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| REVIEW ARTICLE

Deployable AI Systems for Healthcare, Industry, Business, and Smart Infrastructure: A Cross-Domain Review

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| ABSTRACT

Artificial intelligence has progressed from laboratory benchmark systems to operational tools embedded in healthcare diagnostics, industrial monitoring, business analytics, smart infrastructure, agriculture, cybersecurity, and assistive technologies. However, the transition from a high-performing model to a deployable AI system remains a persistent challenge: clinical, industrial, and organizational deployment requires far more than predictive accuracy, demanding workflow integration, data interoperability, real-time feasibility, explainability, privacy, security, governance, and sustained post-deployment maintenance. This structured critical review synthesizes using a six-axis deployment-centered taxonomy encompassing application domain, data modality, architecture family, deployment pathway, deployment-readiness concern, and decision-support function. Seven application domains are examined: healthcare and biomedical AI, human-centered and assistive AI, industrial monitoring and cyber-physical systems, smart infrastructure and IoT, agriculture and sustainability, business and enterprise analytics, and cybersecurity and distributed intelligence. Eight architecture families are characterized, from conventional machine learning and CNNs through vision transformers, graph neural networks, Bayesian physics-guided models, generative AI, and federated learning systems, each associated with distinct deployment constraints and trustworthiness requirements. Synthesis identifies recurrent cross-domain deployment gaps including validated explainability, uncertainty quantification, privacy-preserving inference at scale, lightweight edge deployment, evidence maturity, and governance-aligned reporting. A structured future research agenda addresses these gaps with actionable directions and evaluation requirements. This review provides researchers, engineers, and practitioners with a deployment-focused roadmap for building AI systems that are not only capable but trustworthy, sustainable, and ready for real-world use.

| KEYWORDS

Deployable AI, AI deployment, Clinical AI, Edge AI, Federated learning; Explainable AI, Industrial AI, Cross-domain deployment taxonomy.

| ARTICLE INFORMATION

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1. Introduction

The expansion of artificial intelligence from competitive benchmarks into operational deployment environments has created a pressing need for deployment-centered evaluation frameworks. Across healthcare, industry, business, smart infrastructure, agriculture, cybersecurity, and assistive technologies, AI systems are increasingly embedded in workflows that affect patients, infrastructure operators, organizational decision-makers, and the public. Yet the research literature remains dominated by model-centric evaluations—accuracy, F1, AUC—that treat deployment as a post-research concern rather than a design requirement that should shape every phase of system development.

Deployable AI systems must satisfy requirements that extend well beyond predictive accuracy. A clinical decision support system must integrate into existing electronic health record workflows, produce interpretable outputs for clinicians, comply with patient data privacy regulations, and maintain reliable performance across patient demographics and clinical sites. An industrial monitoring AI must operate in real time under sensor noise and environmental variability, produce explainable fault diagnoses that maintenance engineers can act upon, and degrade gracefully rather than catastrophically under novel conditions. A business analytics AI must generate auditable decision logs, avoid discriminatory outcomes, and integrate with enterprise information systems without disrupting existing governance structures. A smart infrastructure AI must function on resource-constrained edge hardware with low latency, tolerate network instability, and maintain security under adversarial conditions. Figure 1 illustrates the deployment gap created by workflow integration, latency, privacy, explainability, robustness, governance, and maintenance requirements.

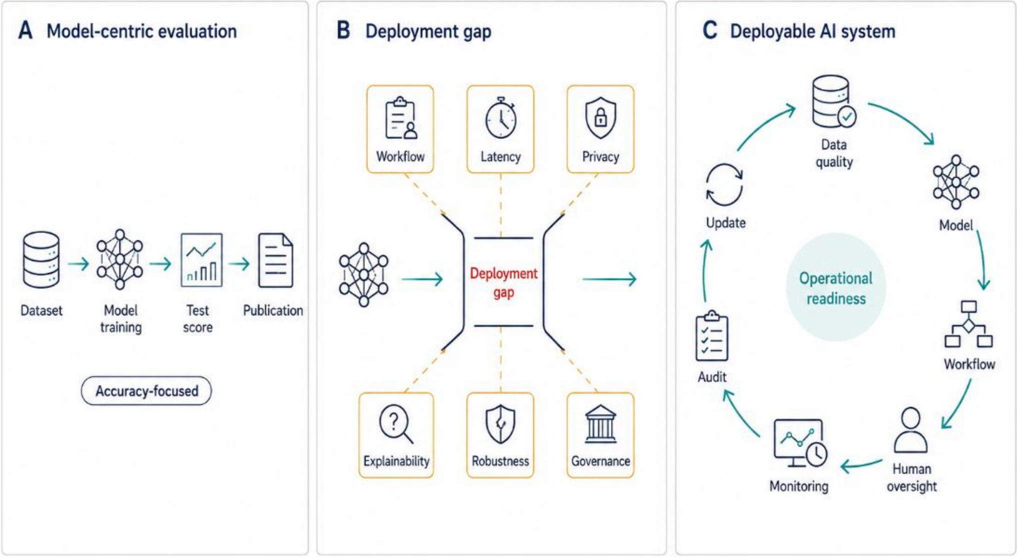

Figure 1. Transition from benchmark AI to deployable AI.

This review addresses the deployment gap by constructing a six-axis deployment-centered taxonomy, synthesizing architecture and deployment evidence across seven application domains, and identifying the cross-domain research directions most critical for advancing AI from model development to real-world deployment. Papers representing healthcare AI [63, 33, 58], industrial monitoring [60, 76, 68], business analytics [34, 11, 44], smart infrastructure [10, 8, 15], agricultural AI [79, 13, 75], cybersecurity [18, 47, 53], and assistive and human-centered AI [72, 57, 62] collectively illustrate the breadth of deployment contexts and the shared structural challenges they present.

2. Review Scope and Deployment-Centered Taxonomic Framework

Axis 1 classifies by application domain: (i) healthcare and biomedical AI, (ii) human-centered, neuro-affective, and assistive AI, (iii) industrial monitoring, cyber-physical systems, and robotics, (iv) smart infrastructure, IoT, energy, and communications, (v) agriculture, environment, and sustainability, (vi) business, enterprise, and organizational analytics, and (vii) cybersecurity, privacy, and distributed intelligence. Axis 2 classifies by data modality, spanning medical images, facial and affective signals, EEG and physiological signals, IoT and sensor streams, acoustic-emission and industrial signals, text and natural language, graph and knowledge-structured data, business and tabular data, and multimodal data. Axis 3 identifies the architecture family across eight categories from conventional ML to federated learning systems. Axis 4 defines the deployment pathway: web-based screening, IoT-enabled monitoring, edge or lightweight deployment, cloud or distributed deployment, federated or privacy-preserving deployment, enterprise information-system integration, cyber-physical or robotic autonomy, and human-in-the-loop decision support. Axis 5 catalogues the deployment-readiness concern across ten categories including data quality, scalability, latency, explainability, privacy, robustness, human oversight, governance, maintenance, and evidence maturity. Axis 6 classifies the decision-support function: screening and triage, diagnosis or classification support, monitoring and fault detection, forecasting and prediction, risk assessment, resource optimization, workflow automation, strategic decision support, and communication or accessibility support.

The full deployment evidence map is provided in Section 5. The taxonomy enables both domain-specific vertical analysis—how deployment constraints manifest within a sector—and cross-domain horizontal analysis—which deployment challenges recur systematically across sectors.

3. Architecture Families for Deployable AI Systems

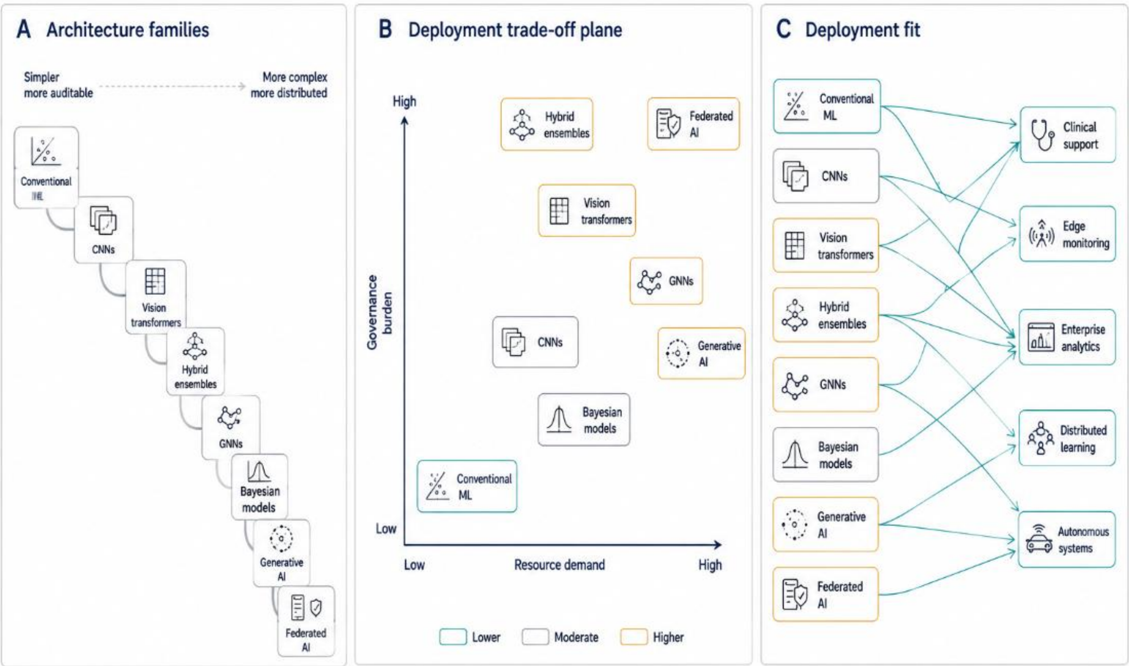

Figure 2. Architecture–deployment fit landscape for deployable AI systems.

3.1 Conventional Machine Learning and Structured Analytics

Conventional machine learning, including gradient-boosted trees, random forests, logistic regression, LSTM networks, and support vector machines, remains highly relevant in deployable AI systems, particularly where structured data, interpretability, and computational efficiency are required. Clinical decision support for heart disease prediction using structured patient data [64] exemplifies a deployment-ready ML pipeline: structured feature inputs, well-understood feature importance outputs, and manageable computational requirements for embedding in clinical information systems. In business analytics, retail demand forecasting using LSTM and gradient boosting [69], credit scoring for financially underserved small businesses [49], predictive project risk analytics [73], e-commerce pricing optimization [67], and small-business ML for customer retention, financial forecasting, and inventory optimization [77] collectively demonstrate that conventional ML architectures constitute the operational backbone of enterprise decision support. Data-driven sentiment extraction from drug reviews [2] and Bengali social media sentiment classification [78] illustrate text-based ML in human-centered contexts. The deployment advantage of conventional ML is auditability: feature-level attribution methods are well-characterized, computationally inexpensive, and compatible with organizational audit requirements. The deployment limitation is representational capacity: structured models may not generalize to the heterogeneous, high-dimensional inputs characteristic of industrial sensor streams, medical images, or multimodal clinical data. Figure 2 summarizes how architecture choice should be aligned with the intended deployment setting rather than selected solely on predictive performance.

3.2 CNN-Based Deep Learning and Transfer Learning

CNNs and their transfer-learned variants offer high representational capacity for image and signal data but introduce deployment challenges around model size, inference latency, training data requirements, and interpretability. Transfer learning for sleep stage classification under limited data [28] and early leukemia diagnostics using image processing and transfer learning [16] illustrate how pre-trained feature extractors address the data-scarcity problem prevalent in medical and industrial datasets. Facial emotion recognition via a bidirectional Elman neural network [66] and a hybrid deep belief optimization system [51] demonstrate CNN extensions to affective computing. The lightweight deep learning approach for concrete crack characterization via acoustic-emission signals [56] and lightweight ResNeXt for aquaculture disease diagnosis [9] specifically address the deployment constraint of resource-limited edge environments: model compression, quantization, and architecture efficiency are not aesthetic choices but operational requirements for embedded industrial and agricultural deployment. The tradeoff between transfer learning efficiency and negative transfer risk—where pre-trained features from a source domain impede learning in the target domain, is a deployment-critical consideration that is rarely characterized in the evaluated papers.

3.3 Vision Transformers and Attention-Based Architectures

Vision transformers have become a dominant architecture family in image-based decision support across medical and agricultural domains, driven by their long-range dependency modeling and the interpretability potential of attention maps. The hybrid vision transformer for lung cancer diagnosis [63], explainable transformer for skin lesion classification [61], Swin Transformer for cervical cell classification with web deployment [6], and hierarchical Swin Transformer ensemble for breast cancer with decentralized deployment [58] demonstrate the architecture's versatility across oncological imaging tasks. The global–local attention model for kidney disease classification from CT images [46] illustrates how dual-scale attention can support multi-class diagnostic discrimination. The dual-branch visual transformation models for ASD classification [32] extend ViTs to affective computing. In precision agriculture, the lightweight cross-scale attention ViT MaizeFormerX [79] and the MaxViT soybean disease model [12] demonstrate that transformer architectures are beginning to achieve the efficiency needed for agricultural edge deployment. The ViX-MangoEFormer ensemble with XAI for mango disease recognition [13] combines stacking and transformer architectures with explicit explainability mechanisms. A deployment-critical caution applies to all transformer-based systems: attention maps offer visual communicability but do not constitute validated causal explanations, and clinical, industrial, or regulatory deployment requires additional explainability validation beyond attention visualization.

3.4 Hybrid, Ensemble, and Multimodal Fusion Systems

Hybrid and ensemble architectures improve generalization and provide richer post-hoc explanation opportunities but introduce additional deployment challenges: increased model complexity, higher maintenance burden, longer inference pipelines, and greater difficulty in providing unified explanations. The explainable deep stacking ensemble for brain tumor diagnosis [24] and the stacking ensemble for breast cancer with real-time web deployment [43] demonstrate that ensemble architectures can be packaged into web-deployable screening tools, though latency management requires careful engineering. The ensemble transformer with post-hoc XAI for depression emotion and severity detection [35] extends ensemble explainability to affective computing, where label ambiguity demands ensemble uncertainty rather than point predictions. Vision-audio multimodal object recognition using hybrid tensor fusion [48] and the hybrid multimodal emotion recognition framework using InceptionV3DenseNet [23] address the modality fusion challenge—how to integrate heterogeneous inputs without introducing cross-modal interference or reducing explanation coherence. Multimodal systems must also address differential sensor availability at inference time: a model designed for simultaneous vision and audio input may fail non-gracefully if one modality is unavailable in deployment.

3.5 Graph Neural Networks and Knowledge-Graph Reasoning

Graph-based architectures offer structurally distinct deployment properties from image or tabular models: relational, traceable, and entity-linked reasoning that is inherently auditable by domain experts. The GNN-enhanced gas-pipeline monitoring system [76] models fault propagation across sensor networks, providing interpretable fault localization grounded in the physical topology of the pipeline. Knowledge-graph and NLP integration for heuristic reasoning [52] and the AddManBERT knowledge-graph construction for additive manufacturing design support [41] demonstrate that symbolic knowledge graphs can be integrated with neural NLP to produce reasoning chains auditable by engineers. The deployment limitation of knowledge-graph systems is their maintenance requirement: graphs must be updated as domain knowledge evolves, a curation burden that does not arise in purely data-driven systems. For industrial and enterprise domains where knowledge is relatively stable and accountability are high, this tradeoff generally favors knowledge-graph approaches over black-box deep learning.

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

Uncertainty-aware models are a critical but underrepresented architecture family in the corpus. The physics-guided Bayesian neural network for sensor fault detection in wind turbines [60] represents the most principled deployment approach to this challenge: physical priors constrain model behavior under novel inputs, while Bayesian inference provides calibrated uncertainty estimates that can trigger human oversight when model confidence is insufficient. In safety-critical industrial deployments—wind energy, structural health monitoring, chemical processing models that cannot express its own uncertainty is not deployable regardless of its average accuracy, because it cannot signal when expert review is needed. The deployment case for Bayesian and physics-guided architectures is strongest precisely in the domains where they are least represented: medical imaging, industrial monitoring, and autonomous systems. Closing this gap is one of the most important directions for deployment-oriented AI research.

3.7 Generative, Agentic, and Enterprise AI

Generative AI and agentic systems introduce qualitatively new deployment challenges that existing governance frameworks are not fully equipped to address. Generative AI in enterprise information systems for business intelligence and strategic decision support [34] embeds large language model capabilities into organizational workflows, introducing hallucination risk, factual unreliability, and the absence of auditable reasoning chains as deployment-critical concerns. Automated risk assessment and collaborative AI in agile project management [26] represents agentic AI deployment, where systems do not merely predict but coordinate workflows and stakeholder interactions—amplifying governance demands. AI for risk and decision in agile IT projects [59] addresses the organizational embedding of these systems, where trustworthiness frameworks must match the pace of organizational adoption. AI-driven business analytics for IT strategy [11] and AI-enabled management information systems for governance [44] illustrate enterprise AI in which accountability, audit trails, and real-time data integration are simultaneously required. The deployment readiness of generative and agentic AI systems is currently lower than that of discriminative models in most high-stakes domains, primarily because the accountability mechanisms—explanation, audit, and governance—have not yet matured to match the deployment pace.

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

The distributed intelligence and privacy-preserving deployment framework combining edge inference, cloud aggregation, 6G connectivity, and federated learning for secure and auditable decision support [47] represents the architectural frontier for large-scale, privacy-respecting AI deployment. Federated learning enables collaborative model training across data-sovereign institutions without centralizing raw data property critical for healthcare, workforce, and government applications. Privacy-preserving behavior analytics for workforce retention [27] and the multimodal privacy-preserving cancer diagnosis framework [40] demonstrate operational privacy-preserving systems, though with architecture-specific utility-privacy tradeoffs that must be characterized in each deployment context. The stacking ensemble breast cancer classifier with real-time web deployment [43] and Swin Transformer cervical cell screening with web interface [6] illustrate that requires engineering attention to latency, cross-browser compatibility, user-interface design, and inference pipeline packaging—concerns that are architectural but not typically addressed in model-development papers. The resilience-by-design framework [53] and trustworthy AI for high-stakes decision support [65] provide the governance and accountability perspectives that must underline all distributed deployment architectures.

4. Sector-Specific Deployment Synthesis

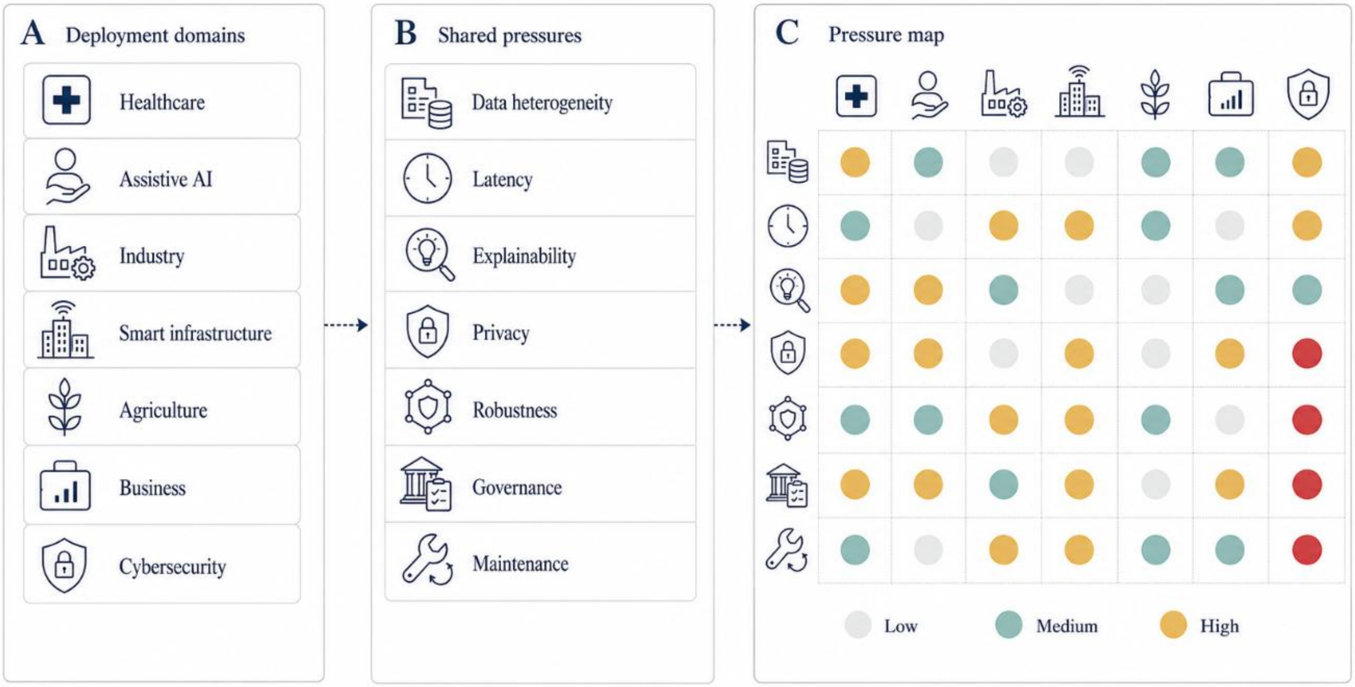

Figure 3. Cross-domain deployment pressure map.

4.1 Healthcare and Biomedical AI Deployment

Healthcare is the most deployment-demanding sector in the corpus, combining regulatory scrutiny, patient privacy obligations, interpretability expectations from clinicians, and the severity of consequences from diagnostic error. Cancer diagnosis applications—spanning skin cancer [33, 61], lung cancer [63, 30], breast cancer [58, 43], cervical cancer [6, 38], brain tumor [24], leukemia [16], prostate cancer [54], and cytological cancer classification [31], collectively demonstrate that oncological imaging is the most architecturally diverse healthcare AI subfield and also the most consistent in demanding post-hoc explainability. The multimodal privacy-preserving cancer diagnosis framework [40] addresses the privacy dimension that multicenter clinical deployment requires. Kidney disease classification from CT images [46] and Parkinson's screening via personalized voice biomarkers [71] illustrate the modality diversity of healthcare AI: from image to physiological signal, each modality carries distinct preprocessing, quality assurance, and deployment-feasibility requirements. Sleep stage classification with limited training data [28] addresses the scarcity challenge common in sleep medicine and demonstrates the deployment relevance of transfer learning for data-constrained clinical contexts. The multichannel CT lung cancer analysis for imbalanced data [30] directly addresses class imbalance, a deployment-critical property, since models trained on imbalanced datasets may produce unreliable triage decisions at the deployment boundary. Heart disease prediction from structured data [64] and diabetes management through AI-integrated healthcare information systems [22] represent the simpler but operationally important case of structured-data clinical AI, where deployment is technically feasible, but governance and integration are the principal barriers.

Deployment barriers recur across healthcare, assistive AI, industrial monitoring, smart infrastructure, agriculture, business analytics, and cybersecurity, but their relative intensity differs by domain, as shown in Figure 3. Neural machine learning has been investigated for stroke-risk prediction [82], whereas breast cancer diagnosis has been enhanced through neural networks, dimensionality reduction, morphological feature analysis, and optimized model architectures [81], [80]. Interpretability is also emphasized as a critical requirement, with explainable deep learning helping to improve the transparency and practical trustworthiness of AI-assisted medical diagnosis [85]. In parallel, privacy-first federated learning supports distributed healthcare data processing while reducing dependence on centralized data sharing [83]. Related applications in AI-driven cybersecurity and digital twin–enabled predictive maintenance further demonstrate the value of intelligent systems for protecting essential infrastructure and improving operational reliability in industrial IoT environments [86], [84].

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

Assistive and human-centered AI systems serve users with cognitive, communicative, or affective needs—a context that amplifies both the importance and the difficulty of trustworthy deployment. ASD classification models using dual-branch visual transformation [72] and the ASDnet architecture [32] illustrate high-stakes developmental AI where misclassification has lasting consequences. The ASD facial expression database [17] provides the foundational data resource for this research cluster, and the AI-powered digital health platform for ASD students [57] illustrates how classification systems can be embedded in therapeutic and educational workflows. Multimodal EEG analysis of neural synchrony using ML [25] and the standard tDCS model [7] address neuro-affective AI in clinical neuroscience contexts, where safety and clinical oversight are paramount. Facial emotion recognition systems—including the bidirectional Elman neural network [66], hybrid deep belief optimization system [51], and hybrid InceptionV3DenseNet framework [23]—address affective computing in contexts where emotional ground truth is inherently ambiguous and deployment must account for individual and cultural variability. Suicidal ideation detection using NLP and deep learning [55] represents a deployment context in which false negatives carry catastrophic consequences and model confidence calibration is clinically non-negotiable. The flex sensor hand glove for deaf and mute people [62], iris detection and recognition [37], and Bengali social media sentiment classification [78] extend assistive AI to accessibility, biometric identification, and multilingual communication support. The adaptive feedback system for learner improvement [4] and drug review sentiment extraction [2] address educational and informational deployment contexts.

4.3 Industrial Monitoring, Cyber-Physical Systems, and Robotics

Industrial monitoring AI must satisfy simultaneous requirements for real-time reliability, safety, uncertainty communication, and fault-explainability that distinguish it from research-grade model evaluation. Gas-pipeline condition diagnosis via acoustic-emission signal imaging [68] and GNN-enhanced gas-pipeline monitoring [76] address a safety-critical infrastructure monitoring application where false negatives have severe physical consequences and fault localization must be traceable. The lightweight deep learning system for concrete crack characterization using acoustic-emission signals [56] demonstrates that industrial inspection can be addressed with edge-deployable models, provided model compression preserves the diagnostic fidelity required for structural safety decisions. The physics-guided Bayesian neural network for wind-turbine sensor fault detection [60] is the most deployment-principled architecture in the industrial cluster: uncertainty-aware fault detection directly supports the human oversight requirement in maintenance workflows. Vision-audio multimodal object recognition via hybrid tensor fusion [48] addresses perceptual multi-sensor fusion in industrial robotics contexts. The question of full autonomy in underwater robotics [14] directly engages the human oversight axis: the framing as an open prospect reflects the genuine difficulty of establishing deployment conditions for unsupervised autonomous systems in unstructured environments, where safety accountability cannot be transferred to algorithmic systems without formal safety certification. The knowledge-graph approach for additive manufacturing design support [41] extends industrial AI to design decision support, where traceable and auditable reasoning is a quality-system requirement.

4.4 Smart Infrastructure, IoT, Energy, and Communications

Smart infrastructure AI is characterized by edge-hardware constraints, network instability, low-latency requirements, and the need for AI inference under real-time operational conditions. IoT-based wireless battery monitoring for solar micro-grids [15], smart energy metering [8], and the smart healthcare medical box for elderly patients [10] represent embedded AI monitoring in energy and healthcare infrastructure, where inference must occur on resource-constrained hardware with minimal latency. Wireless mesh network routing optimization [42] and MANET routing protocol simulation [20] address network-layer decision support in distributed infrastructure, where AI recommendations must be executed within network scheduling constraints. HAPs communication systems optimization [29] extends infrastructure AI to airborne communication platforms operating under dynamic channel conditions. Across all smart infrastructure applications, the deployment architecture is constrained by physical hardware, processor capability, memory, power budget, and communication bandwidth—in ways that medical or business AI deployments are not. Model compression, quantization, and efficient inference are not research options but operational requirements, and deployment readiness evaluation must explicitly characterize the resource-performance tradeoff under realistic hardware constraints.

4.5 Agriculture, Environment, and Sustainability

Agricultural AI deployment faces a distinct combination of challenges: lightweight inference on field hardware, environmental variability in illumination and imaging conditions, explanations accessible to non-technical users, and deployment in low-resource settings. The lightweight cross-scale attention vision transformer MaizeFormerX [79], the MaxViT soybean disease model [12], the ViX-MangoEFormer ensemble with XAI [13], the explainable transformer for cotton leaf diagnostics [75], and advanced deep learning for tea leaf disease precision [39] constitute a precision crop pathology cluster in which explainability, lightweight deployment, and speed are co-prioritized. Lightweight ResNeXt for aquaculture disease diagnosis [9] extends the lightweight deployment requirement to aquaculture, where inference must occur at pond-side on mobile hardware. AI-driven smart agriculture for crop yield optimization [70] and AI-driven solar financing for rural clinics and health businesses [74] address the systemic dimension, integrating AI into sustainable agricultural and rural health management frameworks. The resilience-by-design framework [53] provides the cross-sectoral accountability lens under which agricultural sustainability, rural health, and infrastructure resilience are jointly addressed.

4.6 Business, Enterprise, and Organizational AI Deployment

Business and enterprise AI deployment spans the widest governance spectrum in the corpus, from transactional forecasting to strategic organizational decision-making. Credit scoring for financially underserved businesses [49] introduces fairness and access as deployment-critical properties: audit trails and disparate-impact evaluation are regulatory requirements, not optional enhancements. Automated risk assessment in agile project management [26] and AI for agile IT project risk [59] position AI within organizational governance frameworks. Market basket analysis for healthcare service bundling [50] bridges health and business analytics. Blockchain and ML integration for supply chain management [21] introduces distributed ledger mechanisms as trust infrastructure alongside predictive AI. Enhanced market trend forecasting [1], retail demand forecast [69], e-commerce pricing optimization [67], customer satisfaction and hospitality analytics [19], and small-business ML [77] constitute the operational forecasting cluster. The attention-enhanced deep learning system for business strategy optimization [36] and AI-driven business analytics for IT strategy [11] extend transformer-based architecture into enterprise decision support. Generative AI for enterprise business intelligence [34], digital transformation analytics for IT excellence [3], AI-ERP integration in dark factories [45], and AI-enabled management information systems for governance [44] address the strategic and governance layer where AI deployment has the broadest organizational consequences. Predictive analytics for project risk [73] and comprehensive small-business ML [77] complete the business analytics deployment evidence. Across this domain, the deployment requirement for audit trails, explainable decision logs, and governance-aligned reporting is at least as important as predictive accuracy.

4.7 Cybersecurity, Privacy, and Distributed Intelligence

Cybersecurity AI deployment must function in adversarial environments where the threat landscape evolves continuously and model reliability is actively challenged by attackers. The intelligent cybersecurity framework integrating ML-driven data protection and threat intelligence [18] addresses real-time threat detection in digital communications, where latency is as operationally critical as accuracy. AI as a strategic engine for data security, analytics, and digital communication resilience [5] positions AI at the organizational level of security governance. Privacy-preserving behavior analytics for workforce retention [27] operationalizes differential privacy in organizational analytics—a deployment model with broad applicability across sectors that process sensitive personal data. The trustworthy AI framework for high-stakes decision support [65] provides the cross-sector governance perspective that underpins all critical deployments. The resilience-by-design framework [53] addresses the interdependency of security, sustainability, and health resilience in infrastructure-scale AI. The distributed edge-cloud-6G-federated learning framework [47] represents the architectural frontier for secure and auditable distributed AI, integrating multiple trust mechanisms into a unified deployment stack. As AI systems are deployed at greater scale in digital infrastructure, the security-accuracy tradeoff, ensuring that security mechanisms do not degrade model utility—becomes a first-class deployment engineering problem.

5. Deployment Challenges Across Domains

5.1 Data Quality, Interoperability, and Heterogeneity

Data quality failures are among the most common reasons AI systems fail to deploy successfully. Medical imaging datasets are subject to scanner-protocol heterogeneity, acquisition-site variability, and labeling inconsistency across institutions [40, 58]. The multichannel CT lung cancer analysis for imbalanced data [30] highlights class imbalance as a deployment-critical data quality issue: models trained on imbalanced datasets may achieve impressive overall accuracy while performing poorly on the rare-but-critical class. Agricultural datasets face illumination variability, growth-stage confounds, and regional crop variety differences [12, 79]. Business datasets span heterogeneous source transactional records, social media, web data, and external economic indicators [1, 19]—that require principled integration. Multimodal systems [23, 48] must manage cross-modal quality differences, where one modality may be clean while another is noisy, and the fusion architecture must handle this asymmetry gracefully. Standard interoperability frameworks for AI-ready data, analogous to FHIR in healthcare—are needed across all domains to reduce the pre-deployment data engineering burden.

5.2 Workflow Integration and Human Oversight

Successful AI deployment requires integration into existing decision workflows, not replacement of them. The clinical decision support system for heart disease [64] and the AI-integrated healthcare information system for diabetes management [22] illustrate different workflow integration models: the former provides point-of-care prediction support, while the latter embeds AI into a broader health information platform. The question of full autonomy in underwater robotics [14] directly addresses the human oversight axis: the framing as a realistic prospect question reflects genuine uncertainty about when autonomous decision-making without human oversight is responsible. The adaptive feedback system for learners [4] and the ASD digital health platform [57] model AI as assistive tools that augment professional judgment. Automated risk assessment AI in agile project management [26] positions AI as a workflow participant that coordinates with stakeholders rather than a solitary decision-maker. The trustworthy AI framework [65] explicitly addresses the governance conditions under which different levels of AI decision autonomy are appropriate framework applicable across all seven deployment domains.

5.3 Real-Time Feasibility, Latency, and Resource Constraints

Real-time inference under resource constraints is a deployment requirement that affects architectural choices from the beginning of the model development pipeline, not at the end. Lightweight ResNeXt for aquaculture diagnosis [9], MaizeFormerX lightweight ViT [79], and lightweight deep learning for concrete crack characterization [56] all explicitly address the accuracy-efficiency tradeoff under edge deployment constraints. IoT-based solar micro-grid monitoring [15] and smart energy metering [8] embed AI inference in hardware with strict processor and memory limits. HAPs communication optimization [29] and MANET routing simulation [20] address the network-layer constraints that determine whether real-time data can reach cloud-based inference pipelines reliably. For applications where cloud latency is unacceptable, industrial fault detection, medical triage, agricultural field monitoring deployment is not optional, and deployment-readiness evaluation must explicitly characterize inference speed and memory footprint under realistic hardware conditions.

5.4 Explainability, Auditability, and User Trust

Explainability is a deployment requirement, not a research amenity. The post-hoc XAI methods integrated into stacking ensembles [24, 38], vision transformers [6, 61], and hybrid deep learning systems [33] provide explanation outputs, but the deployment requirement is not merely the presence of an explanation but its validity, relevance to the intended audience, and support for accountability. Comparative explainable ML for cancer cytology [31] illustrates the value of systematic XAI comparison but does not resolve the question of which explanation method is most clinically valid. Knowledge-graph reasoning in gas-pipeline monitoring [76] and additive manufacturing design support [41] provides a structurally auditable explanation—entity-linked reasoning traceable by domain experts that post-hoc attribution methods cannot match. For governance and regulatory purposes, explanation outputs must be logged, version-controlled, and linked to the model version that produced them, requirements that are architectural as much as analytical. As presented in Table 1, audit-ready explanation requires linkage between the model version, input record, explanation output, decision log, human action, and observed outcome.

Table 1. Explainability-to-Auditability Validation.

Explanation output	Deployment use	Validation requirement	Audit-ready evidence
Heatmap / saliency map	Visual localization in image-based diagnosis or inspection	Stability under perturbation and expert relevance check	Input image, model version, heatmap, stability result, expert note, decision log
Attention map	Communicating model focus in transformer-based systems	Fidelity or ablation testing before causal interpretation	Input, model checkpoint, attention output, confidence score, ablation result, reviewer note
Feature importance	Interpreting structured clinical, business, or forecasting models	Consistency across resampling, subgroups, and explanation methods	Feature ranking, data version, subgroup stability, calibration status, threshold record
Counterfactual explanation	Showing which input changes may alter a decision	Plausibility, feasibility, and domain-validity assessment	Original input, counterfactual instance, changed variables, feasibility check, user action
Graph / knowledge trace	Entity-linked reasoning in GNN or knowledge-graph systems	Consistency with current domain knowledge or physical topology	Graph version, node–edge path, evidence source, timestamp, expert validation
Uncertainty signal	Deferral, escalation, or human-review routing	Calibration and out-of-distribution sensitivity testing	Prediction, uncertainty estimate, calibration report, deferral threshold, outcome feedback
Decision log	Retrospective accountability and post-deployment review	Complete linkage between input, model, explanation, action, and outcome	Input metadata, model version, explanation file, user action, timestamp, outcome

5.5 Privacy, Security, and Distributed Deployment

Privacy-preserving AI deployment is both a regulatory obligation and an ethical requirement in health, workforce, and government contexts. The federated learning framework for secure and auditable decision support [47] provides the most architecturally complete response to privacy-preserving deployment in the corpus, but introduces communication overhead, device heterogeneity, and model poisoning risks that must be managed in the security layer. Privacy-preserving behavior analytics for workforce retention [27] demonstrates operational privacy-preserving analytics, while the multimodal privacy-preserving cancer diagnosis framework [40] illustrates the utility-privacy tradeoff in healthcare multimodal fusion. The intelligent cybersecurity ML framework [18] and AI for data security and digital resilience [5] address the security layer of AI deployments—the adversarial threat surface that exists in any network-connected AI system. The resilience-by-design framework [53] addresses systemic failure scenarios in interdependent infrastructure, where security, sustainability, and health systems interact and may fail together.

5.6 Robustness, Monitoring, and Maintenance

Model deployment is not a one-time event but a continuous operational commitment. Distribution shift—the degradation of model performance when deployment conditions diverge from training conditions—affects medical imaging [40, 58], agricultural monitoring [12, 79], business forecasting [1, 69], and industrial sensing [60] in different ways and at different timescales. The physics-guided Bayesian neural network [60] addresses robustness through physical priors that constrain model behavior under novel inputs; no other architecture in the corpus provides comparable formal robustness guarantees. Post-deployment monitoring requires infrastructure for detecting performance degradation in real time, triggering retraining or rollback when degradation is identified, and maintaining version control of models, training data, and explanation outputs. These requirements are familiar in software engineering but underrepresented in AI deployment research.

5.7 Governance, Accountability, and Evidence Maturity

Governance frameworks for AI deployment must address accountability, reproducibility, fairness, and evidence maturity in terms that are operationally actionable for practitioners and auditable by regulators. The trustworthy AI framework [65] and the AI-enabled management information systems for governance [44] address organizational-level governance. The AI-ERP integration conceptual framework [45] illustrates governance within autonomous industrial environments. The credit scoring model for underserved businesses [49] introduces fairness and access as governance properties with regulatory dimensions. Evidence maturity to which an AI system's claims are supported by rigorous, reproducible, externally validated evidence is the governance property most consistently underaddressed in the corpus. No shared evidence maturity standard, analogous to clinical trial phases, currently governs AI deployment across healthcare, industrial, agricultural, or business domains. Developing such a standard is a foundational requirement for responsible cross-domain AI deployment. Table 2 presents an evidence maturity checklist for deployable AI systems.

Table 2. Evidence Maturity Checklist for Deployable AI.

Evidence maturity stage	Core objective	Minimum evidence required	Deployment-readiness interpretation
Proof of concept	Demonstrate technical feasibility	Clear task definition, dataset description, baseline comparison, internal test performance, and preliminary error analysis	Suitable only for early research; not sufficient for operational use
Internal validation	Test model reliability within the development setting	Patient-/site-/unit-level split where relevant, calibration assessment, subgroup analysis, sensitivity to missing or noisy data, and reproducible evaluation protocol	Supports controlled evaluation but remains vulnerable to dataset-specific bias
External validation	Assess generalization beyond the development environment	Independent dataset or external site validation, domain-shift analysis, robustness testing, calibration transfer, and comparison with existing practice	Provides stronger evidence for broader applicability but does not confirm workflow readiness
Workflow pilot	Evaluate use within a real decision process	Human-in-the-loop testing, latency measurement, usability feedback, explanation review, deferral rules, and decision-log capture	Indicates practical feasibility under supervised deployment conditions
Monitored deployment	Sustain safe and accountable real-world use	Continuous performance monitoring, drift detection, audit trail, rollback plan, model-update policy, privacy/security controls, and governance oversight	Represents deployment-ready evidence when monitoring, accountability, and maintenance are operationalized

6. Future Research Directions

Future research on deployable AI should move beyond isolated model performance and prioritize evaluation frameworks that assess operational readiness across domains. A key need is the development of cross-domain deployment-readiness benchmarks that jointly evaluate accuracy, latency, explainability, robustness, privacy, and governance, using measurable indicators such as a deployment-readiness index, multi-domain leaderboard, and governance compliance score [65]. Human-in-the-loop AI workflows should also be strengthened through structured deferral mechanisms that activate expert review when model uncertainty exceeds predefined thresholds; such systems should be evaluated by comparing decision quality with and without AI, override frequency, and downstream clinical or industrial outcomes [14, 60]. In parallel, edge-deployable and lightweight AI remains essential for embedded, IoT, and mobile settings. Future work should therefore optimize vision transformers and ensemble models for low-resource environments while preserving explainability, with evaluation based on inference latency, memory footprint, and the accuracy–efficiency Pareto frontier [9, 56, 79].

Privacy-preserving and distributed deployment also requires further methodological progress. Federated learning should be scaled to multi-sector and multi-institutional settings with formal privacy accounting, while evaluation should report privacy budget consumption, model utility under federation, and communication efficiency [27, 40, 47]. Explainability research should move from visual explanation generation toward formal auditability standards, including fidelity metrics and validation protocols for transformers, ensemble, and graph neural network explanations. These systems should be assessed using explanation fidelity scores, regulatory acceptability, and user comprehension studies [6, 24, 65]. Robustness and uncertainty monitoring should likewise become core deployment requirements, especially through the integration of physics-guided and Bayesian uncertainty estimation with post-deployment drift detection. Relevant evaluation criteria include calibration error, out-of-distribution detection rate, and drift-alert latency [53, 60].

Finally, deployable AI systems require stronger post-deployment maintenance, governance-aware reporting, scalable enterprise integration, and evidence maturity frameworks. Automated monitoring, retraining triggers, rollback protocols, and version-control procedures should be established, with performance assessed through time to degradation detection, retraining frequency, and audit completeness. Reporting standards similar to CONSORT or TRIPOD should be adapted for AI deployment studies to specify data sources, validation design, explanation methods, governance procedures, and monitoring plans, using complete reporting, reproducibility, and governance compliance as evaluation indicators [44, 65]. Enterprise and infrastructure AI systems should incorporate real-time data pipelines, integrated audit trails, and governance-aligned decision logs, with assessment based on pipeline throughput, audit completeness, and governance integration [11, 34, 44]. More broadly, the field requires evidence maturity levels for deployable AI, progressing from proof-of-concept development to pilot testing and deployment-validated systems. Such frameworks should assign evidence levels according to external validation, workflow readiness, monitoring capacity, and deployment-readiness classification.

7. Limitations of the Review

The synthesis is thematic, architectural, and deployment-level in nature rather than quantitative. Specific performance metrics, dataset characteristics, sample sizes, 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 deployment 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 deployment feasibility, computational requirements, explanation quality, or validation rigor. The curated corpus may not comprehensively represent all active deployment research threads; domains such as autonomous vehicles, legal AI, financial systemic risk, and social welfare AI are not well represented and are acknowledged as important adjacent fields. The six-axis deployment taxonomy is one defensible organization; alternative taxonomies emphasizing different deployment properties may yield complementary insights.

8. Conclusion

This structured critical review has synthesized across seven application domains, healthcare and biomedical AI, human-centered and assistive AI, industrial monitoring and cyber-physical systems, smart infrastructure and IoT, agriculture and sustainability, business and enterprise analytics, and cybersecurity and distributed intelligence, using a six-axis deployment-centered taxonomy of domain, modality, architecture, deployment pathway, readiness concern, and decision-support function. The synthesis reveals a field in which architectural capability is advancing rapidly across vision transformers, ensemble systems, graph neural networks, and federated learning frameworks, while deployment-readiness properties validated explainability, uncertainty quantification, privacy-preserving inference, post-deployment monitoring, and governance-aligned reporting remain inconsistently addressed. The cross-domain view reveals that the same deployment gaps recur across sectors: models are evaluated on held-out test sets but not on deployment-realistic distributions; explainability mechanisms are implemented but not validated for fidelity; privacy is discussed but rarely formally quantified; governance frameworks are proposed but infrequently operationalized; and evidence maturity standards are absent. The path toward deployable AI systems requires treating deployment not as a post-research challenge but as a design requirement that shapes architecture selection, data strategy, evaluation protocol, and governance structure from the earliest phase of system development. Workflow-integrated, trustworthy, privacy-preserving, resource-efficient, and governance-aware AI systems are not simply better research products, they are the only kind of AI system that can responsibly fulfill the promise of intelligent decision support across the healthcare, industry, business, and infrastructure domains that shape human welfare at scale. Future progress requires coordinated investment in deployment-readiness benchmarks, evidence maturity frameworks, edge-deployable architectures, federated privacy standards, and governance-aligned reporting standards that span domain boundaries and create a shared language for responsible AI deployment.

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