Swin Transformer ensemble for breast cancer diagnosis [31] and Swin Transformer–driven cervical cell classification with web-based deployment [61] specifically demonstrates the compatibility of transformer architectures with decentralized and web-deployed screening workflows. In precision agriculture, MaizeFormerX, a lightweight cross-scale attention vision transformer [25], and the MaxViT-based soybean disease identification model [33] illustrate that transformer efficiency advances are beginning to close the gap with CNN-based lightweight models, enabling deployment on resource-constrained agricultural hardware. Global–local attention modeling for kidney disease classification from CT images [63] represents a further architectural refinement, combining coarse global context with fine-grained local feature attention that is particularly relevant for multi-class lesion discrimination. The convergence of explainability requirements with transformer attention maps [62] offers promising but still-maturing interpretability mechanisms.

3.4. Hybrid, Ensemble, and Multimodal Fusion Systems

Hybrid and ensemble systems are prominent in domains requiring both high accuracy and some form of post-hoc justification. The explainable deep stacking ensemble for brain tumor diagnosis [32] and the stacking ensemble with explainable AI for breast cancer diagnosis and web deployment [52] exemplify the combination of heterogeneous base learners with ensemble aggregation, achieving improved generalization while preserving the interpretability needed for clinical endorsement. The ensemble transformer with post-hoc explanations for depression and severity detection [27] extends this architecture to affective computing, where label ambiguity and subjective ground truth make ensemble uncertainty estimation particularly valuable. Multimodal fusion represents an important sub-category: the hybrid multi-modal emotion recognition framework based on InceptionV3DenseNet [6] and the vision-audio multimodal object recognition system using hybrid tensor fusion [29] address the challenge of integrating heterogeneous modalities without introducing cross-modal interference. The multimodal machine learning framework for privacy-preserving and scalable cancer diagnosis [51] is notable in that it combines fusion with privacy constraints, foreshadowing the next generation of privacy-aware multimodal clinical systems. The attention-enhanced deep learning framework for business strategy optimization [53] extends multimodal fusion principles to business intelligence, while the explainable transformer for cotton leaf diagnostics and fabric defect detection [28] applies them to dual-task agricultural and manufacturing inspection.

3.5. Graph Neural Networks and Knowledge-Graph Reasoning

Graph-structured data and knowledge-graph reasoning occupy a specialized but important niche in high-stakes AI, particularly where relational dependencies among entities carry decision-relevant information. The enhancement of acoustic-emission-driven gas-pipeline monitoring using graph neural networks [18] illustrates how GNNs can model the propagation structure of physical signals across networked sensor arrays, enabling more accurate fault localization than signal-level classifiers alone. Knowledge-graph and NLP integration for facilitating heuristic reasoning [17] addresses a different but complementary need: enabling AI systems to leverage structured domain knowledge in support of reasoning tasks that resist purely statistical approaches. The AddManBERT combinatorial triples extraction and knowledge-graph construction for additive manufacturing design support [23] demonstrates that BERT-based language models and knowledge graphs can be coupled to create semantic decision-support tools in specialized engineering domains. Together, these architectures suggest that relational and symbolic reasoning are not superseded by deep learning but rather constitute a complementary layer of high-stakes decision support, particularly in safety-critical industrial and engineering contexts.

3.6. Bayesian, Physics-Guided, and Uncertainty-Aware Models

Uncertainty quantification is a fundamental requirement in safety-critical systems, and Bayesian and physics-guided approaches represent the most principled available framework for this purpose. The physics-guided Bayesian neural network for sensor fault detection in wind turbines [54] is directly relevant: by embedding physical priors into the network architecture, the model addresses the twin challenges of sensor data sparsity and the need for calibrated uncertainty estimates in a safety-sensitive industrial context. This architecture family is underrepresented in the broader corpus, reflecting a maturity gap in the literature: while Bayesian deep learning and physics-informed neural networks have attracted substantial methodological attention, their integration into domain-specific high-stakes applications remains limited. The deployment implications are significant, systems that cannot quantify their own uncertainty cannot reliably support human oversight, particularly in contexts such as wind-energy management, structural health monitoring, and clinical diagnostics where false confidence carries severe consequences.

3.7. Generative, Agentic, and Enterprise AI

Generative AI and agentic systems represent the most recent and rapidly evolving frontier in high-stakes decision support. Generative AI in enterprise information systems for transforming business intelligence and strategic decision support [74] addresses the organizational embedding of large language model capabilities into enterprise workflows, a transition that introduces new questions of factual reliability, audit trails, and accountability. Automated risk assessment and collaborative decision-making AI in agile project management and stakeholder engagement [69] exemplifies agentic AI—systems that not only predict but also initiate decision workflows, coordinate among stakeholders, and adapt to feedback. AI-driven business analytics for IT strategy [66] and AI-enabled management information systems for economic resilience and governance [76] further illustrate the enterprise AI cluster, where real-time data integration, organizational agility, and governance compliance are simultaneously demanded. The sustainability framing of AI-ERP integration in dark factories [65] introduces additional complexity: autonomous industrial environments require AI systems that are not only accurate but also auditable, energy-efficient, and aligned with broader sustainability objectives.

3.8. Edge-Cloud, Federated, Privacy-Preserving, and Distributed AI

The deployment of AI at the edge of networks, on IoT devices, clinical sensors, and distributed infrastructure, introduces a distinct set of architectural constraints. Privacy-preserving behavior analytics for workforce retention [44] and the multimodal privacy-preserving cancer diagnosis framework [51] illustrate the operational demand for analytics that never expose raw personal data to centralized servers. The distributed intelligence and privacy-preserving deployment framework encompassing edge-cloud, 6G connectivity, and federated learning for secure and auditable decision support [79] represents the most comprehensive architectural response to this demand, integrating multiple privacy-preserving mechanisms into a unified deployment stack. Stacking ensemble-based breast cancer classification with real-time web deployment [52] and Swin Transformer cervical cell classification with web-based screening [61] demonstrate that deployment-readiness, including latency, user-interface integration, and cross-platform accessibility, is itself an architectural concern that must be addressed during model design, not as an afterthought. The intelligent cybersecurity framework integrating ML-driven data protection and threat intelligence [73], AI for data security and digital communication resilience [72], and the resilience-by-design framework [75] collectively constitute an emerging distributed AI security cluster in which privacy, auditability, and real-time threat response must be simultaneously maintained.

4. Application Domains

4.1. Healthcare and Biomedical Decision Support

Healthcare constitutes the largest and most architecturally diverse domain in the corpus. Cancer diagnosis applications span skin cancer [26, 62], lung cancer [20, 30], breast cancer [31, 32, 52], cervical cancer [35, 61], leukemia [36], and prostate cancer [48], collectively demonstrating that transformer-based, CNN-based, and ensemble architectures are all actively explored for oncological image analysis. The comparative analysis of explainable ML for cancer classification using cytological features [50] and the multimodal privacy-preserving cancer diagnosis framework [51] illustrate the dual push toward interpretability and privacy compliance that characterizes mature healthcare AI. Beyond oncology, kidney disease classification from CT images [63], Parkinson's disease screening via voice biomarkers [45], sleep stage classification with transfer learning [47], heart disease prediction from structured clinical data [49], and AI-integrated healthcare information systems for diabetes management [71] demonstrate the breadth of modality and architecture diversity within this domain. Sentiment analysis of online drug reviews [39] and market basket analysis for healthcare service bundling [43] extend decision support into health services research. The consistent emphasis on explainability across these works, reflected in post-hoc XAI methods, attention visualization, and transparent ensemble reporting, reflects clinical regulatory and professional requirements that AI recommendations be interpretable by clinicians. Neural network methods combined with dimensionality reduction can enhance breast cancer diagnosis by simplifying high-dimensional feature representations while retaining clinically meaningful diagnostic patterns [80].

4.2. Human-Centered, Neuro-Affective, and Assistive AI

This domain addresses AI systems designed to support humans with cognitive, communicative, or affective needs. ASD classification using facial grid-wise emotion features and dual-branch visual transformation [1, 4] represents a high-stakes application in which misclassification carries significant developmental and social consequences. The facial expression database of ASD children [5] provides the foundational data resource for this research cluster. Multimodal EEG analysis of neural synchrony in phrase processing [2] and the standard tDCS model [13] address neuro-affective AI in clinical neuroscience contexts. Emotion recognition systems, including the InceptionV3DenseNet hybrid [6], bidirectional Elman NN [7], and hybrid deep belief optimization [8], target affective computing applications where training data quality and subject variability introduce systematic reliability challenges. The flex sensor–based hand glove for deaf and mute people [14] and iris detection and recognition system [22] represent sensor-based assistive AI. Suicidal ideation detection using NLP and deep learning [37] is a critical mental health application where both false positives and false negatives carry severe consequences, demanding calibrated uncertainty and human oversight. The adaptive feedback system for learner improvement [19] and the AI-powered digital health platform for ASD students [67] address adaptive and personalized decision support in educational and therapeutic settings. Bengali social media sentiment classification [38] and sentiment extraction from drug reviews [39] provide modality evidence for text-based human-centered AI.

4.3. Smart Infrastructure, IoT, Robotics, and Cyber-Physical Systems

Smart infrastructure encompasses a diverse set of sensor-rich, real-time, and safety-critical environments. IoT-based wireless battery monitoring for solar micro-grids [3] and smart energy metering [10] illustrate AI-assisted monitoring in energy infrastructure. The IoT-based smart healthcare medical box for elderly patients [9] extends IoT decision support into clinical care contexts. Wireless mesh network routing [11] and MANET routing protocol simulation [12] address network-layer decision support in distributed infrastructure. High-altitude platform communications optimization [15] represents a communication-systems application of simulation-based AI. The question of full autonomy in underwater robotics [16] directly engages the human oversight axis: the framing as a prospect question reflects genuine uncertainty about whether autonomous decision-making in unstructured aquatic environments is currently reliable enough for unsupervised deployment. Gas-pipeline condition diagnosis through acoustic-emission signal imaging [24] and GNN-based smart gas-pipeline monitoring [18] address safety-critical industrial infrastructure where fault detection failures have severe physical consequences. Concrete crack characterization using acoustic-emission and lightweight deep learning [21] and vision-audio multimodal object recognition using tensor fusion [29] contribute additional modality and architecture evidence for the infrastructure monitoring cluster.

4.4. Agriculture, Environment, and Sustainability

Agricultural AI decision support encompasses disease detection, yield optimization, and sustainability-oriented resource management. Maize leaf disease diagnosis with a lightweight vision transformer [25], cotton leaf diagnostics with an explainable transformer [28], soybean leaf and seed disease identification with MaxViT [33], mango leaf disease recognition with an ensemble vision transformer [34], tea leaf disease precision diagnosis with deep learning [77], and aquaculture disease diagnosis with lightweight ResNeXt [46] collectively constitute a precision agriculture cluster in which lightweight, explainable, and real-time-feasible architectures are prioritized for field deployment. AI-driven smart agriculture for crop yield optimization and sustainability [70] addresses the systemic dimension, integrating AI into broader agricultural management frameworks. AI-driven solar financing for rural clinics and small health businesses [41] introduces sustainability and resilience framing into health infrastructure, connecting agricultural and health domains through shared energy and financing challenges. The resilience-by-design framework [75] provides a cross-cutting lens for sustainability-oriented AI across infrastructure, health, and environmental systems.

4.5. Business, Enterprise, and Organizational Decision Support

Business decision support is the most thematically diverse domain in the corpus, spanning credit scoring, project management, demand forecasting, supply chain analytics, digital transformation, and enterprise information systems. Credit scoring models leveraging alternative data for underserved businesses [40] address fairness and access in financial AI. Predictive analytics for project risk identification and mitigation [42] and automated risk assessment in agile project management [69] illustrate AI's role in organizational risk governance. Market basket analysis for healthcare service bundling [43] bridges health and business analytics. Blockchain applications in supply chain management [56] introduced ledger technology as a trust mechanism complementary to predictive AI. Retail demand forecasting using LSTM and gradient boosting [57], small-business management using predictive ML [58], e-commerce pricing optimization [55], market trend forecasting with external factor integration [60], and customer satisfaction in hospitality [59] represent a forecasting and optimization cluster where ML methods address operational decision support. The attention-enhanced deep learning system for business strategy optimization [53] extends transformer architecture into enterprise analytics. AI-driven business analytics for IT strategy [66], digital transformation analytics for IT project excellence [68], agile IT project risk and AI thematic analysis [64], and AI-ERP integration in dark factories [65] constitute the enterprise AI governance cluster. Generative AI for enterprise business intelligence [74] and AI-enabled management information systems for economic resilience [76] represent the most strategic layer of this domain, addressing how AI reshapes organizational decision architectures rather than merely optimizing individual predictions.

4.6. Cybersecurity, Privacy, and Distributed Intelligence

Cybersecurity and privacy-preserving AI represent both a standalone application domain and a horizontal deployment requirement across all other domains. The intelligent cybersecurity framework integrating ML-driven data protection and threat intelligence [73] and AI for data security, analytics, and digital communication resilience [72] address real-time threat response in digital infrastructure. Privacy-preserving behavior analytics for workforce retention [44] illustrates the application of differential privacy and anonymization techniques in organizational analytics. Trustworthy AI for high-stakes decision support across critical sectors [78] provides a governance and framework perspective spanning all domains. The resilience-by-design AI framework for security, sustainability, and health in interdependent systems [75] emphasizes that AI security cannot be designed in isolation from sustainability and health system resilience. Distributed intelligence with edge-cloud-6G-federated learning for secure and auditable decision support [79] represents the architectural frontier of privacy-preserving deployment, integrating edge inference, cloud aggregation, 6G communication, and federated training into a unified auditable stack.

5. Deployment Challenges

Figure 2 summarizes recurring pathways through which AI systems may fail after development. Data-level limitations, model-level overconfidence, environmental distribution shifts, and governance weaknesses can jointly convert a technically promising model into an unreliable decision-support system.

5.1. Data Quality, Heterogeneity, and Imbalance

High-stakes AI systems encounter heterogeneous data at every layer. Medical imaging corpora vary in scanner protocol, resolution, acquisition site, and annotation convention, making cross-institutional generalization a persistent challenge [20, 51]. Agricultural disease datasets are subject to lighting variability, growth-stage confounds, and regional crop variety differences that compromise model transferability [25, 34, 77]. Business datasets are often imbalanced across class labels property directly relevant to credit scoring models for underserved populations [40] and demand forecasting under rare-event conditions [57]. The facial expression database for ASD children [5] highlights the challenge of constructing domain-specific datasets with sufficient diversity to support generalizable models in sensitive populations. Data heterogeneity is not merely a technical obstacle but a governance concern: models trained on non-representative data risk encoding systematic biases that propagate into high-stakes decisions.

5.2. Explainability and Post-Hoc Interpretability

Explainability is the deployment requirement most consistently addressed in the corpus, and it is represented across all six application domains. The post-hoc explanation strategies integrated into ensemble transformers [27], stacking ensembles [32, 35], vision transformers [25, 28, 61, 62], and CNN-based systems [26, 50] reflect the institutional and regulatory expectation that AI recommendations in healthcare, agriculture, and business settings be accompanied by intelligible justifications. The Swin Transformer with web-deployed explainability for cervical cell screening [61] illustrates that explainability mechanisms must be preserved under deployment constraints, including web-based inference pipelines. However, attention visualization and saliency mapping, while increasingly ubiquitous, do not provide the formal guarantees of causal or counterfactual explanation that high-stakes settings may eventually require [78]. The gap between current post-hoc explainability practices and deployment-grade interpretability standards represents an important research frontier.

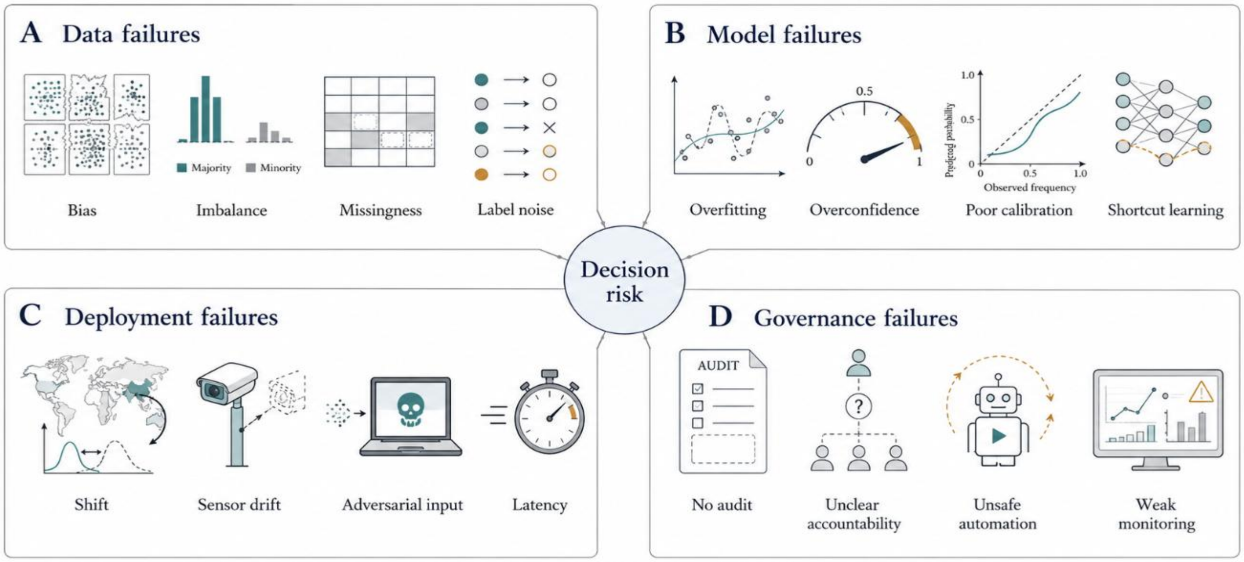

Figure 2. Shared failure modes in high-stakes AI deployment.

5.3. Robustness and Distribution Shift

Robustness to distribution shifts the degradation of model performance when test conditions diverge from training conditions is particularly consequential in high-stakes deployment. Medical imaging models face cross-scanner and cross-population distribution shifts [31, 51, 63]. Agricultural models face seasonal, geographical, and phenological shifts [33, 46, 70]. Industrial monitoring models must remain reliable under varying operational conditions, sensor degradation, and novel fault patterns [18, 54, 24]. Business forecasting models are vulnerable to economic regime changes and external shocks [57, 60]. The physics-guided Bayesian neural network [54] represents an important robustness strategy in industrial settings by embedding domain priors that constrain model behavior under novel inputs. The trustworthy AI framework [78] and resilience-by-design approach [75] address robustness at a systemic rather than model-specific level.

5.4. Privacy, Security, and Federated Deployment

Privacy-preserving AI is no longer a speculative research direction but an operational requirement in health, workforce, and government contexts. Privacy-preserving behavior analytics for workforce retention [44] and the multimodal privacy-preserving cancer diagnosis framework [51] demonstrate that utility and privacy can be simultaneously addressed, though with architecture-specific tradeoffs. Federated learning frameworks, as illustrated by [79], distribute training across data owners without centralizing raw data, enabling multi-institutional model development without privacy violation. The intelligent cybersecurity framework [73] and the AI-driven resilience framework [72] address the security layer of AI deployments, where adversarial attacks, data poisoning, and model inversion represent active threats. Blockchain integration in supply chain AI [56] introduces distributed ledger mechanisms as complementary trust infrastructure. As 6G-enabled edge deployments proliferate, the convergence of privacy, security, and real-time inference, addressed architecturally in [79], will become a central design constraint.

5.5. Real-Time Feasibility and Resource Constraints

Real-time inference on resource-constrained devices is a deployment-critical requirement in IoT, agricultural, and clinical point-of-care contexts. The lightweight cross-scale attention transformer for maize disease [25], lightweight ResNeXt for aquaculture [46], and lightweight deep learning for concrete crack characterization [21] all explicitly address the inference-speed and memory-footprint tradeoffs required for edge deployment. IoT-based systems for solar micro-grid monitoring [3], smart energy metering [10], and smart medical boxes [9] require embedded inference with real-time response guarantees. Web-based deployment for cervical cell screening [61] and breast cancer diagnosis [52] demonstrates that cloud-hosted inference can satisfy real-time requirements while maintaining model complexity, provided network latency and interface design are appropriately managed. HAPs communication systems [15] and MANET routing [12] address the network-layer constraints that govern real-time AI in distributed infrastructure.

5.6. Human Oversight and Accountability

The question of how much autonomy AI systems should exercise in high-stakes decisions is a governance and safety question as much as a technical one. The framing of full autonomy in underwater robotics as an open prospect [16] reflects genuine uncertainty about the conditions under which unsupervised autonomous decision-making is responsible. The automated risk assessment and collaborative decision-making AI in agile project management [69] explicitly positions AI as a collaborator rather than a sole decision-maker, a design principle with broad applicability in high-stakes settings. The trustworthy AI framework [78] and AI-enabled management information systems for governance [76] embed human oversight as a design requirement. The adaptive feedback system for learner improvement [19] and AI-powered ASD digital health platform [67] similarly position AI as an assistive system that augments human professional judgment rather than replacing it. High-stakes AI systems should, in general, be designed to support decision-makers rather than supplant them, and evaluation frameworks should reflect this distinction. Table 1 distinguishes levels of AI involvement in high-stakes decision support, ranging from informative assistance to constrained automation.

Table 1. Human–AI interaction modes and accountability boundaries.

Mode	AI role	Human role	Accountability boundary
Informative	Provides scores, alerts, or rankings	Interprets and decides	Human accountable
Assistive	Suggests decision with explanation	Reviews, accepts, modifies, or rejects	Human retains final authority
Deferral-based	Flags uncertain or high-risk cases	Resolves ambiguous cases	AI accountable for deferral reliability; human for final decision
Collaborative	Supports evidence synthesis or scenario analysis	Integrates AI output with expert judgment	Shared responsibility through documented decision trail
Constrained automation	Executes predefined low-risk actions	Monitors and intervenes when needed	Organization accountable for limits, monitoring, and override
Unsupervised autonomy	Acts without real-time review	Provides retrospective supervision	Highest risk; rarely suitable for high-stakes use

5.7. Benchmarking, Reproducibility, and Evidence Maturity

The corpus reveals inconsistent benchmarking practices across domains. Medical imaging studies frequently report accuracy, sensitivity, and specificity on held-out test sets, but cross-institutional or external validation is less common. Agricultural studies use domain-specific datasets that are rarely shared across research groups. Business analytics studies employ varied train-test split conventions and rarely report confidence intervals or statistical significance tests. The absence of a shared evidence maturity framework, analogous to the CONSORT or TRIPOD reporting standards in clinical research, makes cross-domain comparison difficult. A comparative analysis of explainable ML for cancer classification [50] and the multimodal cancer diagnosis framework [51] illustrate the value of systematic comparison but do not resolve the benchmarking gap. Future reviews and meta-analyses in this space will require standardized reporting of dataset provenance, class balance, validation protocol, uncertainty estimates, and deployment constraints. Table 2 summarizes a staged framework for judging whether an AI system has progressed from technical feasibility to externally validated, human-supervised, deployment-ready, and continuously monitored decision support.

6. Future research directions

Future research should move from isolated model development to evidence that is standardized, auditable, and deployment ready. Cross-domain benchmarks are needed to test AI systems across modalities, architectures, and decision settings using multi-domain holdout sets and clinical or engineering-style reporting standards. Foundation models, generative AI, and large language models should be assessed in high-stakes enterprise and healthcare contexts for hallucination, factual accuracy, audit-trail completeness, and governance alignment [74,69]. Human-in-the-loop systems should use structured deferral for uncertain predictions and be evaluated by decision quality, expert override rates, and outcomes with and without AI support [16,78]. Federated and edge-cloud AI should be tested across institutions with clear reporting of privacy budget, federated utility, and communication efficiency [79,51]. Transformer and ensemble models also require formal explainability audits, including explanation fidelity, user comprehension, and regulatory acceptability [27,35,78]. Robustness and uncertainty should be built into deep-learning pipelines through Bayesian and physics-guided methods, with calibration error, distribution-shift performance, and out-of-distribution detection reported [54,75]. Lightweight models should be optimized for IoT, embedded, and point-of-care use based on latency, memory use, and accuracy–efficiency trade-offs [25,46,21]. Finally, governance-aware reporting standards and evidence maturity frameworks should classify systems from proof-of-concept to deployment-validated AI using reproducibility, external validation, governance compliance, and deployment-readiness indicators [78,76].

Table 2. Evidence-readiness levels for high-stakes AI studies.

Level	Evidence status	Minimum requirement	Deployment meaning
Level 1	Proof-of-concept	Internal dataset; basic train-test or cross-validation; baseline comparison	Technical feasibility only
Level 2	Internal validation	Predefined split; leakage control; class-wise metrics; calibration summary	Stronger internal evidence
Level 3	External/temporal validation	Independent site, cohort, device, or time-period testing	Generalization evidence
Level 4	Human-in-the-loop evaluation	Expert review; AI-assisted versus unaided comparison; override/deferral analysis	Workflow usefulness
Level 5	Monitored pilot deployment	Prospective or controlled deployment; privacy, safety, and monitoring protocol	Deployment readiness
Level 6	Post-deployment evidence	Drift monitoring; audit logs; incident reporting; model-update governance	Sustained operational maturity

7. Limitations of the review

This review is based on a curated provided as titles only. Consequently, the synthesis is thematic, architectural, and deployment-level in nature rather than quantitative. It was not possible to extract specific performance metrics, dataset characteristics, sample sizes, experimental protocols, or statistical validation details. The synthesis should therefore be interpreted as a structured evidence map and taxonomic analysis rather than a quantitative meta-analysis. Full paper-level extraction, including access to abstracts, methods, results, and supplementary materials, would be required to support meta-analytic comparison of model performance, dataset characteristics, or validation rigor across papers. Additionally, the corpus reflects a curated selection and may not comprehensively represent all active research threads in high-stakes AI. Domains such as legal AI, financial systemic risk, and autonomous vehicles are not well represented and are acknowledged as important adjacent fields. The four-axis taxonomy proposed here represents one defensible organization of the evidence space, not the only possible one.

8. Conclusion

This structured critical review has mapped the application of artificial intelligence to high-stakes decision support across six domain healthcare and biomedical systems, human-centered and assistive AI, smart infrastructure and cyber-physical systems, agriculture and sustainability, business and enterprise analytics, and cybersecurity and distributed intelligence, using a four-axis taxonomy of domain, modality, architecture, and deployment concern. The synthesis of 79 papers reveals a rich and rapidly advancing landscape in which vision transformers, ensemble methods, graph neural networks, lightweight CNN architectures, and federated learning systems are each contributing to a qualitatively new generation of decision-support capabilities. The cross-domain view discloses structural commonalities, recurrent explainability demands, universal data quality challenges, shared real-time feasibility constraints, and consistent governance gaps, that are invisible within single-domain reviews. Further evidence reveals that architecture selection in high-stakes AI is not a purely performance-driven choice but is shaped by deployment constraints including computational resources, privacy requirements, interpretability obligations, and human oversight needs. Looking forward, the critical research priorities are not architectural innovation per se, but the responsible operationalization of existing advances. Trustworthy AI frameworks [78], privacy-preserving federated pipelines [79], governance-aware management information systems [76], and resilience-by-design infrastructure [75] collectively point toward a research agenda that prioritizes auditability, human oversight, and deployment readiness alongside predictive performance. The field requires standardized evidence maturity frameworks, cross-domain benchmarking suites, formal explainability audit protocols, and reporting standards that reflect the multi-dimensional demands of real-world high-stakes deployment. Progress on these fronts will determine whether AI decision support fulfills its potential not merely as a technically capable system, but as a trustworthy, equitable, and accountable partner in consequential human decisions.

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