Frontiers in Computer Science and Artificial Intelligence
ISSN: 2978-8048
DOI: 10.32996/fcsai
Journal Homepage: www.al-kindipublisher.com/index.php/fcsai

FCSAI
AL-KINDI CENTER FOR RESEARCH AND DEVELOPMENT

| REVIEW ARTICLE

Cross-Domain Applications of Artificial Intelligence: A Systematic Review of Models, Data Modalities, and Deployment Readiness

Md Golam Sarwar[1], Shahadat Hossain[1], and Md Risalat Hossain Ontor[2]
[1]*Department of Information Systems, Pacific States University, 3530 Wilshire Boulevard, Suite 1110, Los Angeles, CA 90010, USA*
[2]*Doctor of Management, International American University, 3440 Wilshire Blvd., 10th Floor, #1000, Los Angeles, CA 90010, USA*
Corresponding Author: Md Risalat Hossain Ontor, **E-mail**: risalatontor99@gmail.com

| ABSTRACT

Artificial intelligence is applied across a wide and growing range of domain healthcare, agriculture, industry, business analytics, cybersecurity, smart infrastructure, assistive technologies, education, and sustainability, yet cross-domain synthesis of AI evidence has lagged behind domain-specific development. A systematic cross-domain review must classify studies not only by application area, but also by data modality, model architecture, decision-support function, deployment pathway, and deployment-readiness concern, to reveal the structural patterns and gaps that single-domain reviews cannot expose. This review presents systematic-style evidence mapping analysis of corpus using a seven-axis taxonomy: application domain, data modality, model family, decision-support function, deployment pathway, deployment-readiness concern, and evidence role. Seven application domains are synthesized, healthcare and biomedical AI, human-centered and assistive AI, agriculture and sustainability, industrial monitoring, smart infrastructure and IoT, business and enterprise analytics, and cybersecurity and distributed intelligence, across ten model families from conventional ML through vision transformers, graph neural networks, Bayesian physics-guided models, generative AI, and federated learning systems. Synthesis reveals that model architecture diversity has advanced substantially, while deployment-critical properties, validated explainability, privacy-preserving inference, robustness, human oversight, and governance-aligned reporting, remain inconsistently addressed. A ten-direction research agenda identifies the most consequential future priorities for cross-domain deployable AI. Note that full PRISMA reporting would require explicit database-search records, screening procedures, and eligibility criteria beyond what this curated corpus provides.

| KEYWORDS

Cross-domain AI, Systematic evidence mapping, Deployment readiness, Explainable AI, vision transformers, Federated learning, Trustworthy AI, Data modalities

| ARTICLE INFORMATION

ACCEPTED: 15 April 2026 **PUBLISHED:** 22 May 2026 **DOI:** 10.32996/fcsai.2026.5.7.4

1. Introduction

Artificial intelligence has transitioned from a specialized research tool into an operational presence across virtually every domain of human activity. In healthcare, AI classifies medical images, supports clinical decisions, and monitors patient data. In agriculture, AI detects crop diseases and optimizes resource use. In industry, AI monitors infrastructure, detects faults, and supports manufacturing design. In business, AI forecasts demand, manages risk, and supports strategic decisions. In cybersecurity, AI detects threats and protects data. In smart infrastructure, AI manages energy, communications, and IoT networks. In assistive and human-centered applications, AI supports communication, emotion recognition, and personalized learning. The breadth of this deployment creates both an opportunity and a methodological challenge: the architectures, data modalities, deployment pathways, and trustworthiness requirements differ substantially across domains, and domain-specific reviews cannot capture the cross-domain structural patterns that reveal universal gaps in AI deployment readiness. This review addresses the cross-domain synthesis gap through systematic-style evidence mapping: classifying along seven axes covering application domain, data modality, model family, decision-support function, deployment pathway, deployment-readiness concern, and evidence role. The central argument is that deployment readiness requires more than predictive accuracy, demands validated explainability, privacy-preserving deployment, robustness under distribution shift, computational efficiency for resource-constrained environments, human oversight mechanisms, and governance-aligned reporting. These requirements are visible across all seven domains examined but are inconsistently addressed within each. The corpus spans conventional ML baselines [40, 45, 79], CNNs and transfer learning [34, 60, 74], vision transformers [15, 22, 48, 57, 62], hybrid and ensemble systems [3, 6, 16, 51], graph neural networks [37, 39, 42], Bayesian physics-guided models [19], generative and agentic AI [59, 78], and federated privacy-preserving systems [12, 13, 55]. Together, these papers provide cross-domain evidence for the current state of AI architecture, modality diversity, and deployment readiness.

2. Review scope and systematic evidence-mapping framework

Full systematic-review reporting would require explicit database search strings, screening records, eligibility criteria, and quality appraisal instruments beyond what this curated corpus provides. The corpus was assembled to ensure balanced coverage across seven application domains, ten model families, eleven data modalities, and multiple deployment pathways, enabling structured cross-domain evidence synthesis. A seven-axis taxonomy organizes the evidence. Axis 1 classifies by application domain: healthcare and biomedical AI, human-centered and assistive AI, agriculture and sustainability, industrial monitoring and cyber-physical systems, smart infrastructure and IoT, business and enterprise analytics, and cybersecurity and distributed intelligence. Axis 2 classifies data modality across eleven categories from medical images to multimodal data. Axis 3 identifies the model family across ten categories from conventional ML to federated systems. Axis 4 records the decision-support function served. Axis 5 classifies the deployment pathway. Axis 6 identifies the dominant deployment-readiness concern. Axis 7 assigns each paper to an evidence role: model evidence, data-modality evidence, domain evidence, deployment-readiness evidence, trustworthiness evidence, infrastructure or system-design evidence, or comparative or baseline evidence. Figure 1 illustrates the organizing logic of the review by linking seven application domains to the dominant data modalities, representative AI model families, and deployment-readiness concerns that shape real-world adoption.

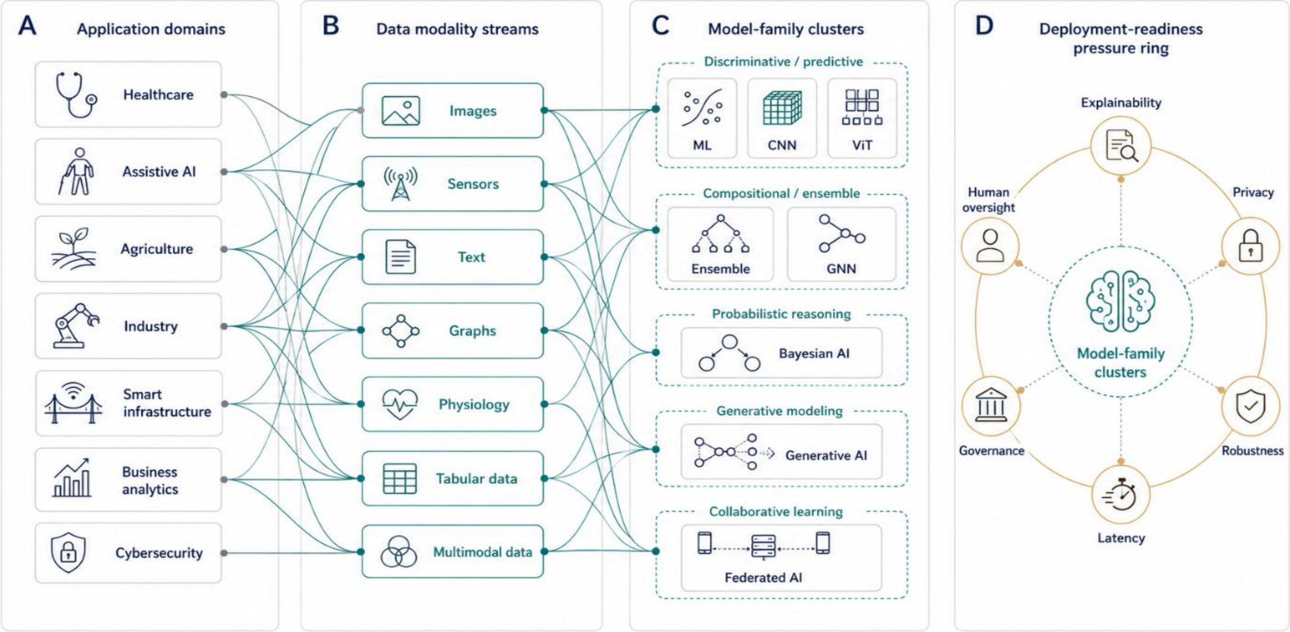

Fig. 1: Cross-domain AI evidence landscape across application domains, data modalities, model families, and deployment-readiness pressures.

3. Model families in cross-domain ai applications

3.1. Conventional Machine Learning and Structured Analytics

Conventional machine learning, including logistic regression, random forests, gradient-boosted trees, and LSTM networks applied to structured data, remains the most widely deployed model family for tabular and text-based decision support. Clinical decision support for heart disease prediction from structured patient data [40] and personalized ML for Parkinson's screening via voice biomarkers [75] represent structured ML in clinical contexts. Retail demand forecasting using LSTM and gradient boosting [1], market trend forecasting with external factor integration [32], e-commerce pricing optimization [58], small-business management ML [45], and credit scoring for financially underserved businesses [79] constitute the operational business analytics cluster. The interpretability advantage of conventional ML, directly auditable feature importance, computationally efficient retraining, and well-characterized failure modes, directly supports deployment readiness, making it the appropriate baseline for domains where tabular data, auditability, and regulatory compliance are the primary requirements.

3.2. CNN-Based Deep Learning and Transfer Learning

CNN-based architectures and transfer learning address the representation-learning demands of image, signal, and sequential data at domain-specific scales. Early leukemia diagnostics using image processing and transfer learning [34] and transfer learning for sleep stage classification under data-constrained conditions [74] illustrate the data-efficiency advantage of pre-trained CNN features in medical contexts. Lightweight ResNeXt for aquaculture disease [60] and the lightweight DL approach for concrete crack characterization via acoustic-emission signals [8] demonstrate the deployment pathway from representative capacity to edge feasibility. The multichannel CNN for imbalanced CT lung cancer data [63] illustrates the class-imbalance challenge that is directly relevant to medical screening deployment readiness.

3.3. Transformers and Attention-Based Models

Transformers architecture represents the dominant model family in image-based healthcare and agricultural AI. The Swin Transformer with XAI and web deployment for cervical cell classification [62] combines transformer-based accuracy with integrated explainability and accessible deployment. The LMVT hybrid vision transformer for lung cancer with XAI [48], the hierarchical Swin Transformer ensemble for breast cancer with decentralized deployment [15], and the global-local attention model for kidney disease classification from CT images [26] illustrate the architecture's versatility across oncological contexts. The explainable transformer for skin lesion classification [5] and FuseAttenX attention-enhanced deep learning for business strategy optimization [72] extend transformer attention to dermatological and enterprise domains. In precision agriculture, MaizeFormerX lightweight cross-scale ViT with XAI [57], the MaxViT soybean disease model [7], the ViX-MangoEFormer ensemble with XAI [22], and the explainable transformer for cotton leaf diagnostics [76] constitute the agricultural transformer cluster where explainability and lightweight deployment are jointly optimized. The critical caution for all transformer evidence is that attention maps, while visually communicable, are not equivalent to formally validated explanations and must be evaluated beyond visual plausibility for deployment in regulated domains.

3.4. Hybrid, Ensemble, Stacking, and Multimodal Systems

Hybrid and ensemble architectures improve generalization and support richer explanation strategies. The explainable deep stacking ensemble for brain tumor diagnosis [16] and the stacking ensemble for cervical cancer with XAI [24] demonstrate post-hoc explainability combined with ensemble diversity in oncological imaging. The stacking ensemble-based breast cancer classifier with real-time web deployment [3] illustrates the deployment pathway for web-accessible clinical screening. The ensemble transformer with post-hoc XAI for depression emotion and severity detection [10] extends ensemble explainability to affective computing. The explainable AI hybrid deep learning framework for skin cancer [6] integrates CNN feature learning with post-hoc explanation. Vision-audio multimodal object recognition via hybrid tensor fusion [51] contributes multimodal fusion evidence for industrial perception.

3.5. Graph Neural Networks and Knowledge-Graph Reasoning

Graph-structured architecture provides relational, entity-linked reasoning that is directly auditable. The GNN-enhanced gas-pipeline monitoring system [42] models fault propagation across sensor network topology. Knowledge-graph and NLP integration for heuristic reasoning [39] and the AddManBERT knowledge-graph for additive manufacturing design support [37] demonstrate BERT-based language models coupled with knowledge graphs for engineering decision accountability. The traceability of knowledge-graph reasoning, entity-linked chains that domain experts can validate—provides a qualitatively different form of deployment-relevant explainability than attention maps or post-hoc saliency.

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

The physics-guided Bayesian neural network for sensor fault detection in wind turbines [19] represents the most principled uncertainty-aware architecture in the corpus: physical priors constrain the hypothesis space, and Bayesian inference produces calibrated uncertainty estimates that directly support human oversight by signaling when predictions are insufficiently confident for autonomous action. This architecture family is underrepresented in the corpus relative to its deployment-readiness importance, particularly in safety-critical industrial and clinical contexts where uncalibrated predictions are a deployment liability.

3.7. Generative, Agentic, and Enterprise AI

Generative AI in enterprise information systems for transforming business intelligence [78] and automated risk assessment and collaborative AI in agile project management [59] represent the generative and agentic AI cluster. These architectures introduce accountability challenges specific to their architecture families: generative models may produce fluent but factually unreliable outputs, and agentic systems that initiate decision workflows require governance frameworks that specify accountability across workflow steps. AI-enabled MIS for economic resilience and governance [36] and AI-driven business analytics for IT strategy [33] address the organizational deployment context where these systems must operate under audit requirements.

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

The distributed intelligence edge-cloud-6G federated learning framework for secure and auditable decision support [12] provides the most architecturally complete privacy-preserving deployment architecture in the corpus. Privacy-preserving behavior analytics for workforce retention [55] demonstrates operational differential privacy in organizational settings. The multimodal privacy-preserving cancer diagnosis framework [13] illustrates the convergence of privacy, scalability, and multimodal integration in healthcare deployment. The trustworthy AI framework [23] and the resilience-by-design framework [31] provide the governance and accountability foundations that must underpin all distributed and privacy-preserving deployments. Table 1 presents the input modalities, strengths, deployment advantages, limitations, and validation requirements associated with major AI architecture families discussed in the review.

Table 1. Model-family suitability for cross-domain deployment contexts.

Model family	Main use	Deployment value	Key concern	Validation need
Conventional ML	Tabular, clinical, business, financial data	Efficient, interpretable, auditable	Feature quality, drift	Calibration, fairness, temporal testing
CNN / transfer learning	Images, signals, physiological data	Strong feature extraction; lightweight options	Domain shift, imbalance	External and robustness testing
Transformers / attention models	Medical and agricultural images, multimodal tokens	Captures global and multiscale patterns	Compute demand; weak explanation fidelity	XAI fidelity, calibration, external testing
Hybrid / ensemble / multimodal systems	Fused image, text, signal, or feature data	Better stability and complementary evidence	Complexity, error attribution	Ablation, calibration, explanation stability
GNN / knowledge-graph models	Networks, relations, industrial and knowledge data	Traceable relational reasoning	Incomplete or noisy graphs	Graph perturbation, expert validation
Bayesian / physics-guided models	Sensors, cyber-physical systems	Uncertainty-aware decisions	Prior design, implementation complexity	Calibration, OOD and drift testing
Generative / agentic AI	Enterprise and workflow automation	Synthesis and decision support	Hallucination, accountability	Factuality, auditability, governance review
Federated / privacy-preserving AI	Multi-site healthcare, IoT, distributed systems	Privacy-preserving collaboration	Non-IID data, communication cost	Site-wise validation, privacy accounting

4. Data modalities across AI application domains

4.1. Image-Based AI

Medical image modalities span CT imaging for lung cancer classification [63] and kidney disease [26], MRI for prostate cancer [61], histopathological imaging for breast cancer [3, 15], dermoscopy and clinical images for skin lesion [5, 6], cytological images for cancer classification [4], and cervical cell images [24, 62]. Agricultural image modalities span leaf images for soybean [7], mango [22], cotton [76], maize [57], tea [67], and aquaculture [60]. Infrastructure imagery includes acoustic-emission imaging for pipeline diagnosis [2] and crack characterization [8]. Each modality carries distinct preprocessing, quality assurance, and deployment-feasibility requirements that affect cross-domain generalizability.

4.2. Sensor and IoT Data

IoT sensor streams are deployed in smart energy metering [68], solar micro-grid battery monitoring [69], and smart healthcare medical boxes for elderly patients [77]. Industrial sensors contribute to wind-turbine fault detection through physics-guided Bayesian inference [19] and to pipeline monitoring through acoustic-emission GNN analysis [42]. The multivariate acoustic-emission imaging system for pipeline diagnosis [2] illustrates how sensor streams can be processed as imaging data to leverage CNN and deep learning representations.

4.2. Text, Language, and Social Data

Text modalities span Bengali social media sentiment classification [9], suicidal ideation detection using NLP [47], and drug review sentiment extraction [54]. Knowledge-graph NLP for heuristic reasoning [39] and AddManBERT for additive manufacturing [37] demonstrate structured knowledge extraction from text. The ensemble transformer with post-hoc XAI for depression detection [10] and the adaptive feedback system for learner improvement [29] extend text-based AI to mental health and educational contexts.

4.4. Graph and Knowledge-Structured Data

Graph and knowledge-structured data provide relational representations unavailable in flat feature vectors. The GNN-enhanced pipeline monitoring system [42] models spatial sensor dependencies. Knowledge-graph NLP for heuristic reasoning [39] and AddManBERT for additive manufacturing design [37] demonstrate entity-linked reasoning. The trustworthy AI framework [23] and resilience-by-design framework [31] provide cross-domain knowledge-structured governance evidence.

4.5. Physiological, Affective, and Assistive Data

Physiological modalities include EEG neural synchrony analysis using ML [56], voice biomarkers for Parkinson's screening [75], sleep stage physiological signals processed through transfer learning [74], and tDCS neuromodulation modeling [50]. Facial and affective signal modalities span facial emotion recognition via bidirectional Elman NN [28], hybrid deep belief optimization [70], hybrid multimodal InceptionV3DenseNet [66], ASD classification via dual-branch ViT [65, 73], and the ASD facial expression database [44]. Assistive modalities include the flex sensor hand-glove for deaf and mute individuals [17] and iris detection for biometric access [46].

4.6. Business and Enterprise Data

Business and tabular data modalities span credit scoring [79], retail demand forecasting [1], market trend forecasting [32], e-commerce pricing [58], small-business ML [45], market basket analysis for healthcare bundling [71], blockchain supply chain analytics [43], and customer satisfaction analytics [18]. Enterprise analytics modalities include AI-driven business analytics for IT strategy [33], AI-enabled MIS for governance [36], digital transformation analytics [53], generative AI in enterprise BI [78], and agile project management AI [59].

4.7. Multimodal and Multi-Source Evidence

Multimodal AI addresses the representational gap that single-modality systems cannot close. Vision-audio multimodal object recognition via hybrid tensor fusion [51] demonstrates cross-modality integration for industrial perception. The multimodal privacy-preserving cancer diagnosis framework [13] integrates multiple clinical data sources under privacy constraints. The hybrid multimodal emotion recognition framework using InceptionV3DenseNet [66] and the multimodal EEG neural synchrony analysis [56] illustrate cross-modal fusion in human-centered and neuro-affective contexts. The distributed edge-cloud-6G federated learning framework [12] provides the infrastructure for multi-source privacy-preserving integration at scale. Figure 2 shows how modality-specific data properties shape deployment risk.

5. Domain-specific Cross-Domain Synthesis

5.1. Healthcare and Biomedical AI

Healthcare provides the densest and most architecturally diverse AI evidence cluster in the corpus. Cancer classification systems span skin cancer [5, 6], lung cancer [48, 63], breast cancer [3, 15], cervical cancer [24, 62], brain tumor [16], leukemia [34], prostate cancer [61], and cytological cancer [4]. The multimodal privacy-preserving cancer diagnosis framework [13] addresses the intersection of privacy and multimodal integration in clinical AI. Heart disease prediction from structured data [40] and Parkinson's screening via personalized voice biomarkers [75] represent structured and physiological modality evidence. Transfer learning for sleep stage classification [74] illustrates data-scarce clinical AI. AI-integrated healthcare information systems for diabetes management [14], market basket analysis for healthcare service bundling [71], and depression emotion and severity detection [10] extend healthcare AI into health informatics and mental health. Web-based deployment of cervical cell screening [62] and real-time web deployment of breast cancer classification [3] demonstrate the deployment pathway most accessible to clinical systems without specialized infrastructure investment. Neural network–based models have shown strong potential for improving breast cancer diagnosis through dimensionality reduction and optimized architectural design using morphological features [80], [81], while machine learning approaches have also supported more accurate stroke prediction and risk stratification in healthcare settings [82]. Beyond individual diagnostic tasks, federated learning offers a privacy-first framework for scalable healthcare data processing across distributed institutions without direct data sharing [83]. In parallel, AI-driven cybersecurity methods are increasingly important for protecting healthcare systems and essential infrastructure from evolving digital threats, supporting safer and more resilient deployment of intelligent technologies in high-stakes environments [84].

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

Human-centered AI addresses communication, cognitive, and affective support for diverse users. ASD classification via dual-branch ViT [65, 73] and the ASD facial expression database [44] anchor the developmental assessment cluster. The AI-powered digital health platform for ASD students [21] illustrates adaptive, personalized therapeutic AI. The multimodal EEG neural synchrony analysis [56] and the tDCS model [50] address neuro-affective clinical AI. Facial emotion recognition systems [28, 70, 66] span multiple deep learning architectural stages. Suicidal ideation detection via NLP [47] and the ensemble transformer with post-hoc XAI for depression [10] represent mental health AI where calibrated uncertainty and ethical oversight are deployment critical. The flex sensor hand-glove for deaf and mute individuals [17], iris detection and recognition [46], the adaptive feedback system for learner improvement [29], and drug review sentiment extraction [54] extend the human-centered domain.

5.3. Agriculture, Environment, and Sustainability

Agricultural AI illustrates the evolutionary pressure toward lightweight, explainable, and field-deployable systems. MaizeFormerX lightweight cross-scale ViT with XAI [57], the MaxViT soybean disease model [7], ViX-MangoEFormer with XAI [22], the explainable transformer for cotton leaf diagnostics [76], advanced deep learning for tea leaf disease [67], and lightweight ResNeXt for aquaculture disease [60] constitute the precision crop disease detection cluster. AI-driven smart agriculture for crop yield optimization [35] addresses the systemic sustainability dimension. AI-driven solar financing for rural health businesses [25] connects agricultural sustainability to rural health infrastructure resilience.

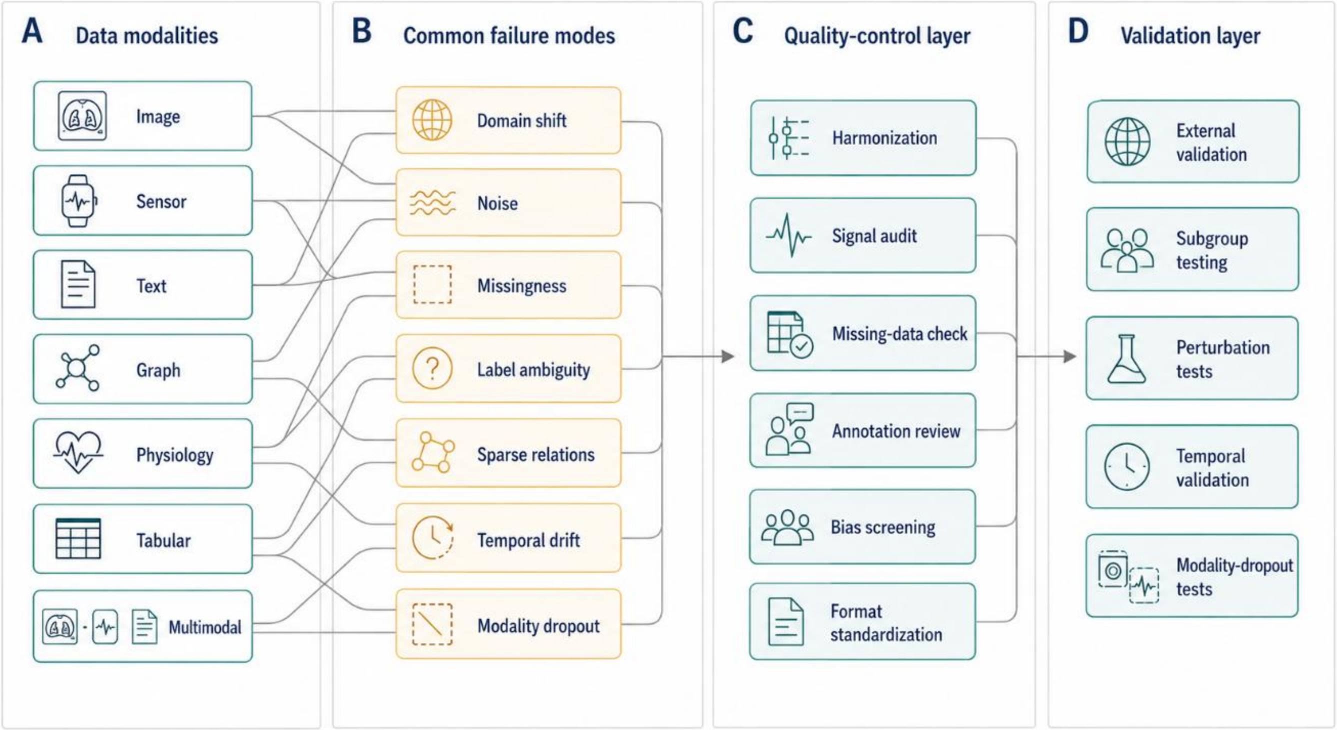

Figure 2: Data modality failure-mode map for cross-domain AI deployment.

5.4. Industrial Monitoring and Cyber-Physical Systems

Industrial monitoring AI must satisfy simultaneous real-time, safety, and accountability requirements. The GNN-enhanced gas-pipeline monitoring system [42] and the multivariate acoustic-emission imaging system for gas-pipeline diagnosis [2] address pipeline safety monitoring at different levels of relational abstraction. The lightweight DL system for concrete crack characterization [8] demonstrates edge-deployable infrastructure monitoring. The physics-guided Bayesian neural network for wind-turbine sensor fault detection [19] provides uncertainty-aware inference for safety-critical renewable energy infrastructure. The vision-audio multimodal tensor fusion system [51] provides industrial perception evidence. The question of full autonomy in underwater robotics [11] engages the human oversight axis at the autonomous industrial frontier.

5.5. Smart Infrastructure, IoT, Energy, and Communication Systems

Smart infrastructure AI operates under hardware constraints that determine which model families are deployable. IoT-based solar micro-grid battery monitoring [69], smart energy metering [68], and smart healthcare medical boxes for elderly patients [77] represent embedded AI in energy and healthcare infrastructure. Wireless mesh network load-balancing routing [27] and MANET routing protocol simulation [30] address network-layer decision support. HAPs communication systems optimization [52] extends infrastructure AI to airborne communication platforms with dynamic channel conditions. The deployment constraint shared across this domain, strict processor and memory budgets, makes the edge feasibility dimension of deployment readiness the primary bottleneck.

5.6. Business, Enterprise, and Organizational Analytics

Business AI spans the widest governance diversity in the corpus. Credit scoring for financially underserved businesses [79] introduces fairness-critical accountability. Predictive project risk analytics [38] and automated risk assessment AI in agile project management [59] illustrate governance-structured organizational AI. Market basket analysis for healthcare bundling [71] and customer satisfaction analytics [18] represent operational forecasting. Blockchain and ML in supply chain management [43] introduces distributed trust infrastructure. AI-driven business analytics for IT strategy [33], AI-enabled MIS for governance [36], digital transformation analytics [53], and AI-ERP integration [49] address the strategic and governance layer. Generative AI in enterprise information systems [78] introduces accountability challenges that current governance frameworks are not yet fully equipped to address. E-commerce pricing ML [58], small-business management ML [45], and market trend forecasting [32] complete the operational analytics evidence.

5.7. Cybersecurity, Privacy, and Distributed Intelligence

Cybersecurity AI operates under adversarial conditions that demand continuous adaptation. The intelligent cybersecurity ML framework for data protection and threat intelligence [41] addresses real-time threat detection. AI as a strategic engine for data security and digital communication resilience [64] positions security AI at the organizational governance level. Privacy-preserving behavior analytics [55] demonstrates operational differential privacy in organizational settings. The distributed edge-cloud-6G federated learning framework [12] provides the privacy-secure deployment architecture for cross-institutional AI. The trustworthy AI framework [23] and resilience-by-design framework [31] provide cross-sector governance foundations. Table 2 maps AI use cases to likely deployment routes, human oversight roles, and domain-specific operational risks.

Table 2. Decision-support functions and deployment pathways across domains.

Domain	Decision-support function	Deployment pathway	Human oversight	Key risk
Healthcare and biomedical AI	Screening, diagnosis, triage, risk prediction	Web-CDSS, cloud, hospital system, federated network	Clinician review	Poor external validation, privacy, miscalibration
Human-centered and assistive AI	Emotion recognition, accessibility, mental-health support, adaptive learning	Mobile app, assistive device, web/digital health platform	User, caregiver, educator, clinician	Bias, ethical sensitivity, weak human-in-loop testing
Agriculture and sustainability	Crop disease detection, yield support, resource optimization	Mobile, edge, field imaging, cloud advisory system	Farmer or agronomist	Environmental shift, limited field validation
Industrial monitoring	Fault detection, structural monitoring, predictive maintenance	Edge monitoring, sensor network, cloud alert system	Engineer or maintenance operator	Sensor drift, real-time failure, safety risk
Smart infrastructure and IoT	Energy monitoring, battery tracking, routing, elderly-care monitoring	IoT device, edge-cloud system, embedded platform	Operator, technician, caregiver	Latency, interoperability, hardware limits
Business and enterprise analytics	Forecasting, pricing, risk assessment, workflow automation	ERP/MIS, BI dashboard, analytics platform	Manager, analyst, auditor	Fairness, drift, opaque automation
Cybersecurity and distributed intelligence	Threat detection, secure analytics, privacy-preserving decision support	Security platform, federated edge-cloud, privacy pipeline	Security analyst or compliance officer	Adversarial shift, privacy leakage, governance gaps

6. Deployment readiness across domains

6.1. Data Quality, Interoperability, and Modality Mismatch

Data quality failures affect deployment readiness across all domains. The multichannel CT lung cancer analysis for imbalanced data [63] directly addresses class imbalance, a medical screening deployment liability. Cross-scanner heterogeneity in multi-institutional medical imaging [15, 61] and environmental variability in agricultural image datasets [7, 57] represent distribution-shift vulnerabilities. Business datasets [1, 32] are subject to volatility-driven distributional change. IoT sensor streams [68, 69] may have variable quality, sampling rates, and missing-data profiles. Interoperability standards compatible with downstream model deployment pipelines are needed across all domains.

6.2. Workflow Integration and Human Oversight

Deployment readiness requires integration into existing decision workflows and human oversight structures. Clinical decision support systems [40, 14, 62] must align with clinical information system architectures and professional role definitions. Industrial monitoring AI [19, 42] must trigger appropriate human maintenance review when uncertainty is high. The question of full autonomy in underwater robotics [11] directly addresses the human oversight governance boundary. The trustworthy AI framework [23] and resilience-by-design framework [31] establish that human oversight is a structural deployment requirement, not an optional safeguard.

6.3. Explainability, Auditability, and User Trust

Explainability is the deployment-readiness concern most consistently addressed in the corpus. Post-hoc XAI methods in stacking ensembles [16, 24], hybrid deep learning [6], and ensemble transformers [10] provide explanation outputs for clinical and affective computing contexts. The Swin Transformer cervical cell screening tool [62] integrates attention-based explanation with web deployment. Knowledge-graph reasoning in pipeline monitoring [42] and additive manufacturing design [37] provides structurally auditable explanation. The comparative explainable ML analysis [4] and the trustworthy AI framework [23] together establish that explanation validity, not just explanation presence, is the relevant deployment-readiness standard.

6.4. Privacy, Security, and Distributed Deployment

Privacy and security are deployment-readiness requirements in healthcare, organizational, and cybersecurity contexts. The federated learning framework [12] and multimodal privacy-preserving cancer diagnosis framework [13] provide technical approaches to privacy-preserving multi-institutional deployment. Privacy-preserving workforce analytics [55] demonstrates organizational privacy deployment. The cybersecurity framework [41] and AI for digital resilience [64] address the adversarial security dimension. As AI systems operate in increasingly interconnected digital infrastructure, the security-accuracy tradeoff becomes a first-class deployment engineering problem requiring explicit characterization.

6.5. Real-Time Feasibility, Latency, and Computational Efficiency

Computational efficiency directly constrains which model families are deployable in IoT, agricultural, and clinical point-of-care contexts. Lightweight ViT MaizeFormerX [57], MaxViT [7], ViX-MangoEFormer [22], and explainable transformer for cotton leaf [76] demonstrate agricultural transformer efficiency. Lightweight ResNeXt [60] and lightweight DL for crack characterization [8] demonstrate CNN compression for edge deployment. IoT energy metering [68], solar monitoring [69], and healthcare medical boxes [77] impose strict hardware constraints. Web-based deployment for medical screening [3, 62] demonstrates that cloud-hosted inference can satisfy real-time requirements, provided latency management is engineered explicitly.

6.6. Robustness, Monitoring, and Distribution Shift

Robustness under distribution shift is universally relevant but unevenly addressed. Medical imaging models face cross-scanner and cross-demographic shifts [13, 15]. Agricultural models face seasonal and geographic shifts [7, 57]. Industrial models must tolerate sensor degradation and novel fault patterns [19, 42]. Business forecasting models face economic regime changes [1, 32]. Cybersecurity models face continuously evolving adversarial patterns [41]. The physics-guided Bayesian model [19] and the resilience-by-design framework [31] provide the most principled robustness strategies in the corpus.

6.7. Evidence Maturity and Reproducibility

Evidence maturity, the degree to which AI deployment claims are supported by rigorous, reproducible, externally validated evidence is inconsistently addressed across 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 infrequently shared across groups. Business analytics studies rarely report confidence intervals or statistical significance. The trustworthy AI framework [23] and the resilience-by-design framework [31] provide governance-level frameworks for evidence accountability, but domain-specific evidence maturity standards, analogous to clinical trial phases are absent for most AI application domains.

7. Future Research Directions

Future research should address the cross-domain AI benchmark gap by developing standardized evaluation suites that jointly assess accuracy, explainability, robustness, privacy, and governance, supported by multi-domain leaderboards, explanation-validity indices, and governance-compliance scores [23, 31]. Deployment-readiness scoring is also needed through domain-specific frameworks that evaluate computational efficiency, validation quality, and governance readiness using deployment-readiness indices, scoring rubrics, and maturity-level classifications [23]. In addition, human-in-the-loop evaluation should assess structured deferral mechanisms across autonomy levels using decision quality, override frequency, and outcome differences with and without AI support [11, 19]. Further priorities include formal explainability and auditability standards for transformer, ensemble, and GNN models, evaluated through explanation fidelity, regulatory acceptance, and user-comprehension studies [4, 23]. Privacy-preserving and federated AI should be scaled to multi-institutional deployment with privacy-budget reporting, federated utility-loss analysis, and communication-efficiency evaluation under 6G settings [12, 13, 55]. Lightweight and edge-deployable models should preserve XAI capability while optimizing inference latency, memory footprint, and explanation fidelity at the edge [7, 8, 57, 60]. Moreover, strengthening multimodal and graph-enhanced systems through cross-modal explanation and knowledge-graph fusion, evaluated by attribution fidelity, knowledge-graph coverage, and modality-dropout stability [13, 51, 39, 42]. Robustness and uncertainty monitoring should integrate Bayesian uncertainty, physics-guided priors, and drift detection, using calibration error, OOD detection rate, and drift-alert latency [19, 31]. Finally, governance-aware reporting standards and evidence maturity frameworks should adapt CONSORT/TRIPOD-style guidance to classify AI systems from proof-of-concept to deployment-validated stages using completeness, reproducibility, external validation, governance compliance, and deployment-readiness indices [23, 31].

8. Limitations of the review

This review performs systematic-style evidence mapping and thematic synthesis rather than full quantitative meta-analysis. Full systematic-review reporting would require explicit database names, search strings, screening procedures, eligibility criteria, quality appraisal instruments, and full-text extraction of methods, results, and statistical evidence. These elements are not available from paper titles alone. The review should be interpreted as a structured cross-domain evidence map and taxonomic analysis rather than a comprehensive, reproducible systematic review. Full paper-level extraction would be required to support meta-analytic comparisons of model performance, deployment environment, computational requirement, or validation rigor. The curated corpus may not comprehensively represent all active AI research threads across the seven application domains; autonomous vehicles, legal AI, financial systemic risk, climate modeling AI, and social welfare AI are underrepresented. The seven-axis taxonomy is one defensible organization; alternative frameworks may yield complementary insights.

9. Conclusion

This systematic-style evidence mapping review has synthesized across seven application domains, healthcare and biomedical AI, human-centered and assistive AI, agriculture and sustainability, industrial monitoring and cyber-physical systems, smart infrastructure and IoT, business and enterprise analytics, and cybersecurity and distributed intelligence, using a seven-axis cross-domain taxonomy of domain, modality, model family, decision-support function, deployment pathway, deployment-readiness concern, and evidence role. The synthesis reveals an AI landscape in which model architecture diversity has advanced substantially: vision transformers, ensemble systems, graph neural networks, and federated learning frameworks are deployed across medical, agricultural, industrial, and organizational domains, with explicit explainability integration increasingly treated as an architectural requirement. Data modality coverage is broad, spanning medical images, agricultural imagery, acoustic-emission signals, IoT sensor streams, text, knowledge graphs, physiological signals, and business tabular data. Decision-support functions range from screening and diagnosis through fault detection, forecasting, risk assessment, resource optimization, and strategic governance. The persistent gap revealed by this cross-domain synthesis is the uneven maturation of deployment-readiness properties relative to predictive performance. Validated explainability, calibrated uncertainty, privacy-preserving inference at scale, post-deployment robustness monitoring, and governance-aligned evidence reporting are addressed in selected works but not systematically across domains. Future AI development must treat deployment readiness, encompassing explainability, privacy, robustness, human oversight, scalability, and governance accountability, as a first-class design requirement from the earliest stage of model development. Cross-domain evidence maturity frameworks, deployment-readiness scoring systems, and governance-aware reporting standards are needed to create a shared language for responsible AI deployment across the healthcare, agricultural, industrial, business, and infrastructure domains that the global AI ecosystem serves.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

References

[1] Shak MS, Mozumder MSA, Hasan MA, Das AC, Miah MR, Akter S, Hossain MN. Optimizing retail demand forecasting: A performance evaluation of machine learning models including LSTM and gradient boosting. The American Journal of Engineering and Technology. 2024;6(09):67-80. doi:10.37547/tajet/Volume06Issue09-09.

[2] Hasan MJ, Noman K, Navid WU, Li Y, Haruna A, Ashfak K. Intelligent diagnosis of gas pipeline condition through multivariate analysis of acoustic emission signal-based imaging. Nondestructive Testing and Evaluation. 2025. doi:10.1080/10589759.2025.2456088.

[3] Jashim FB, Refat FR, Karim MH, Mahmud FU, Sakib AH. Stacking ensemble-based breast cancer classification: Enhancing diagnostic accuracy with deep learning and real-time web deployment. International Journal of Science and Research Archive. 2025;15(02):1417-1431. doi:10.30574/ijsra.2025.15.2.1502.

[4] Siddiqui MIH, Rahman MS, Kabir AA, Mahmud FU, Rashid SU, Shammah RS. Comparative analysis of explainable machine learning models for cancer classification using cytological features. Journal of Medical and Health Studies. 2023;4(5):110-150. doi:10.32996/jmhs.2023.4.5.14.

[5] Linkon AA, Shakil MR, Ahmed S, Miah MR, Malik AH. Explainable transformer-based skin lesion classification from clinical images. Journal of Medical and Health Studies. 2026;7(5):46-55. doi:10.32996/jmhs.2026.7.5.7.

[6] Al Sakib A, Swapno SMMR, Ahamed F, Mohiuddin AB, Bhuiyan MIH, Khan S, Khushbu KG, Haque R, Alahmadi TJ, Moni MA. Explainable AI-driven hybrid deep learning framework for accurate skin cancer diagnosis. Digital Health. 2026;12:20552076261438923. doi:10.1177/20552076261438923.

[7] Pranta ASUK, Fardin H, Debnath J, Hossain A, Sakib AH, Ahmed MR, Haque R, Reza AW, Dewan MAA. A novel MaxViT model for accelerated and precise soybean leaf and seed disease identification. Computers. 2025;14(5):197. doi:10.3390/computers14050197.

[8] Habib MA, Hasan MJ, Kim JM. A lightweight deep learning-based approach for concrete crack characterization using acoustic emission signals. IEEE Access. 2021;9:104029-104050.

[9] Haque R, Islam N, Tasneem M, Das AK. Multi-class sentiment classification on Bengali social media comments using machine learning. International Journal of Cognitive Computing in Engineering. 2023;4:21-35. doi:10.1016/j.ijcce.2023.01.001.

[10] Islam S, Haque R, Khan MA, Mohiuddin AB, Siddiqui MIH, Limon ZH, Khushbu KG, Swapno SMMR, Ahmed MR, Appaji A. Ensemble transformer with post-hoc explanations for depression emotion and severity detection. iScience. 2026;29(2):114605. doi:10.1016/j.isci.2025.114605.

[11] Rohan A, Tolie HF, Hasan MJ, Kannan S. Full autonomy in underwater robotics systems: A realistic prospect? Engineering Applications of Artificial Intelligence. 2025;162(Part C):112638. doi:10.1016/j.engappai.2025.112638.

[12] Shakil MR, Hasan M, Tarek MIH, Polash FI, Meem EJ. Distributed intelligence and privacy-preserving deployment: Edge-cloud-6G-federated learning for secure, auditable decision support. World Journal of Advanced Engineering Technology and Sciences. 2026;18(3):268-279. doi:10.30574/wjaets.2026.18.3.0154.

[13] Kabir AA, Mahmud FU, Rahman MS, Rashid SU, Siddiqui MIH, Shammah RS. Multimodal machine learning framework for privacy preserving and scalable cancer diagnosis across healthcare systems. Journal of Adaptive Learning Technologies. 2024;1(6).

[14] Lucky KY, Haque S, Al-Samad K, Akter R, Faruq O, Azim KS, et al. AI-powered healthcare information systems securing diabetes management through integrated technology solutions and enhanced patient care delivery. Vascular and Endovascular Review. 2025;8(11s):465-476.

[15] Ahmed MR, Rahman H, Limon ZH, Siddiqui MIH, Khan MA, Pranta ASUK, Haque R, Swapno SMMR, Cho YI, Abdallah MS. Hierarchical Swin transformer ensemble with explainable AI for robust and decentralized breast cancer diagnosis. Bioengineering. 2025;12(6):651. doi:10.3390/bioengineering12060651.

[16] Haque R, Khan MA, Rahman H, Khan S, Siddiqui MIH, Limon ZH, Swapno SMMR, Appaji A. Explainable deep stacking ensemble model for accurate and transparent brain tumor diagnosis. Computers in Biology and Medicine. 2025;191:110166. doi:10.1016/j.compbiomed.2025.110166.

[17] Al Mamun A, Polash MSJK, Alamgir FM. Flex sensor based hand glove for deaf and mute people. International Journal of Computer Networks and Communications Security. 2017;5(2):38-48.

[18] Talukder T, Masud SB, Miah MR, Hera A, Faruque MO. An examination of how social media participation and customer satisfaction affect the likelihood that a business will make another transaction in the hospitality sector. Open Access Library Journal. 2025;12:1-15. doi:10.4236/oalib.1112802.

[19] Khan MDA, Rahman A, Mahmud FU, Bishnu KK, Nabil HR, Mridha MF, et al. A physics-guided Bayesian neural network for sensor fault detection in wind turbines. IEEE Open Journal of the Computer Society. 2025;6:931-942. doi:10.1109/OJCS.2025.3577588.

[20] Karshiboev A, Al-Samad K, Tarafdar MTR, Rimi NN, Islam MS, Papel MSI. Artificial intelligence for risk and decision assessment in agile IT projects: A thematic analysis and dynamic structuration framework approach. International Journal of Advances in Signal and Image Sciences. 2026;12(1):387-410. doi:10.29284/9k2nx425.

[21] Haque S, Islam MS, Islam MI, Islam MS, Khan R, Tarafder MTR, Mohammad N. Enhancing adaptive learning, communication, and therapeutic accessibility through the integration of artificial intelligence and data-driven personalization in digital health platforms for students with autism spectrum disorder. Journal of Posthumanism. 2025;5(8):737-756. doi:10.63332/joph.v5i8.3255.

[22] Noman AA, et al. ViX-MangoEFormer: An enhanced vision transformer-EfficientFormer and stacking ensemble approach for mango leaf disease recognition with explainable artificial intelligence. Computers. 2025;14(5):171. doi:10.3390/computers14050171.

[23] Shakil MR, Hasan M, Tarek MIH, Polash FI, Meem EJ. Trustworthy AI for high-stakes decision support across critical sectors. World Journal of Advanced Engineering Technology and Sciences. 2026;18(3). doi:10.30574/wjaets.2026.18.3.0152.

[24] Siddiqui MIH, Khan S, Limon ZH, Rahman H, Khan MA, Al Sakib A, et al. Accelerated and accurate cervical cancer diagnosis using a novel stacking ensemble method with explainable AI. Informatics in Medicine Unlocked. 2025;56:101657. doi:10.1016/j.imu.2025.101657.

[25] Tanim SH, Mithun MMU, Tarannum R. Sustaining vital care in disasters: AI-driven solar financing for rural clinics and health small businesses. American Journal of Technology Advancement. 2025;2(9):123-153. doi:10.31149/ajta.v2i9.2528.

[26] Ahmed S, Miah MR, Shakil MR, Linkon AA, Siddiqui MIH, Malik AH. Global-local attention modeling for reliable multiclass kidney disease classification from CT images. Journal of Medical and Health Studies. 2026;7(5):36-45. doi:10.32996/jmhs.2026.7.5.6.

[27] Alamgir FM, Ahmed F, Miah M, Munna HM, Barua S. A novel routing algorithm for inter-group load balancing in wireless mesh networks. In: 2018 21st Saudi Computer Society National Computer Conference (NCC). IEEE; 2018. doi:10.1109/NCG.2018.8593192.

[28] Alamgir FM, Alam MS. A novel deep learning-based bidirectional Elman neural network for facial emotion recognition. International Journal of Pattern Recognition and Artificial Intelligence. 2022;36(10):2252016. doi:10.1142/S0218001422520164.

[29] Qadir HM, Khan RA, Rasool M, Sohaib M, Shah MA, Hasan MJ. An adaptive feedback system for the improvement of learners. Scientific Reports. 2025;15:17242. doi:10.1038/s41598-025-01429-w.

[30] Ahmed F, Alamgir FM. Simulation-based proportional study of routing protocols for MANET. International Journal of Computer Networks and Communications Security. 2017;5(12):28-36.

[31] Shakil MR, Hasan M, Tarek MIH, Polash FI, Meem EJ. Resilience-by-design: AI for security, sustainability and health in interdependent systems. World Journal of Advanced Engineering Technology and Sciences. 2026;18(3):254-267. doi:10.30574/wjaets.2026.18.3.0153.

[32] Hossain MS, Khan A, Das P, Haque MSU, Kamruzzaman F, Akter S, Ahmed A, Miah MR. Enhanced market trend forecasting using machine learning models: A study with external factor integration. International Interdisciplinary Business Economics Advancement Journal. 2025;6(1):5-12. doi:10.55640/business/volume06issue01-02.

[33] Haque S, Mohammad N, Mambetaliev A, Karshiboev A, Lucky KY, Khan MTH, Islam H. Artificial intelligence-driven business analytics for IT strategy: Advancing decision-making, real-time insights, and organizational agility through intelligent automation and data integration. Journal of Posthumanism. 2025;5(6):1848-1863. doi:10.63332/joph.v5i6.2287.

[34] Haque R, Sakib AA, Hossain MF, Islam F, Aziz FI, Ahmed MR, Kannan S, Rohan A, Hasan MJ. Advancing early leukemia diagnostics: A comprehensive study incorporating image processing and transfer learning. BioMedInformatics. 2024;4(2):966-991. doi:10.3390/biomedinformatics4020054.

[35] Riipa MB, Saha S, Ferdousmou J, Khatoon R, Mohammad N, Hossain M. AI-driven smart agriculture: Optimizing crop yield and sustainability in the U.S. In: 2025 5th International Conference on Electrical, Computer and Energy Technologies (ICECET); 2025; Paris, France. doi:10.1109/ICECET63943.2025.11472088.

[36] Shakil MR, Hasan M, Tarek MIH, Polash FI, Meem EJ. AI-enabled management information systems for economic resilience and organizational performance: Analytics, governance, cyber risk and decision automation. World Journal of Advanced Engineering Technology and Sciences. 2026;18(3):294-307. doi:10.30574/wjaets.2026.18.3.0156.

[37] Haruna A, Noman K, Li Y, Wang X, Hasan MJ, Alhassan AB. AddManBERT: A combinatorial triples extraction and classification task for establishing a knowledge graph to facilitate design for additive manufacturing. Advanced Engineering Informatics. 2025;67:103578. doi:10.1016/j.aei.2025.103578.

[38] Tanim SH, Ahmad MS, Mithun MMU, Tarannum R, Refat FR, Sunny MNM. Leveraging predictive analytics for risk identification and mitigation in project management. Journal of Information Systems Engineering and Management. 2025;10(43s):1041-1052. doi:10.52783/jisem.v10i43s.8523.

[39] Haruna A, Noman K, Li Y, Makanda ILD, Zubair A, Hasan MJ, Alhassan AB. Facilitating heuristic reasoning by utilizing knowledge graph and natural language processing. Knowledge-Based Systems. 2026;334:115153. doi:10.1016/j.knosys.2025.115153.

[40] Rashid SU, Siddiqui MIH, Mahmud FU, Rahman MS, Kabir AA, et al. Machine learning based clinical decision support for heart disease prediction using structured patient data. Journal of Computer Science and Technology Studies. 2024;6(1). doi:10.32996/jcsts.2024.6.1.36.

[41] Shimu F. Intelligent cybersecurity framework: Machine learning-driven data protection and threat intelligence integration for modern digital communications. International Journal of Applied Mathematics. 2025;38(8s):620-632. doi:10.12732/ijam.v38i8s.595.

[42] Arifeen M, Hasan MJ, Rohan A, Kannan S, Prathuru A, et al. Enhancing acoustic emission driven smart gas-pipeline monitoring with graph neural network. In: Manjurul Islam MM, Baptista ML, Tariq F, editors. Artificial Intelligence for Smart Manufacturing and Industry X.0. Cham: Springer; 2025. p. 165-178. doi:10.1007/978-3-031-80154-9_8.

[43] Rahman T, Uddin MK, Hosen MM, Bhattacharjee B, Taluckder MS, Mou SN, Akter P, Hossain MS, Miah MR, Rahman MM. Blockchain applications in business operations and supply chain management by machine learning. International Journal of Computer Science & Information System. 2024;9(11):17-30. doi:10.55640/ijcsis/Volume09Issue11-03.

[44] Alamgir FM, Saif SMH, Hossain SM, Al Hadi A, Alam MS. Facial Expression Database of Autism Spectrum Disorder Children. European Chemical Bulletin. 2023;12(Special Issue 4):21109-21120. doi:10.48047/ecb/2023.12.Si4.1851.

[45] Naznin R, Sarkar MAI, Asaduzzaman M, Akter S, Mou SN, Miah MR, Sajal A. Enhancing small business management through machine learning: A comparative study of predictive models for customer retention, financial forecasting, and inventory optimization. International Interdisciplinary Business Economics Advancement Journal. 2024;5(11):21-32.

[46] Biswas R, Uddin J, Hasan MJ. A new approach of iris detection and recognition. International Journal of Electrical and Computer Engineering. 2017;7(5):2530-2536. doi:10.11591/ijece.v7i5.pp2530-2536.

[47] Haque R, Islam N, Islam M, Ahsan MM. A comparative analysis on suicidal ideation detection using NLP, machine, and deep learning. Technologies. 2022;10(3):57. doi:10.3390/technologies10030057.

[48] Debnath J, Uddin Khondakar Pranta AS, Hossain A, Sakib A, Rahman H, Haque R, Ahmed MR, Reza AW, Swapno SMMR, Appaji A. LMVT: A hybrid vision transformer with attention mechanisms for efficient and explainable lung cancer diagnosis. Informatics in Medicine Unlocked. 2025;57:101669. doi:10.1016/j.imu.2025.101669.

[49] Islam MS, Islam MI, Mozumder AQ, Khan MTH, Das N, Mohammad N. A conceptual framework for sustainable AI-ERP integration in dark factories: Synthesising TOE, TAM, and IS success models for autonomous industrial environments. Sustainability. 2025;17(20):9234. doi:10.3390/su17209234.

[50] Sourav MSU, Rahman A, Al Mamun A, Alamgir FM. Standard transcranial direct current stimulation (tDCS) model. International Journal of Computer Networks and Communications Security. 2017;5(12):264-270.

[51] Ahmed MR, Haque R, Rahman SMA, Reza AW, Siddique N, Wang H. Vision-audio multimodal object recognition using hybrid and tensor fusion techniques. Information Fusion. 2025;126:103667. doi:10.1016/j.inffus.2025.103667.

[52] Adnan BM, Chakma S, Alam MMJ, Alamgir FM. Performance simulation and comparison in High Altitude Platforms communications systems under PSK, DPSK, QAM and FSK modulation schemes and AWGN, Rician and Rayleigh communication channels. In: 2016 IEEE 7th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON); 2016; Vancouver, BC. p. 1-11. doi:10.1109/IEMCON.2016.7746080.

[53] Faruq O, Islam MI, Islam MS, Tarafder MTR, Rahman MM, Islam MS, Mohammad N. Re-imagining digital transformation in the United States: Harnessing artificial intelligence and business analytics to drive IT project excellence in the digital innovation landscape. Journal of Posthumanism. 2025;5(9):333-354. doi:10.63332/joph.v5i9.3326.

[54] Haque R, Laskar SH, Khushbu KG, Hasan MJ, Uddin J. Data-driven solution to identify sentiments from online drug reviews. Computers. 2023;12(4):87. doi:10.3390/computers12040087.

[55] Tanim SH, Tarannum R, Mithun MMU. Privacy-preserving behavior analytics for workforce retention approach. American Journal of Engineering, Mechanics and Architecture. 2023;1(9):188-215.

[56] Majumdar J, Apu MH, Rahman M, Zaman T, Hassan MM. Multimodal EEG analysis of neural synchrony in minimal phrase processing using machine learning. Conference paper; 2025 Nov.

[57] Rahman MM, Gony MN, Ullah MS, Shuvra SMK, et al. MaizeFormerX: A lightweight vision transformer with cross-scale attention for explainable maize leaf disease diagnosis. Scientific Reports. 2026. doi:10.1038/s41598-026-44550-0.

[58] Chowdhury MS, Shak MS, Devi S, Miah MR, Al Mamun A, Ahmed E, Hera SAA, Mahmud F, Mozumder MSA. Optimizing e-commerce pricing strategies: A comparative analysis of machine learning models for predicting customer satisfaction. The American Journal of Engineering and Technology. 2024;6(09):6-17. doi:10.37547/tajet/Volume06Issue09-02.

[59] Haque S, Chowdhury S, Faruq O, Akter R, Joy MSI, Munny MA, Shimu F. Automated risk assessment and collaborative decision-making AI applications in agile project management and stakeholder engagement. International Journal of Advances in Signal and Image Sciences. 2026;12(1):915-923. doi:10.29284/v2jv8q59.

[60] Masum AKM, Khan MFI, Mahmud FU, Hassan MM, Khaliluzzaman M. Improving aquaculture disease diagnosis with lightweight ResNeXt architectures. In: 2025 3rd International Conference on Artificial Intelligence, Blockchain, and Internet of Things (AIBThings); 2025. doi:10.1109/AIBThings66987.2025.11296219.

[61] Debnath J, Mohiuddin AB, et al. Hybrid vision transformer model for accurate prostate cancer classification in MRI images. In: 2025 International Conference on Electrical, Computer and Communication Engineering (ECCE). IEEE; 2025. doi:10.1109/ECCE64574.2025.11013952.

[62] Shakil MR, Malik AH, Siddiqui MIH, Ahmed S, Miah MR, Linkon AA. Swin Transformer-driven cervical cell classification with explainable AI and web-based screening. Journal of Medical and Health Studies. 2026;7(5):25-35. doi:10.32996/jmhs.2026.7.5.5.

[63] Sohaib M, Hasan MJ, Zheng Z. A multichannel analysis of imbalanced computed tomography data for lung cancer classification. Measurement Science and Technology. 2024;35(8):085401. doi:10.1088/1361-6501/ad437f.

[64] Faruq O, Chowdhury S, et al. Artificial intelligence as the strategic engine of data security, analytics, and digital communication for a resilient digital future. Journal of Information and Knowledge Management. 2025;20(2):1764-1773.

[65] Alamgir FM, Zaman T, Hossain MS, Hassan MM, Alam MS. ASDnet: Classification model for individuals with autism spectrum disorder using facial grid-wise expressions features and dual-branch visual transformation. Biomedical Signal Processing and Control. 2026;120:109999. doi:10.1016/j.bspc.2026.109999.

[66] Alamgir FM, Alam MS. Hybrid multi-modal emotion recognition framework based on InceptionV3DenseNet. Multimedia Tools and Applications. 2023;82:40375-40402. doi:10.1007/s11042-023-15066-w.

[67] ZakirHossain M, Khan MM, Thapa S, Uddin R, Meem EJ, Niloy SK, et al. Advanced deep learning techniques for precision diagnosis of tea leaf diseases. In: 2025 IEEE International Conference on Emerging Technologies and Applications (MPSec ICETA); 2025. doi:10.1109/MPSecICETA64837.2025.11118779.

[68] Haque MM, Choudhury ZH, Tejesh GS, Alamgir FM. IoT based smart energy metering system for power consumers. In: 2019 2nd International Conference on Innovation in Engineering and Technology (ICIET). IEEE; 2019. doi:10.1109/ICIET48527.2019.9290661.

[69] Mahamud S, Hossain MS, Hassan MM, Maruf MY, Rafi MAH, et al. IoT based wireless battery monitoring system for enhanced solar micro-grid performance in Bangladesh. In: Arefin MS, Kaiser MS, Bhuiyan T, Based MA, Ray K, editors. Proceedings of the 3rd International Conference on Big Data, IoT and Machine Learning. BIM 2025. Lecture Notes in Networks and Systems, vol. 1798. Cham: Springer; 2026. p. 474-489. doi:10.1007/978-3-032-15346-3_33.

[70] Alamgir FM, Alam MS. An artificial intelligence driven facial emotion recognition system using hybrid deep belief rain optimization. Multimedia Tools and Applications. 2023;82:2437-2464. doi:10.1007/s11042-022-13378-x.

[71] Rimon RH, Nurujjaman, Mithun MMU. Market basket analysis for healthcare services to identify bundled care offerings. Frontiers in Computer Science and Artificial Intelligence. 2025;4(3):44-67.

[72] Mahmud FU, Rahman A, Khan MA, Bishnu KK, Eva AA, Maua J. FuseAttenX: Leveraging attention-enhanced deep learning for business strategy optimization. In: 2025 IEEE 4th International Conference on Computing and Machine Intelligence (ICMI). 2025. doi:10.1109/ICMI65310.2025.11141140.

[73] Alamgir FM, Zaman T. Classification model for autism spectrum disorder individuals: Utilizing facial grid-wise emotion features and dual-branch visual transformation. In: 2024 IEEE International Conference on Power, Electrical, Electronics and Industrial Applications (PEEIACON). IEEE; 2024. doi:10.1109/PEEIACON63629.2024.10800506.

[74] Mahmud FU, Rahman H, Limon ZH, Khan MA, Jashim FB. Transfer learning approach for sleep stage classification with limited training data. International Journal of Science and Research Archive. 2025;15(2). doi:10.30574/ijsra.2025.15.2.1506.

[75] Ghosh BP, Bhuiyan MS, Bishnu KK, Mahmud FU, et al. Personalized machine learning models for Parkinson's disease screening via voice biomarkers: Accounting for age, gender, and linguistic variability. The International Medicine. 2025 Dec.

[76] Rahman Swapno SMM, Sakib A, Uddin Khondakar Pranta AS, Hossain A, Debnath J, Al Noman A, et al. Explainable transformer framework for fast cotton leaf diagnostics and fabric defect detection. iScience. 2026 Feb 20;29(2):114411. doi:10.1016/j.isci.2025.114411.

[77] Al-Mahmud O, Khan K, Roy R, Alamgir FM. Internet of Things (IoT) based smart health care medical box for elderly people. In: 2020 International Conference for Emerging Technology (INCET). IEEE; 2020. doi:10.1109/INCET49848.2020.9153994.

[78] Haque S, Islam H, Sharmin F, Joy MSI, Naher K, Rimi NN, et al. Generative artificial intelligence in enterprise information systems: Transforming business intelligence and strategic decision support processes. Journal of Information and Knowledge Management. 2025;20(2):887-897. doi:10.18848/8p0s2e25.

[79] Mithun MM, Tanim SH, Tarannum R. Developing AI-Powered Credit Scoring Models Leveraging Alternative Data for Financially Underserved US Small Businesses. Repository Antis Publisher. 2025 Oct 18:699254.

[80] Khan MA, Parveen R, Ahmed I, Milon MH, Khan TA. High-Accuracy Breast Cancer Diagnosis Using Neural Networks and Dimensionality Reduction Techniques. In2025 IEEE 19th International Conference on Open Source Systems and Technologies (ICOSST) 2025 Dec 1 (pp. 1-6). doi:10.1109/ICOSST69113.2025.11315291.

[81] Raja MR, Milon MH, Ahmed I, Papel MS, Khan MA, Islam MZ. Optimizing Neural Architectures for Accurate Diagnosis of Breast Cancer from Morphological Features. In2025 3rd International Conference on Cyber Resilience (ICCR) 2025 Jul 3 (pp. 1-6). doi:10.1109/ICCR67387.2025.11292567.

[82] Khan MA, Papel MS, Milon MH, Ahmed I, Islam MZ, Raja MR. Optimizing Stroke Prediction in Healthcare with Neural Machine Learning Algorithms. In2025 3rd International Conference on Cyber Resilience (ICCR) 2025 Jul 3 (pp. 1-7). doi:10.1109/ICCR67387.2025.11292555.

[83] Ahmed I, Papel MS, Raja MR, Islam MZ, Khan MA, Milon MH. Privacy-First Federated Learning Models for Scalable Healthcare Data Processing. In2025 3rd International Conference on Cyber Resilience (ICCR) 2025 Jul 3 (pp. 1-6). doi:10.1109/ICCR67387.2025.11291736.

[84] Islam MZ, Siam MA, Ahmed I, Khan MA, Islam MA, Milon MH. Fortifying Healthcare and Essential Infrastructure with AI-Driven Cybersecurity Technologies. In2025 International Conference on Metaverse and Current Trends in Computing (ICMCTC) 2025 Apr 10 (pp. 1-9). doi:10.1109/ICMCTC62214.2025.11196395.