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| REVIEW ARTICLE

AI-Enabled Resilient Systems: Healthcare, Sustainability, Cybersecurity, Energy, and Organizational Decision-Making

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| ABSTRACT
Resilience, the ability of a system to support continuity, adaptation, risk awareness, and recovery under uncertainty or disruption, has emerged as a central requirement for AI-enabled decision systems across critical domains. Healthcare systems must sustain diagnostic accuracy and patient privacy under data constraints and clinical heterogeneity. Energy and infrastructure systems must maintain monitoring reliability under sensor drift and communication instability. Cybersecurity systems must protect data and detect threats in adversarial environments. Agricultural and sustainability systems must function in variable field conditions with constrained hardware. Business and organizational systems must remain agile under economic volatility and pressure of governance. Human-centered AI systems must preserve accessibility, personalization, and ethical oversight for vulnerable users. This structured critical review synthesizes a curated corpus using a seven-axis resilience taxonomy encompassing resilience domain, resilience function, data modality, architecture family, system layer, deployment concern, and decision-support level. Seven resilience domains are examined and mapped across architecture families from conventional ML and CNNs through vision transformers, graph neural networks, physics-guided Bayesian models, generative AI, and federated privacy-preserving systems. Synthesis reveals that while AI capability has advanced substantially, resilience-specific properties robustness, uncertainty quantification, privacy-preserving collaboration, post-deployment monitoring, and governance accountability—remain inconsistently addressed. A twelve-direction research agenda addresses these gaps with actionable future directions and evaluation requirements for AI-enabled resilient systems.

| KEYWORDS
AI resilience; Healthcare AI, Sustainability AI, Cybersecurity AI, Federated learning, Trustworthy AI, Organizational decision-making, Cross-domain AI taxonomy

| ARTICLE INFORMATION
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1. Introduction
Resilience has historically been associated with engineering systems that maintain function under stress—bridges that withstand loading, power grids that recover from outages, supply chains that adapt to disruption. The integration of artificial intelligence into the systems that underpin healthcare, energy infrastructure, cybersecurity, agriculture, and organizational decision-making introduces a new dimension to resilience: the capacity of AI-enabled decision processes to support continuity, adaptation, and recovery, not just under normal operating conditions, but under the data heterogeneity, distribution shift, adversarial pressure, resource constraints, and governance demands that characterize real-world deployment. The resilience-by-design framework [1] articulates this systemic view, positioning AI as a co-determinant of security, sustainability, and health resilience in interdependent systems. The trustworthy AI framework for high-stakes decision support [8] further establishes that resilient AI requires explainability, robustness, privacy, security, governance, and evidence maturity as co-equal requirements rather than optional enhancements.

The resilience imperative is visible across all critical domains examined in this review. In healthcare, AI systems must maintain diagnostic accuracy under scanner heterogeneity, class imbalance, and privacy constraints [26, 32, 45]. In energy and IoT infrastructure, AI must support continuous monitoring under sensor noise, communication instability, and resource limits [2, 6, 27]. In cybersecurity, AI must adapt to evolving threat landscapes and maintain adversarial robustness [4, 12, 20]. In agriculture, AI must function in variable field conditions with lightweight deployable models [14, 42, 59]. In organizational settings, AI must support business continuity under economic volatility, governance requirements, and workforce uncertainty [16, 29, 36, 41]. In human-centered AI, systems must preserve accessibility, personalization, and ethical oversight for users with cognitive, communicative, or affective needs [28, 50, 63].

This review constructs a resilience-centered taxonomy and evidence map to organize across these domains, identifying where AI-enabled resilience is strongest, where gaps persist, and where the most consequential research and governance challenges lie.

2. Review Methodology

The corpus was assembled to provide balanced representation across resilience domains, architecture families, data modalities, and deployment concerns. A seven-axis resilience taxonomy organizes the evidence: (Axis 1) resilience domain across seven sectors; (Axis 2) resilience function—early detection, fault monitoring, risk assessment, forecasting, resource optimization, continuity of care, decision automation, privacy-preserving collaboration, threat intelligence, and sustainability; (Axis 3) data modality across ten categories; (Axis 4) architecture family across eight families from conventional ML to federated systems; (Axis 5) system layer from data acquisition through governance and post-deployment maintenance; (Axis 6) deployment concern across nine dimensions; and (Axis 7) decision-support level from individual through distributed and federated decision support.

An important methodological note: not every paper in the corpus is explicitly about resilience. Papers representing medical imaging, agricultural disease detection, business analytics, IoT monitoring, cybersecurity, and human-centered AI are classified by their contribution to the broader resilient-systems landscape, as healthcare resilience evidence, sustainability evidence, organizational decision-making evidence, or deployment and governance evidence, rather than mislabeled as resilience frameworks.

3. Conceptual Foundations of AI-Enabled Resilient Systems

3.1 Resilience as a Decision-System Property

Resilience in AI-enabled decision systems is a system-level property that extends far beyond model accuracy as shown in Figure 1. A clinical AI that achieves high accuracy on a training dataset but fails when deployed on a new scanner, a new patient population, or under missing data conditions is not resilient. An industrial fault detector that performs well under nominal sensor conditions but produces uncalibrated confidence scores under novel fault patterns is not resilient. An organizational forecasting system that ignores rare but catastrophic economic events is not resilient. The resilience-by-design framework [1] defines resilience as the capacity of interconnected AI, infrastructure, health, and sustainability systems to maintain function, adapt to disruption, and recover coherently, a definition that explicitly includes the interdependency between AI performance and system-level outcomes.

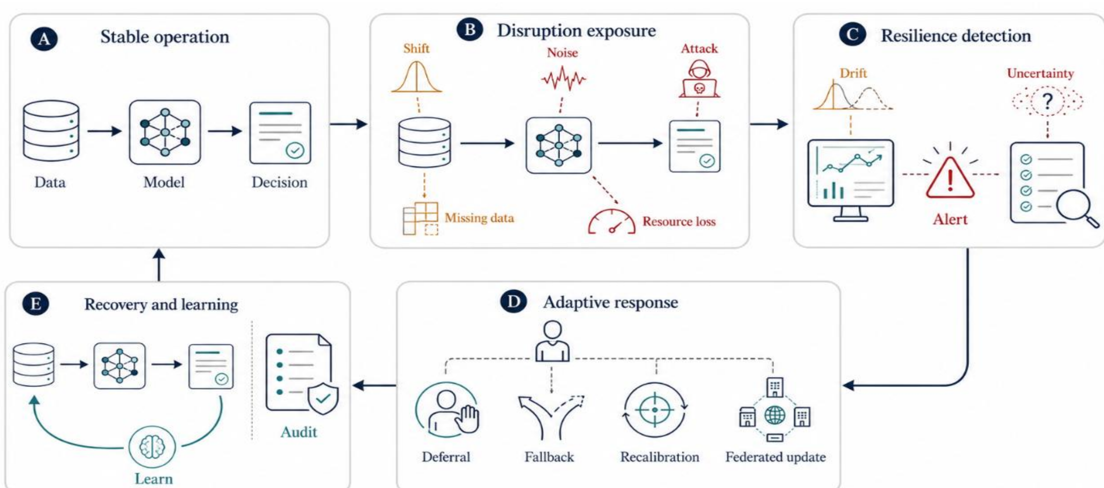

Figure 1. Disruption–response–recovery cycle of resilient AI systems.

3.2 AI Architectures and Resilience Functions

Different architecture families contribute to resilience through different functional pathways. Conventional machine learning architectures [35, 24, 62] contribute through interpretable prediction models that are auditable and maintainable. CNN-based deep learning and transfer learning [9, 38, 74, 75] contribute through robust representation learning in image and signal domains, addressing the data-scarcity challenge that conventional ML cannot overcome. Vision transformers and attention-based models [14, 32, 45, 49, 51, 66] contribute through contextual representation that supports more complete decision coverage. Graph neural networks and knowledge graphs [17, 46, 58] contribute through relational reasoning that supports traceable, entity-linked decision accountability. Physics-guided Bayesian models [2] contribute through uncertainty-aware inference that enables systems to signal their own limitations. Generative and agentic AI [29, 41] contribute through workflow automation and strategic decision support. Federated and privacy-preserving systems [12, 26, 39] contribute through privacy-respecting collaborative learning that enables multi-institutional resilience without data centralization.

3.3 Resilience Across Data Modalities

Data modality shapes the resilience functions available to an AI system. Medical imaging modalities [21, 32, 61, 67] support early detection and screening but require cross-site standardization for resilient multi-institutional deployment. Physiological signals [23, 44, 65] enable patient monitoring but are sensitive to sensor placement variability and individual differences. IoT and sensor streams [6, 13, 27] enable infrastructure monitoring but require edge processing to maintain monitoring continuity under communication disruption. Acoustic-emission and industrial signals [17, 30, 37] support fault detection in industrial systems but require domain-specific preprocessing. Text and natural language data [46, 56, 72] support decision support and sentiment analysis but may carry cultural and linguistic variability that limits generalization. Business and tabular data [7, 24, 31] support organizational forecasting and risk management but may embed historical biases that undermine fairness resilience.

3.4 Trustworthiness as a Prerequisite for Resilience

The trustworthy AI framework for high-stakes decision support [8] establishes that trustworthiness—encompassing explainability, robustness, privacy, security, fairness, governance, and evidence maturity—is a prerequisite for resilient deployment. A system that makes accurate predictions under normal conditions but fails opaquely under disruption is not trustworthy and therefore not resilient. The resilience-by-design framework [1] extends this: interdependent AI systems that lack transparency, security, or governance accountability can propagate failures across connected systems rather than containing them. Trustworthiness and resilience are thus not separable properties but co-constitutive requirements.

3.5 From Isolated Models to Resilient Systems

The transition from standalone predictive models to resilient AI systems requires architectural, operational, and governance changes that go beyond model development. Deployment pathways must support continuous monitoring, post-deployment drift detection, privacy-preserving updates, and human oversight. The distributed edge-cloud-6G federated learning framework [12] illustrates one architectural response: disaggregating model training and inference across nodes to maintain decision continuity under partial system failure. Web-based deployment of clinical screening tools [15, 45] illustrates another pathway: centralizing inference in maintained cloud systems to ensure consistent model versions and explanation outputs. In both cases, resilience is a system-level property of the entire deployment pipeline, not of the trained model alone.

4. Architecture Families for Resilient AI Systems

4.1 Conventional Machine Learning and Structured Analytics

Conventional machine learning architectures provide the interpretable, computationally efficient, and maintainable baseline that resilient organizational and clinical AI systems require. Clinical decision support for heart disease prediction from structured patient data [35] illustrates the deployment value of conventional ML in clinical settings where audit requirements and feature-level accountability are non-negotiable. In business analytics, retail demand forecasting with LSTM and gradient boosting [24], market trend forecasting with external factor integration [62], e-commerce pricing optimization [47], and small-business ML for customer retention and financial forecasting [31] constitute the operational backbone of enterprise resilience analytics. Credit scoring for financially underserved businesses [7] demonstrates conventional ML's role in financial access resilience. The interpretability advantage of conventional ML directly supports resilient deployment: feature importance outputs are auditable, reproducible, and maintainable under model retraining cycles in ways that deep learning attributions are not.

4.2 CNN-Based Deep Learning and Transfer Learning

CNN-based architectures and transfer learning support resilience in image and signal-based decision systems by enabling accurate representation learning from domain-specific data at scale. Early leukemia diagnostics using image processing and transfer learning [38] and transfer learning for sleep stage classification under data-constrained conditions [65] illustrate how pre-trained feature extractors extend coverage to data-scarce clinical contexts. The explainable AI hybrid deep learning framework for skin cancer [9] integrates post-hoc explanation with CNN feature learning, directly addressing the resilience requirement for explainable clinical decision support. Facial emotion recognition via a bidirectional Elman neural network [74] and a hybrid deep belief optimization system [75] extend CNN-based representation to affective computing. The multichannel CNN for imbalanced CT lung cancer data [21] addresses class imbalance, a resilience-critical data quality property in medical screening. The lightweight DL approach for concrete crack characterization via acoustic-emission signals [37] demonstrates edge-deployable CNN inference for structural health monitoring, where deployment continuity under resource constraints is a resilience requirement.

4.3 Vision Transformers and Attention-Based Systems

Vision transformers have become the dominant architecture for image-based healthcare and agricultural AI, with self-attention mechanisms supporting contextual representation that improves diagnostic coverage. The hierarchical Swin Transformer ensemble for breast cancer with decentralized deployment [32] addresses both clinical accuracy and distributed deployment—a direct resilience contribution. The Swin Transformer with XAI and web-based screening for cervical cell classification [45] combines transformer-based accuracy with integrated explanation and accessible deployment. The LMVT hybrid vision transformer for lung cancer with XAI [49], the global-local attention model for kidney disease classification from CT images [51], and the hybrid vision transformer for prostate cancer in MRI [61] demonstrate the architecture's versatility across oncological contexts. FuseAttenX attention-enhanced deep learning for business strategy optimization [66] extends transformer attention to enterprise analytics. MaizeFormerX lightweight cross-scale ViT with XAI [14], the MaxViT soybean disease model [69], and the ViX-MangoEFormer ensemble with XAI [59] illustrate lightweight transformer deployment in precision agriculture. The explainable transformer for skin lesion classification [70] completes the transformer XAI evidence cluster.

4.4 Hybrid, Ensemble, Stacking, and Multimodal Systems

Hybrid and ensemble architectures improve resilience through representational diversity: combining multiple model families reduces the risk that any single architecture's failure mode produces catastrophic output errors. The explainable deep stacking ensemble for brain tumor diagnosis [57] and the stacking ensemble for cervical cancer with XAI [67] demonstrate oncological applications where ensemble diversity is combined with post-hoc explanation for clinical accountability. The stacking ensemble-based breast cancer classifier with real-time web deployment [15] illustrates the deployment pathway for web-accessible clinical screening. The ensemble transformer with post-hoc XAI for depression emotion and severity detection [63] extends ensemble resilience to mental health. The hybrid multi-modal emotion recognition framework using InceptionV3DenseNet [34] addresses affective computing through modality-diverse fusion. The vision-audio multimodal object recognition system via hybrid tensor fusion [68] provides infrastructure monitoring evidence for multi-sensor resilience.

4.5 Graph Neural Networks and Knowledge-Graph Reasoning

Graph neural networks and knowledge-graph architectures provide structurally accountable reasoning that supports resilience through traceability and interpretable system-level inference. The GNN-enhanced acoustic-emission gas-pipeline monitoring system [17] models fault propagation across sensor network topology, providing fault localization grounded in physical system structure. Knowledge-graph and NLP integration for heuristic reasoning [46] and the AddManBERT knowledge-graph construction for additive manufacturing design support [58] demonstrate symbolic reasoning architectures that support engineering decision accountability. The resilience contribution of these architectures is auditability: reasoning chains that domain experts can trace and validate are directly compatible with the governance and accountability requirements of resilient deployment.

4.6 Bayesian, Physics-Guided, and Uncertainty-Aware Systems

The physics-guided Bayesian neural network for sensor fault detection in wind turbines [2] represents the most principled resilience-oriented architecture in the corpus: by embedding physical priors and producing calibrated uncertainty estimates, the system supports decision-makers in distinguishing between high-confidence fault detections that warrant autonomous action and uncertain predictions that require human review. This uncertainty-aware inference capability is the defining resilience contribution of this architecture family—one that no other architecture in the corpus provides in the same formal, calibrated manner. Expanding the application of physics-guided and Bayesian architectures to medical imaging, industrial monitoring, and agricultural AI is among the most consequential research directions for AI-enabled resilience.

4.7 Generative, Agentic, and Enterprise AI

Generative AI and agentic systems contribute to organizational resilience through decision automation, strategic intelligence, and workflow adaptability. Generative AI in enterprise information systems for transforming business intelligence [29] addresses the organizational embedding of generative capabilities, with governance and accountability as primary resilience concerns. Automated risk assessment and collaborative AI in agile project management [41] illustrates agentic AI that supports organizational resilience by identifying and mitigating risks before they become disruptions. AI-enabled management information systems for economic resilience and governance [16] and AI-driven business analytics for IT strategy [36] address strategic and operational resilience at the enterprise level. Digital transformation analytics for IT project excellence [54] and conceptual AI-ERP integration frameworks for dark factories [52] address the governance layer of enterprise AI resilience.

4.8 Edge-Cloud, Federated, Privacy-Preserving, and Distributed AI

Privacy-preserving and federated deployment architectures are essential for resilient multi-institutional AI because they enable collaborative decision support without requiring data centralization—a property critical for healthcare [26], workforce analytics

[39], and cybersecurity [12] resilience. The distributed edge-cloud-6G federated learning framework for secure and auditable decision support [12] provides the most architecturally complete resilience response in the corpus, integrating multiple privacy and security mechanisms into a unified deployment architecture. The multimodal privacy-preserving cancer diagnosis framework [26] demonstrates operational privacy-preserving deployment in healthcare. Privacy-preserving behavior analytics for workforce retention [39] illustrates organizational privacy resilience. The intelligent cybersecurity ML framework [4] and AI as a strategic engine for digital resilience [20] address the adversarial resilience layer.

5. Domain-Specific Synthesis

5.1 Healthcare and Biomedical Resilience

Healthcare AI resilience encompasses the full arc from early detection through privacy-preserving diagnosis, clinical decision support, and continuity of care. Cancer detection applications—spanning skin cancer [9, 70], lung cancer [21, 49], breast cancer [15, 32], cervical cancer [45, 67], brain tumor [57], leukemia [38], prostate cancer [61], kidney disease [51], and cytological cancer classification [18], collectively represent the domain where explainability and privacy are most consistently required alongside accuracy. The comparative explainable ML analysis for cancer cytology [18] provides systematic evidence for the XAI dimension of healthcare resilience. The multimodal privacy-preserving cancer diagnosis framework [26] directly addresses privacy-preserving collaboration, the federated deployment property most critical for multi-institutional clinical resilience. Parkinson's screening via personalized voice biomarkers [23] and sleep stage classification under limited data [65] illustrate physiological signal AI in conditions of data scarcity. Heart disease prediction from structured data [35] and the AI-integrated health information system for diabetes management [3] represent structured data clinical AI. Market basket analysis for healthcare service bundling [64] bridges health and business resilience analytics. The web-based Swin Transformer cervical screening tool [45] demonstrates the deployment pathway most accessible to clinical systems with limited infrastructure investment. Neural network–based approaches have been applied to breast cancer classification through dimensionality reduction, morphological feature analysis, and architecture optimization [80], [81]. Machine learning has also supported stroke prediction by enabling data-driven risk estimation in healthcare settings [82]. At the same time, explainable deep learning remains central to improving the interpretability and clinical acceptability of AI-assisted diagnosis [85]. From a broader systems perspective, federated learning provides a privacy-oriented framework for scalable healthcare data processing [83], while AI-driven cybersecurity and digital twin technologies extend these capabilities to the protection and maintenance of healthcare, industrial IoT, and essential infrastructure environments [86], [84].

5.2 Energy, IoT, and Smart Infrastructure Resilience

Smart infrastructure resilience requires AI that can monitor, predict, and adapt in real time under hardware constraints and communication variability. IoT-based wireless battery monitoring for solar micro-grids [6] and smart energy metering [27] illustrate embedded AI in energy infrastructure. The IoT-based smart healthcare medical box for elderly patients [13] extends IoT resilience to health monitoring. Wireless mesh network load-balancing routing [55] and MANET routing protocol simulation [76] address network-layer resilience. HAPs communication systems optimization [33] extends infrastructure resilience to airborne communication platforms. The physics-guided Bayesian neural network for wind-turbine sensor fault detection [2] is the most architecturally principled infrastructure resilience system in the corpus, its uncertainty-aware outputs directly support human oversight decisions about maintenance and shutdown. The GNN-enhanced gas-pipeline monitoring system [17] and the gas-pipeline diagnosis system using acoustic-emission imaging [30] address pipeline safety resilience.

5.3 Cybersecurity, Privacy, and Digital Resilience

Cybersecurity AI resilience operates in adversarial environments where the threat landscape evolves continuously and model reliability is actively challenged. The intelligent cybersecurity ML framework for data protection and threat intelligence [4] addresses real-time threat detection and adaptive response. AI as a strategic engine for data security and digital communication resilience [20] positions AI at the organizational security governance level. Privacy-preserving behavior analytics for workforce retention [39] demonstrates operational differential privacy in organizational analytics. The distributed edge-cloud-6G federated learning framework [12] provides the privacy-secure deployment infrastructure for cross-institutional AI. The trustworthy AI framework [8] and the resilience-by-design framework [1] provide the governance and accountability foundations that underpin all cybersecurity resilience deployments.

5.4 Industrial Monitoring and Cyber-Physical Resilience

Industrial monitoring resilience requires AI that can provide continuous, explainable, and safety-accountable fault detection under sensor noise and novel fault conditions. The GNN-enhanced gas-pipeline monitoring system [17] and gas-pipeline condition diagnosis via acoustic-emission imaging [30] represent the most safety-critical industrial AI applications in the corpus. The lightweight DL system for concrete crack characterization [37] demonstrates edge-deployable monitoring. The AddManBERT knowledge-graph for additive manufacturing design [58] extends industrial resilience to manufacturing design accountability. The vision-audio multimodal object recognition system via tensor fusion [68] provides multi-sensor perception evidence for industrial automation. The question of full autonomy in underwater robotics [40] directly engages the human oversight dimension of industrial resilience: even a fully capable autonomous system requires governance conditions that determine when and how autonomy is appropriate, and the framing as a realistic prospect question reflects unresolved accountability challenges.

5.5 Agriculture, Environment, and Sustainability Resilience

Agricultural AI resilience addresses food-system continuity under environmental variability, resource constraints, and disease pressure. MaizeFormerX lightweight cross-scale ViT with XAI [14], the MaxViT soybean disease model [69], the ViX-MangoEFormer ensemble with XAI [59], the explainable transformer for cotton leaf diagnostics [42], advanced deep learning for tea leaf disease [25], and lightweight ResNeXt for aquaculture disease [48] collectively constitute the precision agriculture disease detection cluster, where lightweight, explainable, and field-deployable architectures are directly required for agricultural resilience. AI-driven smart agriculture for crop yield optimization [11] addresses systemic agricultural sustainability. AI-driven solar financing for rural clinics and health businesses [5] connects agricultural sustainability to healthcare resilience—illustrating the interdependency that the resilience-by-design framework [1] emphasizes.

Table 1. Resilience evidence gap matrix across AI-enabled domains.

Domain	Robustness	Uncertainty	Privacy / security	XAI / auditability	Monitoring	Governance	Main gap
Healthcare	Moderate	Limited	Moderate	Moderate–strong	Limited	Moderate	Strong model evidence, weak clinical deployment validation
Energy / IoT	Moderate	Moderate	Limited–moderate	Limited	Moderate	Limited	Monitoring focus, but weak governance and audit evidence
Cybersecurity	Moderate	Limited	Strong	Limited–moderate	Moderate	Moderate	Security is central, but uncertainty and XAI remain weak
Industrial systems	Moderate–strong	Moderate	Limited	Moderate	Moderate	Limited	Fault detection is mature; safety governance is underdeveloped
Agriculture / sustainability	Moderate	Limited	Limited	Moderate	Limited	Limited	Field robustness is emerging, but uncertainty and drift monitoring are weak
Business / organizational AI	Limited–moderate	Limited	Moderate	Limited	Limited	Moderate	Governance is discussed more than empirically tested
Human-centered AI	Limited–moderate	Limited	Limited–moderate	Moderate	Limited	Moderate	Ethical relevance is clear, but longitudinal safety evidence is limited

5.6 Business, Enterprise, and Organizational Resilience

Organizational resilience in AI-enabled systems depends on the ability to maintain strategic, operational, and financial decision support under volatility, disruption, and governance pressure (Table 1). Credit scoring for financially underserved businesses [7] addresses access resilience in financial systems. Automated risk assessment AI in agile project management [41] and AI for IT project risk [10] illustrate AI-supported organizational risk management. Market basket analysis for healthcare bundling [64], retail demand forecasting [24], customer satisfaction analytics [43], and small-business ML [31] represent the operational forecasting cluster. Blockchain and ML in supply chain management [22] introduces distributed trust infrastructure alongside predictive AI. Market trend forecasting with external factors [62] and e-commerce pricing optimization [47] address business cycle resilience. Generative AI in enterprise information systems [29], AI-enabled MIS for governance and economic resilience [16], digital transformation analytics [54], AI-ERP integration [52], and AI-driven business analytics for IT strategy [36] address the strategic governance layer of organizational resilience. Predictive project risk analytics [19] and workforce retention analytics [39] complete the organizational resilience evidence synthesis.

5.7 Human-Centered, Educational, Assistive, and Neuro-Affective Resilience

Human-centered resilience addresses the continuity of accessible, personalized, and ethically governed AI services for users with cognitive, communicative, or affective needs. ASD classification via dual-branch visual transformation [50, 73] and the ASD facial expression database [60] represent AI-enabled developmental assessment. The AI-powered digital health platform for ASD students [28] illustrates adaptive and therapeutic digital resilience. The multimodal EEG neural synchrony analysis [44] and the standard tDCS model [53] address neuro-affective and clinical neuroscience contexts with direct safety implications. The ensemble transformer with post-hoc XAI for depression emotion and severity detection [63] addresses mental health resilience.

Suicidal ideation detection via NLP [71] and Bengali social media sentiment classification [72] illustrate text-based mental health and social analytics. Facial emotion recognition systems [74, 75] and the hybrid multimodal emotion recognition framework [34] span multiple deep learning stages in affective resilience. Drug review sentiment extraction [56] and the adaptive feedback system for learner improvement [78] address health informatics and educational resilience. The flex sensor hand glove for deaf and mute individuals [77] and iris detection and recognition [79] extend human-centered resilience to physical accessibility and biometric identification. Figure 2 shows that resilience failures are interdependent, not isolated. For example, cyber disruption may affect healthcare, energy, business continuity, and human-centered services.

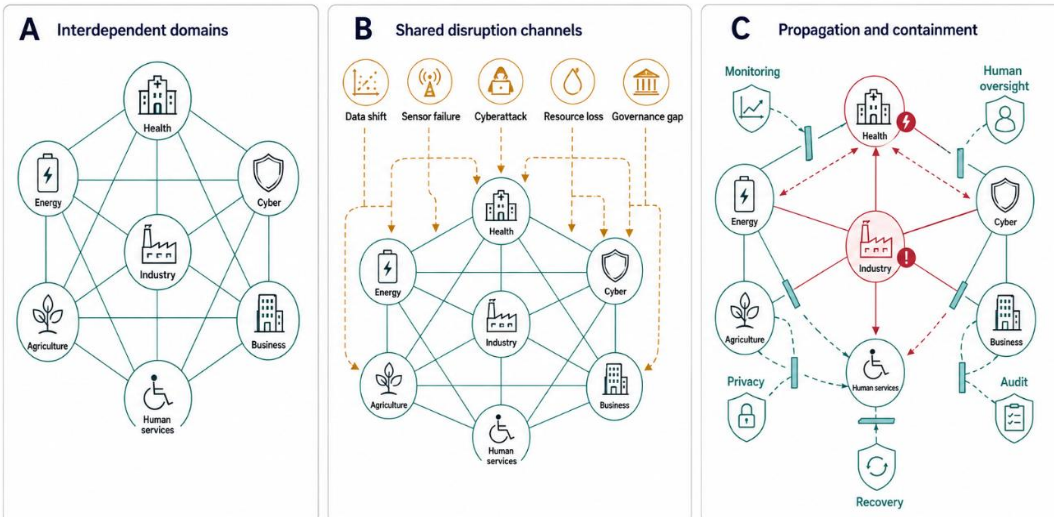

Figure 2. Cross-domain propagation of AI resilience failures.

6. Cross-Domain Challenges for AI-Enabled Resilience

6.1 Defining and Measuring Resilience

Resilience in AI-enabled decision systems resists single-metric evaluation. Accuracy on a held-out test set measures predictive performance under normal conditions but does not measure continuity under distribution shift, recovery under sensor failure, adaptability to novel fault patterns, or governance compliance under regulatory change. The resilience-by-design framework [1] proposes measuring resilience in terms of interdependent system functions, but domain-specific operationalization, what does resilience mean for a clinical screening AI versus a pipeline monitoring AI versus an organizational forecasting system? remains a research gap. Developing resilience-specific evaluation suites that include disruption scenarios, distribution-shift testing, modality-dropout robustness, governance compliance, and recovery metrics is a foundational requirement for the field as presented in Table 2.

Table 2. Disruption-to-evaluation mapping for resilient AI systems.

Disruption category	Example stress scenario	Evaluation focus	Recommended metrics / outputs	Failure signal
Data distribution shift	New site, scanner, population, season, or operating condition	Generalization under non-identical data	External-test performance, subgroup performance, calibration error, worst-case score	Large performance drop across site or subgroup
Missing or corrupted data	Missing features, noisy signals, image artifacts, incomplete sensor streams	Robustness to degraded inputs	Performance under corruption levels, missing-data sensitivity, recovery rate	Unstable prediction or overconfident error
Sensor or acquisition failure	Sensor drift, device malfunction, low-quality acquisition	Monitoring reliability	Drift score, fault-detection rate, false-alert rate, alert latency	Delayed or missed degradation alert
Adversarial or cyber threat	Input manipulation, attack, data breach, model misuse	Security resilience	Attack detection rate, adversarial accuracy, privacy leakage risk, audit traceability	High vulnerability with no alert or audit trail
Resource constraint	Low memory, limited compute, edge deployment, network instability	Operational continuity	Latency, memory use, energy use, fallback success, uptime	Inference delay, service interruption, or failed fallback

Disruption category	Example stress scenario	Evaluation focus	Recommended metrics / outputs	Failure signal
Privacy constraint	Multi-institutional learning without data sharing	Privacy-preserving utility	Federated utility loss, privacy budget, communication cost, site-level fairness	Strong performance loss or privacy risk
Uncertainty and ambiguity	Low-confidence, out-of-distribution, or high-risk case	Safe decision routing	Calibration error, uncertainty quality, deferral rate, human-review yield	Confident prediction on uncertain or unsafe case
Governance and accountability failure	No monitoring plan, unclear responsibility, weak audit process	Deployment accountability	Reporting completeness, audit availability, oversight pathway, update protocol	No traceable decision or unclear escalation route
Post-deployment drift	Longitudinal change after deployment	Lifecycle resilience	Drift detection rate, retraining trigger, recovery time, post-update performance	Silent performance decay over time
Human-AI workflow disruption	User override, workflow mismatch, alert fatigue	Decision-support reliability	Override frequency, expert agreement, usability score, decision turnaround time	Frequent overrides or ignored AI alerts

6.2 Data Heterogeneity, Imbalance, and Interoperability

Data quality challenges affect resilience at every level. The multichannel CT lung cancer analysis for imbalanced data [21] illustrates how class imbalance in medical datasets can undermine triage reliability—a healthcare resilience failure mode. Cross-scanner heterogeneity in multi-institutional medical imaging [32, 61] and environmental variability in agricultural image datasets [14, 59] represent distribution-shift vulnerabilities that models must handle gracefully. Business datasets [7, 24] are subject to distributional change under economic disruption. IoT sensor streams [6, 27] may have varying quality, sampling rates, and missing-data profiles. Interoperability standards, analogous to FHIR in healthcare—are needed across all domains to reduce the data engineering burden of resilience-oriented AI deployment.

6.3 Robustness, Uncertainty, and Distribution Shift

Robustness under distribution shift is the most universal resilience challenge. The physics-guided Bayesian neural network [2] addresses this through physical priors that constrain model behavior under novel inputs—the most principled robustness strategy in the corpus. Medical imaging models face cross-demographic and cross-site shifts [26, 32]. Agricultural models face seasonal and geographic shifts [14, 42, 69]. Industrial models must tolerate sensor degradation and novel fault signatures [17, 30]. Business forecasting models face economic regime changes [24, 62]. Cybersecurity models face continuously evolving adversarial patterns [4, 20]. Uncertainty quantification, the capacity to express calibrated confidence rather than forced predictions, is a prerequisite for resilient deployment that current corpus papers address only partially.

6.4 Privacy, Security, and Federated Collaboration

Privacy-preserving and secure AI deployment is a resilience requirement in healthcare, organizational, and cybersecurity contexts. The federated learning framework [12] and the multimodal privacy-preserving cancer diagnosis framework [26] demonstrate operational approaches to multi-institutional privacy resilience. Privacy-preserving workforce analytics [39] illustrates organizational privacy resilience. The cybersecurity framework [4] and digital resilience framework [20] address adversarial security. As AI systems are deployed at greater scale in interconnected digital infrastructure, the security-accuracy tradeoff, ensuring that security mechanisms do not degrade decision utility—becomes a first-class resilience engineering problem.

6.5 Explainability, Auditability, and Decision Accountability

Resilient AI must be explainable not only to developers but to domain experts, decision-makers, and governance bodies. Post-hoc XAI methods in stacking ensembles [57, 67] and hybrid deep learning [9] provide visual and feature-level explanations that support clinical audit. Knowledge-graph reasoning [17, 46, 58] provides entity-linked reasoning traces that support industrial and organizational accountability. Attention-based explanations in transformer systems [14, 32, 45, 49] offer visual communicability but require formal validation beyond visual plausibility. The trustworthy AI framework [8] positions explanation validity as a governance requirement framing directly compatible with resilience accountability.

6.6 Real-Time Feasibility and Resource Constraints

Resilient deployment in IoT, agricultural, and clinical point-of-care contexts requires inference under hardware constraints that standard deep learning models cannot satisfy without compression. Lightweight ViT MaizeFormerX [14], lightweight ResNeXt for aquaculture [48], and lightweight DL for concrete crack characterization [37] demonstrate that edge feasibility is achievable with model compression. IoT-based monitoring systems [6, 13, 27] impose strict processor and memory constraints. HAPs communications [33] and MANET routing [76] address network-layer constraints that determine data transmission reliability for cloud-based inference.

6.7 Human Oversight, Governance, and Ethical Deployment

Resilient AI systems must support human oversight as a default, particularly in safety-critical and high-stakes settings. The question of full autonomy in underwater robotics [40] directly addresses the governance boundary for autonomous industrial AI: even capable systems require governance conditions that specify when and how autonomy is appropriate. The trustworthy AI framework [8] and the resilience-by-design framework [1] both embed human oversight as a structural resilience requirement. Generative and agentic AI systems [29, 41] that automate strategic decision workflows introduce accountability challenges that governance frameworks must address explicitly.

6.8 Evidence Maturity and Post-Deployment Monitoring

Evidence maturity, the degree to which AI system claims are supported by rigorous, reproducible, externally validated evidence—is the governance property most consistently underaddressed in the corpus. Medical imaging studies report accuracy on held-out test sets but rarely provide cross-institutional external validation. Agricultural studies use domain-specific datasets that are rarely shared across groups. Business analytics studies rarely report confidence intervals or distributional robustness. Post-deployment monitoring, detecting model drift, triggering retraining, and maintaining audit logs—is a resilience requirement that is architecturally underspecified in most current AI deployment frameworks.

7. Future Research Directions

Future research on resilient AI should establish resilience-specific benchmarks that test disruption scenarios, distribution shifts, and recovery performance using resilience indices, recovery scores, and governance compliance ratings [1, 8]. Evaluation should also move beyond accuracy by incorporating continuity, robustness, adaptability, and uncertainty calibration as domain-specific resilience measures [2, 8]. In parallel, human-in-the-loop decision-support systems should use structured deferral mechanisms when uncertainty, distribution shift, or high-risk outputs occur, with evaluation based on decision quality, override frequency, and outcome differences [2, 40]. Further work is needed on federated and privacy-preserving resilience systems for cross-domain, multi-institutional deployment, assessed through privacy budget, federated utility loss, and communication efficiency under 6G settings [12, 26, 39]. Robust deployment also requires physics-guided Bayesian uncertainty, OOD detection, and post-deployment drift monitoring, evaluated through calibration error, OOD detection rate, and drift alert latency [2, 1]. Formal explainability and auditability protocols should be developed for healthcare, industrial, and agricultural resilience contexts, using explanation fidelity, domain usability, and regulatory acceptance as evaluation criteria [8, 9, 18].

Resilient AI should also prioritize lightweight edge deployment, optimizing transformers and ensembles for IoT and field environments while preserving explanation capability, measured by latency, memory use, and edge-level explanation fidelity [14, 37, 48]. Cybersecurity-aware deployment should address adversarial robustness in threat-intelligence contexts using adversarial accuracy, attack detection rate, and security–utility trade-offs [4, 12, 20]. Sustainability must also be integrated through energy consumption, carbon footprint, resource efficiency, and lifecycle impact assessment [1, 5, 11]. At the organizational level, AI-enabled automation should be evaluated for business continuity, decision quality, and governance alignment during economic disruption [16, 29, 41]. Finally, the field needs governance-aware reporting standards, comparable to CONSORT or TRIPOD, covering disruption testing, uncertainty, validation, monitoring, and governance safeguards [8, 1]. An evidence maturity framework should also classify resilient AI systems from proof-of-concept to deployment-validated systems with external validation and post-deployment monitoring requirements [8].

8. Limitations of the Review

The synthesis is thematic, architectural, resilience-oriented, and deployment-level rather than quantitative. Specific performance metrics, dataset characteristics, resilience measurements, validation protocols, computational requirements, deployment environments, user studies, and statistical evidence could not be extracted from titles alone. The review should be interpreted as a structured resilience evidence map and taxonomic analysis rather than a quantitative meta-analysis. Full paper-level extraction—including access to methods, results, experimental details, and supplementary materials—would be required to support meta-analytic comparisons of resilience properties, model performance, or deployment feasibility. The curated corpus may not comprehensively represent all resilience AI research threads; climate adaptation AI, pandemic response systems, nuclear infrastructure monitoring, and social welfare resilience are not well represented. Not every paper in the corpus is explicitly about resilience; papers are classified by their contribution to the broader resilient-systems landscape rather than mislabeled. The seven-axis resilience taxonomy represents one defensible organization; alternative frameworks emphasizing different resilience properties may yield complementary insights.

9. Conclusion

This structured critical review has mapped AI-enabled resilient systems across seven domains, healthcare and biomedical resilience, energy and smart infrastructure resilience, cybersecurity and digital resilience, industrial monitoring and cyber-physical resilience, agriculture and sustainability resilience, business and organizational resilience, and human-centered and assistive resilience. The synthesis reveals a field in which architectural capability has advanced substantially across vision transformers, ensemble systems, graph neural networks, and federated learning frameworks, while resilience-specific properties, uncertainty quantification, validated explainability, privacy-preserving collaboration, post-deployment monitoring, and governance accountability, remain inconsistently addressed. The cross-domain resilience view consistently reveals the same pattern: models are evaluated on held-out test sets but not on disruption scenarios, distribution-shift conditions, or recovery metrics; explainability is provided but not formally validated; privacy is addressed in selected deployments but not systematically; and governance frameworks are proposed but operationalization remains incomplete.

The future of AI-enabled resilient systems requires treating resilience as a first-class design requirement—not as a property that emerges from high accuracy, but as a multi-dimensional system property that must be specified, tested, monitored, and governed from the earliest phase of AI development through the complete operational lifecycle. Robust, explainable, privacy-preserving, secure, resource-efficient, monitored, and governance-aware AI systems that support continuity and adaptation under uncertainty are not simply better-performing models—they are the responsible foundation of the intelligent infrastructure, healthcare systems, agricultural networks, organizational capabilities, and human-centered services that will define resilient societies in an increasingly uncertain world.

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