
| **REVIEW ARTICLE**

Privacy-Preserving, Edge-Cloud, and Federated AI for Scalable Decision Support in Critical Applications

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| **ABSTRACT**

Scalable decision support in critical applications increasingly requires AI systems that can operate across institutions, devices, cloud services, and privacy-sensitive environments. This structured critical review synthesizes on privacy-preserving, edge-cloud, federated, distributed, and deployment-relevant AI for healthcare, cybersecurity, energy, industrial monitoring, business analytics, agriculture, and human-centered technologies. The review develops an eight-axis taxonomy covering application domain, distributed deployment paradigm, privacy and security function, data modality, architecture family, decision-support function, scalability concern, and evidence role. The corpus indicates that privacy-aware decision support cannot be reduced to a single technique. Instead, scalable AI depends on the alignment of model architecture, data modality, governance needs, communication constraints, and human oversight. Healthcare applications highlight privacy-sensitive diagnosis and screening; cybersecurity and digital-resilience studies emphasize data protection and threat-aware operation; IoT and infrastructure systems foreground latency, sensing, and edge feasibility; and enterprise applications show the importance of auditability and accountable automation. Across domains, federated and edge-cloud systems offer a pathway for distributed intelligence, but they introduce challenges related to non-identical data distributions, model update governance, explanation validity, security exposure, and evidence maturity. Future research should prioritize federated benchmarks, privacy-preserving multimodal learning, communication-efficient architectures, deployment monitoring, and governance-aware reporting standards.

| **KEYWORDS**

privacy-preserving AI, federated learning, edge-cloud computing, distributed intelligence, scalable decision support, critical applications, trustworthy AI, deployment readiness

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1. Introduction

Artificial intelligence is increasingly used to support decisions in domains where data are sensitive, infrastructures are distributed, and decisions have operational, clinical, financial, or social consequences. In such settings, the central question is no longer whether an isolated model can classify a single dataset, but whether the resulting decision-support pipeline can operate securely, efficiently, and accountably across real workflows. Privacy-preserving, edge-cloud, and federated AI are therefore emerging as complementary approaches for scalable decision support. They address the practical constraints of data ownership, bandwidth, latency, regulation, interoperability, and institutional trust, while preserving the broader objective of useful decision support.

The supplied corpus illustrates the diversity of this problem. Privacy-aware and distributed designs are directly represented by work on privacy-preserving behavior analytics, scalable cancer diagnosis, and distributed edge-cloud-6G federated learning [37], [45], [56]. Cybersecurity and digital-resilience studies position secure data protection and analytics as core requirements for modern communication and high-stakes decision environments [6], [12], [43], [68]. At the same time, many papers do not explicitly propose federated learning or edge-cloud deployment but remain relevant because they represent the application pressures that motivate distributed and privacy-aware AI. These include privacy-sensitive healthcare screening, industrial fault

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detection, energy monitoring, business analytics, education, assistive technologies, and agricultural diagnosis [1], [7], [9], [19], [23], [42], [65], [79].

This review treats privacy-preserving, edge-cloud, and federated AI as a deployment-oriented design space rather than as isolated algorithmic labels. The aim is to classify how different papers contribute to scalable decision support: some provide direct privacy or distributed-intelligence evidence; others define high-value domains, data modalities, architectures, or governance problems. This framing is important because a medical transformer, an IoT monitoring system, a business forecasting model, and a cyber-threat framework create different privacy, scalability, and accountability requirements. The review therefore develops a controlled taxonomy and uses the citation corpus as structured evidence rather than as a list of unrelated studies.

2. Review Scope and Taxonomic Framework

The review performs taxonomy-driven evidence mapping based on the paper titles and their indicated methods, domains, and deployment implications. This design is appropriate for a heterogeneous corpus that spans medical imaging, smart infrastructure, cybersecurity, business analytics, agriculture, education, assistive technology, and industrial monitoring. The taxonomy uses eight axes. The first axis is the critical application domain, distinguishing healthcare and biomedical decision support; cybersecurity, privacy, and digital resilience; smart infrastructure, IoT, energy, and communication systems; industrial monitoring and cyber-physical systems; business and enterprise analytics; agriculture and sustainability; and human-centered, educational, and assistive technologies. The second axis is the distributed deployment paradigm, ranging from centralized AI baselines to edge AI, cloud AI, edge-cloud collaboration, federated learning, privacy-preserving distributed AI, secure enterprise AI, IoT-enabled monitoring, and cyber-physical deployment. The third axis captures privacy and security function, including privacy-preserving learning, data protection, secure data sharing, user-sensitive behavior analytics, enterprise data governance, and auditability.

The remaining axes clarify how papers contribute technically and operationally. Data modalities include medical images, agricultural images, facial and affective signals, physiological signals, IoT streams, acoustic-emission signals, natural language, graph-structured data, tabular business data, and multimodal evidence. Architecture families include conventional machine learning, deep learning, transfer learning, transformers, hybrid ensembles, graph neural networks, Bayesian and physics-guided models, generative enterprise AI, and edge-cloud or federated systems. Decision-support functions include screening, diagnosis, monitoring, forecasting, risk assessment, resource optimization, workflow automation, strategic decision support, communication support, and governance support. Scalability concerns include communication efficiency, latency, edge resource constraints, cloud scalability, interoperability, security exposure, model maintenance, distribution shift, governance, and evidence maturity. Figure 1 summarizes the interaction among critical domains, heterogeneous data modalities, distributed deployment paradigms, and governance requirements.

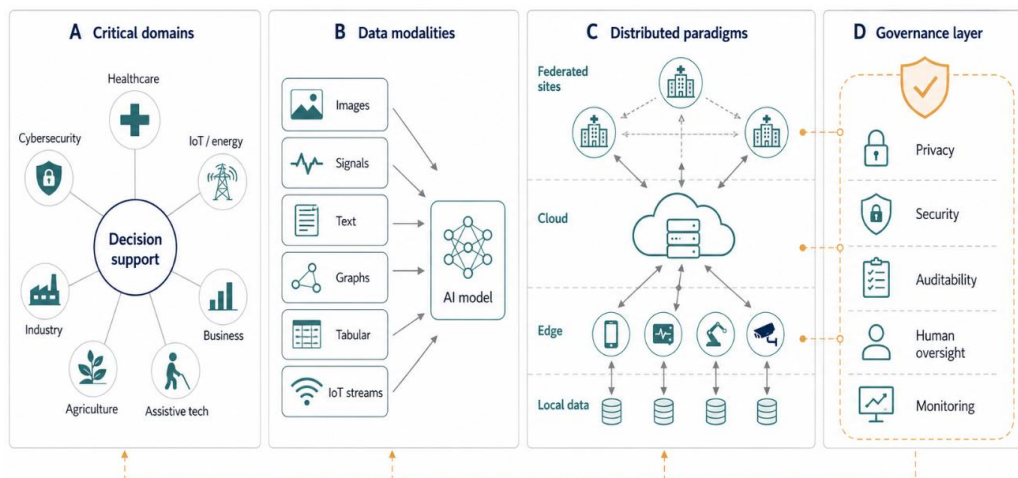


Figure 1. Distributed decision-support design space for critical AI applications

3. Conceptual Foundations

3.1 Why centralized AI is insufficient for critical applications

Centralized AI assumes that data can be pooled, standardized, stored, processed, and governed in a single environment. This assumption is difficult to sustain in critical applications. Medical images, voice biomarkers, EEG signals, facial-expression data, workforce behavior records, enterprise analytics, and cybersecurity logs are all sensitive in different ways. Centralized pooling may conflict with privacy obligations, institutional boundaries, user expectations, or infrastructure constraints. The presence of privacy-preserving cancer diagnosis, privacy-preserving workforce analytics, and distributed edge-cloud federated learning in the corpus shows why data locality and collaborative learning are increasingly relevant [37], [45], [56].

Centralization also struggles when systems must operate close to sensors or users. IoT battery monitoring, smart energy metering, smart healthcare boxes, and communication-network studies illustrate situations in which latency, bandwidth, device resources, and environmental variation shape feasibility [7], [23], [40], [57], [74]. Industrial systems such as gas-pipeline monitoring, concrete crack characterization, and wind-turbine fault detection similarly depend on sensor reliability and timely inference [9], [21], [42], [54]. These examples suggest that scalable AI requires architectures that distribute computation, preserve data control, and support monitoring under real operational constraints.

3.2 Privacy-preserving AI as a decision-support requirement

Privacy-preserving AI is best understood as a decision-support requirement rather than a narrow optimization technique. In healthcare, privacy concerns arise from diagnostic images, clinical records, voice biomarkers, depression indicators, and disease-screening outputs [1], [15], [19], [20], [45], [78]. In human-centered AI, facial expressions, ASD-related data, suicidal ideation signals, EEG, tDCS, and assistive-device information are sensitive because they may encode behavioral, neurological, or accessibility-related characteristics [2], [11], [17], [18], [27], [39], [46], [58], [79]. In business and organizational settings, privacy and governance are linked to credit scoring, workforce retention, customer behavior, pricing, project risk, and enterprise decision automation [24], [26], [37], [50], [51], [61], [67].

These differences require careful language. A title may indicate that a paper is privacy-preserving, but many papers merely represent domains where privacy-aware deployment would be necessary. Therefore, this review distinguishes direct privacy evidence from privacy-relevant application evidence. The distinction prevents overclaiming and enables more accurate synthesis. Figure 2 highlights that privacy-preserving deployment requires explicit management of trade-offs rather than isolated optimization of accuracy.

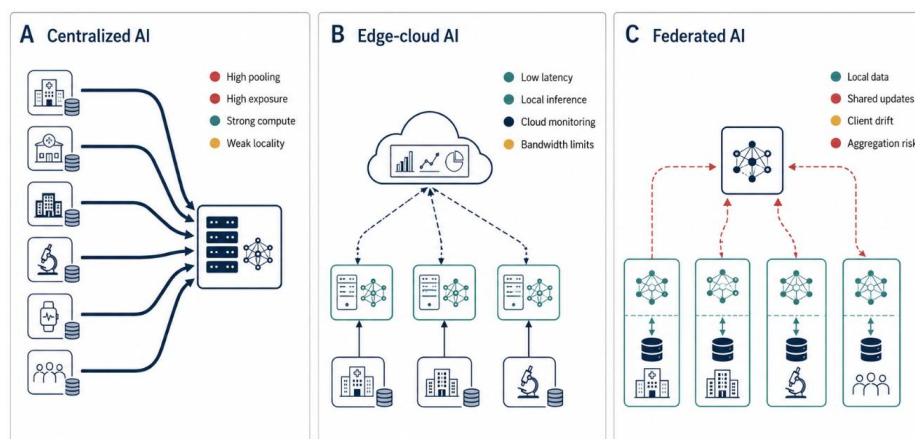


Figure 2. Privacy-utility-scalability trade-off in distributed AI.

3.3 Edge-cloud AI and distributed decision support

Edge-cloud AI distributes computation between local devices, intermediate nodes, and cloud services. Edge processing can reduce latency and preserve data locality, while cloud resources can support heavier training, aggregation, model management, and analytics. This split is particularly relevant for IoT energy systems, smart healthcare devices, wireless mesh networks, MANET routing, and high-altitude platform communication, where communication quality and resource constraints influence system behavior [4], [7], [23], [40], [57], [74]. Distributed decision support is also relevant beyond IoT. Web-based screening in breast and cervical cancer studies indicates cloud-facing decision interfaces [20], [63], while edge or lightweight feasibility is implicit in

aquaculture, crop disease, tea leaf, soybean, maize, mango, and cotton disease applications where field deployment may matter [35], [44], [60], [65], [71], [76], [77]. Edge-cloud design must therefore be evaluated in relation to the data source, user workflow, and acceptable latency, not only in terms of model accuracy.

3.4 Federated AI and collaborative learning

Federated AI enables collaboration across data holders without direct centralization of raw data (Table 1). Within the corpus, the most direct foundation for this discussion is the distributed intelligence and privacy-preserving edge-cloud-6G federated learning paper [56]. The privacy-preserving scalable cancer diagnosis framework also motivates multi-site healthcare learning, where data fragmentation and privacy sensitivity limit conventional pooling [45]. Decentralized breast cancer diagnosis provides a further domain-facing example of distributed model thinking, although its exact deployment mechanism cannot be inferred beyond the title [64].

Federated learning is not automatically a solution to every privacy problem. It introduces new issues: client heterogeneity, non-identical data distributions, communication cost, aggregation governance, privacy leakage from updates, and model drift. These issues are especially important when the participating sites differ in imaging protocols, patient populations, sensor hardware, business processes, or agricultural environments. For this reason, the review treats federated AI as one component of a larger distributed decision-support design space.

Table 1. Edge–cloud–federated architecture reporting checklist.

Reporting item	What to report	Preferred evidence
Architecture type	Centralized, edge, cloud, edge–cloud, federated, or hybrid	System diagram with data/model flows
Data location	Whether raw data stay local or move to cloud/server	Explicit raw-data movement policy
Edge function	Local inference, sensing, preprocessing, or alerting	Latency, memory, hardware, energy use
Cloud function	Aggregation, monitoring, storage, or model management	Cloud workload and update process
Federated setting	Clients, aggregation method, rounds, update frequency	Site-wise or client-wise validation
Privacy mechanism	FL, secure aggregation, DP, encryption, anonymization, access control	Privacy leakage or residual-risk assessment
Communication cost	Update size, bandwidth, rounds, synchronization	Accuracy–communication trade-off
Client heterogeneity	Label, feature, quantity, device, site, or temporal skew	Non-IID and worst-client analysis
Security controls	Authentication, encryption, access control, secure update channel	Threat model or security audit
Human oversight	Review, deferral, override, or escalation pathway	Human-in-the-loop evaluation
Auditability	Logs, explanations, traceability records	Explanation stability and log completeness
Maintenance	Drift detection, recalibration, update, rollback policy	Monitoring thresholds and response plan

3.5 Security, auditability, and governance

Security and governance are central to scalable decision support because distributed systems expand the attack surface and complicate accountability. Cybersecurity and data-protection papers in the corpus address security-oriented digital systems, threat intelligence, and resilient digital futures [6], [12], [43]. Business and enterprise AI papers add governance concerns related to ERP integration, digital transformation, management information systems, blockchain-enabled supply chains, and strategic analytics [14], [24], [33], [55], [72], [75]. These studies are relevant because privacy-preserving decision support must be embedded in accountable organizational and technical infrastructures.

Auditability connects model behavior to decision accountability. Knowledge-graph reasoning, graph neural networks, and AddManBERT-style triple extraction are relevant because relational structures can support traceability and human-readable connections between evidence and decisions [38], [42], [49]. However, traceability should not be treated as a substitute for validation. A system can be auditable but still inaccurate, biased, insecure, or poorly calibrated.

3.6 From model performance to scalable deployment readiness

Deployment readiness extends beyond performance. It includes data interoperability, computational feasibility, human oversight, explanation validity, security, update mechanisms, and evidence maturity. Explainable AI papers in the corpus show how

transparency is becoming part of applied AI design in skin cancer, cervical cancer, lung cancer, brain tumor, kidney disease, crop disease, and cotton defect settings [10], [13], [25], [32], [36], [44], [60], [63], [70], [77]. Yet the presence of explanation in a title does not establish that explanations are valid or usable. Explanation quality requires additional evaluation.

Scalable deployment also requires maintenance. Medical, business, and infrastructure conditions change over time; sensors drift; cloud platforms update; threat environments evolve; and user populations shift. Therefore, scalable decision support should be evaluated as a living system rather than a static classifier.

4. Model architectures

4.1 Conventional machine learning and structured analytics

Conventional machine learning remains important in scalable decision support because many critical decisions rely on structured, tabular, or interpretable variables. The corpus includes clinical decision support for heart disease, Parkinson's screening from voice biomarkers, credit scoring for underserved businesses, e-commerce pricing, retail demand forecasting, market trend forecasting, project risk, customer behavior, and healthcare-service market basket analysis [1], [16], [26], [30], [53], [62], [67], [69], [78]. These systems are not necessarily privacy-preserving by design, but they represent decision contexts where explainability, fairness, governance, and secure data management are important.

In distributed settings, structured analytics can be easier to deploy than complex deep models because feature schemas and computational requirements may be more transparent. However, structured models still face problems of data provenance, missingness, representativeness, and institutional access. Credit scoring and workforce analytics are particularly sensitive because model outputs can affect financial access and employment decisions [26], [37].

4.2 Deep learning and transfer learning

Deep learning and transfer learning extend decision support to complex images, signals, and recognition tasks. The corpus includes transfer learning for sleep staging, leukemia diagnostics, facial emotion recognition, skin cancer diagnosis, breast cancer classification, prostate cancer MRI, tea leaf disease, aquaculture disease, and concrete crack characterization [10], [20], [29], [34], [35], [41], [52], [54], [71]. These papers illustrate the importance of learned representations in domains where hand-crafted features may be insufficient.

For scalable privacy-aware deployment, deep models raise three concerns. First, they may require computational resources that exceed edge-device capacity. Second, they can be difficult to explain to domain users. Third, they often depend on large or carefully curated datasets that may be privacy-sensitive or institutionally fragmented. These concerns do not invalidate deep learning; they define the conditions under which deep models should be integrated into edge-cloud or federated workflows.

4.3 Transformer and attention-based models

Transformers and attention-based models are prominent in applied AI because they can capture contextual and long-range relationships. The corpus includes attention-based and transformer-oriented studies in skin lesions, lung cancer, cervical cells, breast cancer, prostate cancer, kidney CT, maize, mango, soybean, cotton diagnostics, and depression analysis [15], [22], [25], [32], [41], [44], [60], [63], [64], [76], [77]. These papers indicate the growing role of attention and transformer variants across medical and agricultural AI. However, attention should not be equated with validated explanation. In privacy-preserving and distributed settings, transformer models can increase computational cost, memory demand, and communication burden. Lightweight or efficient variants may help, but deployment claims require explicit evidence. For this reason, transformer-based systems are treated here as candidates for scalable decision support rather than as automatically deployment-ready solutions.

4.4 Hybrid, ensemble, stacking, and multimodal systems

Hybrid and ensemble systems combine complementary representations or model families. The corpus contains hybrid deep learning, stacking ensembles, multimodal emotion recognition, vision-audio recognition, tensor fusion, multichannel CT analysis, and attention-enhanced business strategy systems [8], [13], [18], [31], [36], [45], [59]. Such approaches can improve representational coverage by integrating diverse cues or model outputs. This is valuable in critical applications because a single modality may be incomplete, noisy, or biased.

The deployment cost of hybridization is nontrivial. More components mean more parameters, more data dependencies, more interfaces, and more failure modes. In federated or edge-cloud settings, fusion can also increase communication costs and complicate privacy guarantees. Hybrid systems therefore need ablation, modality-contribution analysis, failure-mode testing, and monitoring after deployment.

4.5 Graph neural networks and knowledge-graph reasoning

Graph neural networks and knowledge graphs are useful when decisions depend on relationships rather than isolated records. Gas-pipeline monitoring with graph neural networks and knowledge-graph/NLP reasoning for heuristic design illustrate this direction [42], [49]. AddManBERT extends this theme through triple extraction and classification for additive-manufacturing knowledge graphs [38]. These papers are relevant to privacy-aware decision support because graph structures can improve traceability and support explainable relational reasoning. Graph-based systems also introduce governance questions. Graphs may encode sensitive relationships, industrial dependencies, supply-chain links, or user behavior. Secure graph maintenance, access control, provenance tracking, and update governance are therefore central to scalable deployment.

4.6 Bayesian, physics-guided, and uncertainty-aware systems

Uncertainty-aware models are important when decisions affect safety or maintenance. The physics-guided Bayesian neural network for wind-turbine sensor fault detection is directly relevant to safety-sensitive industrial monitoring because it links learning with domain constraints and uncertainty-aware inference [9]. Similar logic applies to acoustic-emission diagnosis, concrete crack characterization, and gas-pipeline monitoring, where false confidence could affect infrastructure risk [21], [42], [54]. In privacy-preserving and edge-cloud contexts, uncertainty should be communicated across system layers. Edge devices may produce local uncertainty estimates, cloud services may aggregate them, and humans may decide whether escalation is necessary. This makes uncertainty a deployment feature rather than merely a model statistic.

4.7 Generative, agentic, and enterprise AI

Generative and agentic AI are increasingly relevant to enterprise decision support, strategic automation, and workflow integration. The corpus includes generative AI in enterprise information systems, automated risk assessment and collaborative decision-making, agile IT project assessment, IT strategy analytics, digital transformation, AI-enabled management systems, and business strategy optimization [8], [24], [33], [50], [61], [72], [75]. These papers position AI as part of organizational intelligence rather than isolated prediction. For privacy-preserving and distributed deployment, enterprise AI raises governance challenges. Generated outputs, automated recommendations, and risk-assessment workflows must be auditable, controlled, and supervised. Sensitive business records, workforce analytics, customer behavior, and strategic planning data should not be exposed through poorly governed automation.

4.8 Edge-cloud, federated, privacy-preserving, and distributed AI

The core architectural bridge of this review is the transition from centralized models to distributed, privacy-aware decision support. The direct evidence includes privacy-preserving behavior analytics, scalable privacy-preserving cancer diagnosis, distributed edge-cloud-6G federated learning, and decentralized breast cancer diagnosis [37], [45], [56], [64]. These papers provide the clearest conceptual anchor for privacy-preserving and federated AI within the corpus.

Edge-cloud and distributed AI are also motivated by sensor-rich and workflow-sensitive domains: solar micro-grid monitoring, smart energy metering, smart healthcare boxes, routing in wireless mesh networks, MANET simulation, HAP communication, industrial acoustic monitoring, and IoT-enabled healthcare devices [4], [7], [23], [40], [57], [74]. Together, these studies show that scalability depends on where computation occurs, how data move, who controls access, and how decisions are audited.

5. Domain applications

5.1 Healthcare and biomedical decision support

Healthcare is the most privacy-sensitive domain in the corpus. The studies address Parkinson's screening from voice biomarkers, diabetes-oriented healthcare information systems, heart disease decision support, sleep-stage classification, leukemia diagnostics, lung cancer CT analysis, skin cancer and skin lesion classification, prostate cancer MRI, kidney CT classification, cervical cell screening, brain tumor diagnosis, breast cancer classification, cytological cancer classification, depression emotion and severity detection, and privacy-preserving cancer diagnosis [1], [13], [15], [19], [20], [22], [25], [29], [32], [34], [36], [41], [45], [59], [63], [70], [78]. Explainable deep learning has been emphasized as an essential step toward transparent and clinically acceptable decision support [85], while neural machine learning models have been used for stroke prediction and early risk assessment [82]. Similarly, breast cancer diagnosis has benefited from neural network-based classification, dimensionality reduction, and architecture optimization using clinical and morphological features [81], [80]. At the system level, federated learning offers a privacy-preserving pathway for scalable healthcare data processing without requiring centralized data transfer [83]. Beyond healthcare analytics, AI-enabled digital twins and cybersecurity frameworks demonstrate how intelligent technologies can support predictive maintenance in industrial IoT environments and strengthen the protection of healthcare and essential infrastructure [84], [86].

The healthcare cluster illustrates why privacy-preserving and scalable AI cannot be reduced to model accuracy. Clinical data are sensitive, fragmented across institutions, and heterogeneous across devices, populations, and acquisition protocols. Web-based screening and privacy-preserving cancer diagnosis indicate possible deployment pathways [20], [45], [63], but the titles alone do not establish external validation, clinical integration, or regulatory readiness. For this reason, healthcare applications should be framed as decision-support systems requiring human oversight, privacy governance, and continuous monitoring.

5.2 Cybersecurity, privacy, and digital resilience

Cybersecurity and digital resilience form a second core domain. Papers on data security, cyber risk, privacy-preserving behavior analytics, distributed intelligence, trustworthy AI, and resilience-by-design show that secure decision support requires both technical and organizational controls [6], [12], [24], [37], [43], [56], [68]. These studies are central because privacy-preserving AI cannot succeed if communication channels, model updates, data stores, or decision logs are insecure.

The cybersecurity cluster also reframes privacy as a system property. Threat intelligence, secure communication, auditability, and governance are required across healthcare, business, IoT, and industrial systems. Scalable AI therefore needs integrated security evaluation rather than privacy mechanisms considered in isolation.

5.3 Smart infrastructure, IoT, energy, and communication systems

Smart infrastructure and IoT applications include solar micro-grid battery monitoring, smart energy metering, smart healthcare medical boxes, MANET routing, wireless mesh networks, HAP communications, and broader IoT-enabled monitoring [4], [7], [23], [40], [57], [74]. These studies represent deployment contexts in which communication efficiency, latency, energy use, device reliability, and data-stream quality are decisive.

In such settings, edge-cloud design is not optional. Local inference may be required when connectivity is unstable, while cloud services may be required for long-term model management, aggregation, and analytics. Energy monitoring and communication-system studies therefore supply infrastructure evidence for why scalable decision support must be distributed.

5.4 Industrial monitoring and cyber-physical systems

Industrial and cyber-physical systems rely on sensor-derived evidence and often require timely maintenance decisions. The corpus includes acoustic-emission gas-pipeline monitoring, multivariate acoustic imaging, concrete crack characterization, wind-turbine sensor fault detection, underwater robotics autonomy, and additive-manufacturing knowledge-graph extraction [5], [9], [21], [38], [42], [54]. These papers illustrate the intersection of physical safety, sensor reliability, and decision-support automation. For privacy-preserving and edge-cloud AI, industrial systems raise distinctive concerns. Raw sensor streams may be high volume; operational data may be proprietary; and faults may require immediate response. Distributed inference, uncertainty-aware modeling, and auditability are therefore important, but must be evaluated with respect to system safety rather than accuracy alone.

5.5 Business, enterprise, and organizational analytics

Business and enterprise applications include credit scoring, demand forecasting, market trend forecasting, e-commerce pricing, customer satisfaction, market basket analysis, small-business management, workforce retention, blockchain-enabled supply chains, agile project risk, digital transformation, IT strategy, ERP integration, generative enterprise information systems, and management information systems [14], [16], [24], [26], [30], [33], [37], [50], [51], [53], [55], [61], [62], [67], [69], [72], [75]. These papers show that scalable AI is also an organizational problem. Enterprise systems must integrate with existing workflows, preserve sensitive business and workforce data, produce auditable decisions, and support accountability. Privacy-preserving deployment in business contexts therefore includes data governance, access control, role definition, and monitoring of automated recommendations.

5.6 Agriculture, environment, and sustainability

Agricultural and sustainability-oriented papers address smart agriculture, aquaculture disease diagnosis, tea leaf disease, soybean disease, maize leaf disease, mango leaf disease, cotton diagnostics, and solar financing for rural clinics [35], [44], [60], [65], [66], [71], [76], [77]. These studies are relevant because field settings often involve resource constraints, environmental variability, limited connectivity, and the need for lightweight or accessible decision support. Privacy is not always the primary concern in agricultural imaging, but edge feasibility and scalability are highly relevant. Models may need to operate in low-resource environments, on mobile or field devices, or in regions with unstable connectivity. Sustainability-oriented AI should therefore be assessed not only for classification performance but also for deployment cost, maintainability, and local usability.

5.7 Human-centered, educational, and assistive technologies

Human-centered and assistive technologies include ASD classification, ASD facial-expression datasets, adaptive feedback for learners, digital health platforms for students with ASD, tDCS modeling, multimodal EEG analysis, facial emotion recognition,

suicidal ideation detection, Bengali sentiment classification, online drug-review sentiment analysis, flex-sensor gloves, and vision-audio multimodal recognition [2], [3], [11], [17], [18], [27], [28], [31], [39], [46], [47], [48], [52], [58], [73], [79]. This cluster emphasizes user-sensitive data; privacy-aware design should address consent, explanation, accessibility, and overinterpretation of behavioral signals.

6.1 Current challenges

6.1 Privacy-preserving learning versus decision utility

Privacy-preserving learning must protect data while preserving useful decision support. Excessive restriction can limit model learning, while excessive data sharing can expose sensitive information. This tension is visible across healthcare, workforce analytics, ASD-related data, mental-health text, credit scoring, and business intelligence [1], [17], [26], [37], [45], [58], [79]. The key challenge is to define privacy mechanisms alongside decision utility, fairness awareness, and accountable use.

6.2 Data heterogeneity and non-identical distributions

Distributed AI must handle non-identical data distributions across hospitals, devices, regions, sensors, enterprise systems, and user groups. Medical images vary by scanner and protocol; agricultural images vary by field conditions; IoT streams vary by hardware; and business data vary by market and organization [7], [16], [25], [30], [59], [65], [77]. Federated learning can preserve data locality, but it does not eliminate heterogeneity. It makes heterogeneity a central design problem.

6.3 Communication efficiency, latency, and edge constraints

Edge and federated systems must operate under communication and computational constraints. Smart meters, micro-grid monitoring, MANET routing, wireless mesh networks, HAP communication, and smart healthcare boxes illustrate settings where bandwidth, latency, and device resources affect feasibility [4], [7], [23], [40], [57], [74]. Transformers, ensemble, and multimodal systems can increase computational burden, so deployment should report latency, memory, update frequency, and communication cost.

6.4 Security, threat exposure, and adversarial risk

Distributed AI expands the security surface. Model updates, sensor streams, cloud services, edge nodes, APIs, and audit logs can become attack points. Cybersecurity and data-protection studies in the corpus show the importance of threat intelligence, secure digital communication, and data governance [6], [43], [56]. Enterprise and blockchain-related work further suggests that secure workflows and traceability matter when AI systems interact with supply chains and organizational systems [14], [55].

6.5 Explainability, auditability, and accountability

Scalable distributed AI must remain explainable enough for human oversight and accountable action. Explainable cancer models, transformer-based diagnosis systems, post-hoc depression analysis, graph reasoning, and knowledge-graph methods all contribute to this theme [10], [15], [22], [36], [38], [49], [70]. However, explanation outputs should be validated rather than assumed. Attention maps, saliency maps, and feature importance values can support auditing but do not automatically prove model reasoning.

6.6 Robustness, monitoring, and post-deployment maintenance

Post-deployment monitoring is essential because data and environments change. Sensor drift can affect wind-turbine, pipeline, concrete-crack, and IoT monitoring [9], [21], [42], [54]. Population shift can affect healthcare models [1], [19], [78]. Market and organizational changes can affect forecasting, pricing, credit, and management analytics [16], [26], [30], [67]. Scalable AI should therefore include drift monitoring, update governance, and performance auditing.

6.7 Human oversight and governance

Privacy-preserving and federated AI should support human decision-making rather than obscure it. This is especially important in healthcare, education, assistive technologies, business risk, and robotics [3], [5], [46], [61], [62], [79]. Human oversight requires clear role definitions, escalation pathways, audit records, and boundaries between decision support, automation, and autonomy.

6.8 Evidence maturity for scalable distributed AI

Evidence maturity requires transparent reporting of datasets, validation protocols, computational requirements, communication costs, privacy mechanisms, deployment environments, user evaluation, and monitoring plans. Because this review is based on titles, it cannot verify such details. The corpus nevertheless suggests that many applied AI areas are moving toward deployment-relevant concerns, including web screening, decentralized diagnosis, privacy-preserving analytics, smart devices, and enterprise

automation [20], [37], [56], [63], [64], [72], [74]. Table 2 provides a concise framework for assessing whether reviewed AI systems move beyond model performance toward privacy-aware, scalable, auditable, and human-supervised deployment readiness.

Table 2. Concise deployment-readiness scoring rubric for privacy-preserving distributed AI.

Dimension	Low readiness	Moderate readiness	High readiness
Privacy protection	Privacy need only stated	Privacy method described	Leakage risk and residual privacy risk evaluated
Data locality	Raw-data movement unclear	Local retention claimed	Raw-data non-sharing verified
Distributed validation	Centralized dataset only	Simulated multi-client setting	Realistic multi-site/device validation
Non-IID robustness	Not assessed	Heterogeneity tested	Site-wise and worst-client performance reported
Communication efficiency	Not reported	Update size/rounds measured	Accuracy–communication trade-off quantified
Edge feasibility	Not reported	Model size/latency reported	Tested under realistic edge/cloud constraints
Security	General discussion only	Secure access/update described	Threat exposure and audit completeness assessed
Explainability/auditability	Explanation absent or superficial	Explanations/logs provided	Fidelity, stability, and expert usefulness evaluated
Human oversight	Workflow unclear	Review/override pathway described	Deferral and escalation performance tested
Monitoring	Static offline testing only	Drift/calibration mentioned	Post-deployment monitoring and update policy specified
Governance	Not addressed	Roles/compliance discussed	Accountability and approval procedures operationalized
Evidence maturity	Accuracy-focused only	Some deployment evidence	Integrated privacy, utility, scalability, security, and oversight evidence

7. Future Research Directions

Future research should prioritize federated benchmarks for critical applications, with shared multi-site protocols that preserve data locality while reporting client heterogeneity, communication cost, privacy mechanisms, aggregation strategies, and site-wise performance. Privacy-preserving healthcare AI should combine federated learning, privacy-aware feature handling, explainable interfaces, and clinician oversight, with evaluation of leakage risk, calibration, subgroup behavior, explanation utility, and workflow impact. Edge-cloud architectures should use tiered pipelines in which edge devices support time-sensitive inference and cloud services manage aggregation, monitoring, and updates, while reporting latency, bandwidth, energy use, memory footprint, and failure modes. Further work is also needed on communication-efficient federated learning through lightweight models, compression, selective updates, and asynchronous aggregation, with explicit accuracy–communication trade-off analysis. Secure distributed AI should integrate access control, secure update channels, audit logs, and traceable decision records. Privacy-preserving multimodal learning should address images, signals, text, graphs, and tabular data through modality-aware safeguards and robustness testing. Finally, future systems should include human-in-the-loop review, uncertainty and drift monitoring, governance-aware reporting standards, and deployment-readiness scoring so that privacy, scalability, security, auditability, oversight, and maintenance are evaluated alongside predictive performance.

8. Limitations of the Review

This review is limited by the nature of the provided corpus. Only paper titles were available, so the synthesis focuses on thematic, architectural, privacy-preserving, edge-cloud, federated, and deployment-level classification rather than quantitative comparison. The review does not claim to verify datasets, sample sizes, numerical performance, external validation, statistical significance, deployment status, user studies, or regulatory readiness. A full systematic review would require database-search records, inclusion and exclusion criteria, full-text extraction, quality appraisal, and reproducible coding procedures.

The review also uses cautious inference. A title that mentions a transformer, explainable AI, privacy-preserving analytics, IoT, or web deployment indicates relevance to a category, but it does not prove methodological rigor or operational readiness. Future work should extract full methodological details, validation protocols, computational requirements, communication costs, privacy mechanisms, and deployment evidence from the complete papers.

9. Conclusion

Privacy-preserving, edge-cloud, and federated AI provide promising design direction for scalable decision support across healthcare, cybersecurity, business, infrastructure, industrial monitoring, agriculture, and human-centered systems. The reviewed corpus shows that privacy-aware deployment is not limited to a single algorithmic family. It requires alignment among data modality, architecture, deployment paradigm, security function, decision-support role, scalability concern, and governance structure. The next phase of this field should move beyond isolated model performance toward secure, communication-efficient, explainable, robust, human-supervised, and governance-aware distributed AI. Critical applications need evidence of privacy protection, latency feasibility, cross-site robustness, auditability, user oversight, and post-deployment monitoring. Such evidence will determine whether privacy-preserving and federated systems can become dependable components of real decision-support workflows.

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