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| REVIEW ARTICLE

From Machine Learning to Foundation and Agentic AI: Evolution of Intelligent Decision Systems Across Domains

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| ABSTRACT

Intelligent decision systems have undergone a multi-stage architectural evolution—from conventional machine learning and structured analytics through convolutional deep learning, attention-based transformers, graph neural networks, multimodal fusion systems, federated and privacy-preserving frameworks, to generative AI and emerging agentic decision architectures. This evolution is not merely technical: it changes how systems acquire representations, explain decisions, operate across institutional boundaries, integrate into professional workflows, and support high-stakes decisions in healthcare, business, industry, smart infrastructure, agriculture, cybersecurity, assistive technologies, and sustainability. This review characterizes ten evolutionary stages from structured ML through agentic decision systems—and maps their expression across seven application domains. Synthesis reveals that while deep learning and transformer architectures have substantially advanced representational capability, the deployment-critical properties of trustworthiness, validated explainability, uncertainty quantification, and governance accountability have not evolved at the same pace. Generative AI and agentic systems represent a qualitative shift toward interactive and workflow-embedded decision support, but introduce hallucination risk, accountability gaps, and governance demands that exceed current frameworks. A structured research agenda addresses evolution-aware benchmarks, trustworthy foundation-model adaptation, human-in-the-loop evaluation, federated multimodal intelligence, and governance-aware reporting standards for agentic decision systems.

| KEYWORDS

AI evolution, Foundation models, Agentic AI, Decision support systems, Trustworthy AI, Explainable AI, Federated learning, Cross-domain AI taxonomy

| ARTICLE INFORMATION

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1. Introduction

The history of AI-based decision systems is a history of expanding representational ambition. Each major architectural transition from handcrafted features and structured models through convolutional networks, attention-based transformers, graph reasoning systems, multimodal fusion, federated distributed AI, generative models, and emerging agentic architectures—has extended the scope of problems that AI can address while simultaneously introducing new requirements for explainability, validation, governance, and human oversight. Understanding this evolutionary arc is essential for researchers and practitioners navigating the current landscape: what has changed, what has been gained, what has been lost, and where the most consequential unresolved challenges lie.

The evolutionary pattern is visible across all major application domains. In healthcare, the transition from structured ML for heart disease prediction [29] through CNN-based cancer imaging toward transformer-based explainable diagnosis [4, 17, 24] and privacy-preserving multimodal frameworks [66] traces the same arc as in agriculture—from task-specific image classifiers toward lightweight, explainable, sustainability-aware field-deployable systems [51, 9, 26]. In business and enterprise settings, the

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transition from predictive analytics [23, 41] toward generative AI for enterprise intelligence [1, 10] and emerging agentic risk assessment and decision automation [68, 15] illustrates the qualitative shift toward AI systems that do not merely predict but reason, plan, coordinate, and adapt. In cybersecurity and distributed systems, the shift from rule-based monitoring toward distributed federated intelligence and resilience-by-design architectures [71, 78] reflects both expanded capability and expanded accountability requirements. Our goal is not merely to catalogue what has been built, but to reveal the structural patterns, persistent gaps, and forward-looking research directions that characterize the transition from task-specific machine learning toward the broader horizon of foundation and agentic decision intelligence.

2. Review scope and Evolutionary Taxonomic Framework

The corpus was assembled to span the evolutionary stages of AI decision systems rather than to represent any single domain exhaustively. A six-axis evolutionary taxonomy organizes the evidence. Axis 1, the evolutionary stage axis, classifies papers across ten stages: conventional machine learning and structured analytics; early deep learning and transfer learning; CNN-based domain-specific systems; transformer and attention-based systems; hybrid, ensemble, and multimodal systems; graph neural networks and knowledge-graph reasoning; Bayesian, physics-guided, and uncertainty-aware systems; edge-cloud, federated, and privacy-preserving AI; generative AI and enterprise intelligence; and agentic and collaborative decision systems. Axis 2 classifies by application domain across seven sectors. Axis 3 classifies by data modality across nine categories from medical images to multimodal data. Axis 4 captures the decision-support function served. Axis 5 characterizes the system capability demonstrated, from pattern recognition and predictive modeling through attention-based contextual modeling, relational reasoning, uncertainty-aware inference, distributed learning, generative synthesis, and agentic planning. Axis 6 catalogues the deployment and governance concern.

This taxonomy enables evolutionary analysis, tracing how system capabilities and deployment requirements have changed across stages, as well as cross-domain analysis, identifying which evolutionary stages are underrepresented in specific domains and where the next transitions are most needed.

3. Evolution of Intelligent Decision Architectures

3.1 Conventional Machine Learning and Structured Analytics

Conventional machine learning—logistic regression, random forests, gradient-boosted trees, LSTM networks, and support vector machines applied to structured, tabular, or text data—constitutes the foundational evolutionary stage of AI decision systems and remains operationally relevant in domains where data are structured, interpretability is required, and computational efficiency matters. Clinical decision support for heart disease prediction using structured patient data [29] exemplifies the continued deployment value of conventional ML: feature-level attribution is well-characterized, computational requirements are modest, and clinical information system integration is technically straightforward. In business analytics, retail demand forecasting using LSTM and gradient boosting [41], market trend forecasting with external factor integration [23], e-commerce pricing optimization [6], small-business ML for customer retention and financial forecasting [64], and credit scoring for financially underserved businesses [3] constitute the operational backbone of enterprise ML deployment. Predictive analytics for project risk [55] and the data-driven drug review sentiment system [42] extend conventional ML to governance and human-centered contexts. The evolutionary limitation of this stage is representational capacity: structured models cannot efficiently process images, physiological signals, or the relational structure of knowledge graphs, motivating the transition toward deeper and more expressive architectures. Table 1 summarizes how architectural evolution changes system capability, supported modalities, decision-support roles, and governance requirements.

Table 1. Evolutionary stages of AI decision systems and deployment implications.

Stage	Core architecture	Main capability	Decision role
Structured ML	LR, SVM, RF, GBM, LSTM	Structured prediction	Risk scoring, forecasting
Early DL / transfer learning	DNNs, pretrained CNNs	Learned representation	Domain classification
CNN systems	CNNs, multichannel CNNs,	Spatial feature learning	Screening, diagnosis, defect

Stage	Core architecture	Main capability	Decision role
	lightweight CNNs		detection
Transformers / attention	ViT, Swin, MaxViT, attention models	Contextual visual reasoning	Classification, grading, decision support
Hybrid / multimodal systems	Ensembles, stacking, tensor fusion	Complementary evidence integration	Diagnostic fusion, multimodal recognition
GNN / knowledge graphs	GNNs, KG reasoning, BERT–KG models	Relational reasoning	Fault localization, knowledge extraction
Bayesian / uncertainty-aware AI	Bayesian NNs, physics-guided models	Calibrated uncertainty	Safety-critical fault detection
Federated / privacy-preserving AI	FL, edge-cloud AI, privacy-preserving analytics	Distributed learning	Multi-site decision support
Generative / foundation-oriented AI	Generative AI, reusable workflow models	Synthesis and open-ended reasoning	Strategic analysis, information generation
Agentic decision systems	Agentic AI, collaborative agents, AI-ERP	Planning and workflow coordination	Risk assessment, autonomous support

3.2. Early Deep Learning, CNNs, and Transfer Learning

The shift from hand-crafted features to learned representations through convolutional neural networks and deep learning constitutes the field's most consequential evolutionary transition to date. Transfer learning, using pre-trained features from large-scale datasets and fine-tuning on domain-specific data, addressed the data-scarcity problem that previously constrained deep learning in medical, agricultural, and industrial settings. Transfer learning for sleep stage classification under limited data [75] and early leukemia diagnostics incorporating image processing and transfer learning [60] illustrate the breadth of medical applications enabled by this approach. A facial emotion recognition system based on a bidirectional Elman neural network [62] and a hybrid deep belief optimization system for facial emotion recognition [47] extend deep learning to affective computing. The lightweight deep learning approach for concrete crack characterization via acoustic-emission signals [8] and lightweight ResNeXt for aquaculture disease diagnosis [32] demonstrate the evolutionary pressure toward model compression: as CNN architectures mature, the deployment imperative shifts from accuracy maximization toward efficiency, interpretability, and edge feasibility. Advanced deep learning for tea leaf disease precision diagnosis [79] and the multichannel CNN analysis of imbalanced CT data for lung cancer [37] represent domain-specific CNN deployments at different ends of the size-efficiency spectrum. The evolutionary contribution of this stage is representation learning; its unresolved challenge is interpretability, learned features are powerful but opaque, motivating both post-hoc explanation methods and the subsequent architectural shift toward attention-based transparency.

3.3. Transformer and Attention-Based Decision Systems

The introduction of self-attention mechanisms and transformer architectures into computer vision and multimodal learning represents the current dominant evolutionary stage in image-based decision support. The hybrid vision transformer for lung cancer diagnosis [17] and the Swin Transformer for cervical cell classification with XAI and web deployment [4] demonstrate transformers in clinical oncological imaging. The hierarchical Swin Transformer ensemble for breast cancer with decentralized deployment [24] extends this to federated clinical settings. The hybrid vision transformer for prostate cancer in MRI [67] and the global-local attention model for kidney disease classification from CT images [53] illustrate dual-resolution attention strategies for multi-class diagnostic discrimination. The attention-enhanced deep learning system FuseAttenX for business strategy optimization [46] demonstrates transformer-based attention in enterprise analytics, an important cross-domain evolutionary signal. The lightweight cross-scale attention ViT MaizeFormerX [51], the MaxViT soybean disease model [27], and the explainable transformer for cotton leaf diagnostics [9] illustrate the agricultural application of transformer architectures with an explicit efficiency and explainability mandate. The explainable transformer for skin lesion classification [59] completes the oncological imaging transformer cluster. A critical evolutionary observation applies to this stage: attention mechanisms provide visual communicability that earlier CNNs could not match, but attention-based explanations are not equivalent to causal explanations, and this distinction must be preserved in clinical, regulatory, and governance contexts.

3.4. Hybrid, Ensemble, Stacking, and Multimodal AI.

Hybrid and ensemble architectures represent an evolutionary strategy that combines the representational strengths of multiple model families to address limitations that no single architecture resolves. The explainable deep stacking ensemble for brain tumor diagnosis [63] and the stacking ensemble-based breast cancer classifier with real-time web deployment [65] demonstrate that ensemble diversity can be combined with post-hoc explainability and web-based deployment in oncological imaging. The ensemble transformer with post-hoc XAI for depression emotion and severity detection [70] extends this pattern to affective computing, where ensemble uncertainty estimates are particularly valuable given the inherent ambiguity of emotional ground truth. Multimodal fusion introduces a distinct evolutionary dimension: the hybrid multi-modal emotion recognition framework using InceptionV3DenseNet [30] and the vision-audio multimodal object recognition system via hybrid tensor fusion [74] address the integration of heterogeneous input streams without cross-modal interference. A deployment-critical observation about this evolutionary stage is that increased architectural complexity, more base learners, more modalities, more fusion layers, does not automatically improve explanation coherence. Explanations for stacking and multimodal systems must account for inter-model and inter-modal interactions that post-hoc attribution methods applied to single models cannot capture.

3.5. Graph Neural Networks and Knowledge-Graph Reasoning

The introduction of graph-structured representations into AI decision systems marks a qualitative evolutionary shift: from models that process feature vectors in isolation to systems that explicitly model relational dependencies among entities. The GNN-enhanced acoustic-emission gas-pipeline monitoring system [21] models fault-signal propagation across the physical topology of sensor networks, providing structurally interpretable fault localization that statistical classifiers cannot match. Knowledge-graph and NLP integration for heuristic reasoning support [31] and the AddManBERT combinatorial triples extraction and knowledge-graph construction for additive manufacturing design [39] demonstrate that BERT-based language models and knowledge graphs can be coupled to produce reasoning chains—entity-linked, auditable, and domain-structured—that are qualitatively more transparent than attention-based explanations in neural-only architectures. The evolutionary significance of this stage is that it restores a form of symbolic accountability to AI decision systems that was largely absent from purely statistical deep learning approaches. The deployment limitation, knowledge graph curation and maintenance, represents the primary barrier to scaling this approach to rapidly evolving domains.

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

The capacity to express and communicate uncertainty is a critical evolutionary capability that has advanced separately from the representational power trajectory of CNNs and transformers. The physics-guided Bayesian neural network for sensor fault detection in wind turbines [12] represents the most principled uncertainty-aware architecture in the corpus: physical priors constrain the network's hypothesis space under novel inputs, while Bayesian inference produces calibrated probability distributions over fault states rather than point predictions. This architecture is directly relevant to safety-sensitive industrial deployment, where a model that cannot express its own epistemic limitations cannot reliably support human oversight. The evolutionary observation is that this stage, uncertainty-aware, physics-informed reasoning remains substantially underrepresented relative to its importance in safety-critical deployment. The architectural methods exist; what is lacking is their systematic integration into the domain-specific pipelines that constitute the operational majority of this corpus.

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

The shift from centralized model training and inference toward distributed, federated, and privacy-preserving learning architectures represents an evolutionary response to the deployment constraints that centralized AI cannot satisfy. Privacy-preserving behavior analytics for workforce retention [18] and the multimodal privacy-preserving cancer diagnosis framework [66] demonstrate operational privacy-preserving systems in organizational and healthcare contexts. The distributed intelligence edge-cloud-6G federated learning framework for secure and auditable decision support [71] represents the architectural frontier of this evolutionary stage, integrating edge inference, cloud aggregation, 6G communication, and federated training into a unified auditable deployment architecture. The evolutionary contribution of this stage is not primarily representational—federated models may achieve comparable predictive performance to centralized models—but deployment-structural: by distributing learning across data-sovereign nodes, federated architectures enable collaborative intelligence in contexts where data centralization is legally, ethically, or operationally impossible. The governance challenge introduced at this stage is auditability: distributed learning systems must generate transparent logs at each node, not only at the central aggregator, to maintain accountability.

3.8. Generative AI, Foundation-Model Thinking, and Enterprise Intelligence

Generative AI and the broader transition toward foundation-model thinking represents an evolutionary inflection point: AI systems that can generate, synthesize, and reason over open-ended inputs rather than merely classifying fixed-format data. Generative AI in enterprise information systems for transforming business intelligence and strategic decision support [1] illustrates the organizational embedding of generative capabilities into enterprise analytics workflows. AI-driven business analytics for IT strategy and intelligent automation [10] and digital transformation analytics for US IT project excellence [7] position this evolutionary stage within organizational strategy contexts. AI-enabled management information systems for economic resilience, governance, and decision automation [15] illustrates the governance dimension of enterprise AI at this stage. It is important to be precise about what constitutes foundation-model thinking in this corpus: most papers represent domain-specific models, not general-purpose foundation models. The evolutionary relevance is that the broader shift toward generalizable, reusable, and workflow-integrated decision-support architectures motivating the incorporation of retrieval, instruction-following, and chain-of-thought capabilities into business and healthcare AI is directionally visible in the enterprise AI papers, even when the specific architectures described are not large language models. The deployment challenge introduced at this stage, hallucination, factual unreliability, absence of auditable reasoning chains, and accountability gap, demands governance frameworks that do not yet exist in mature form.

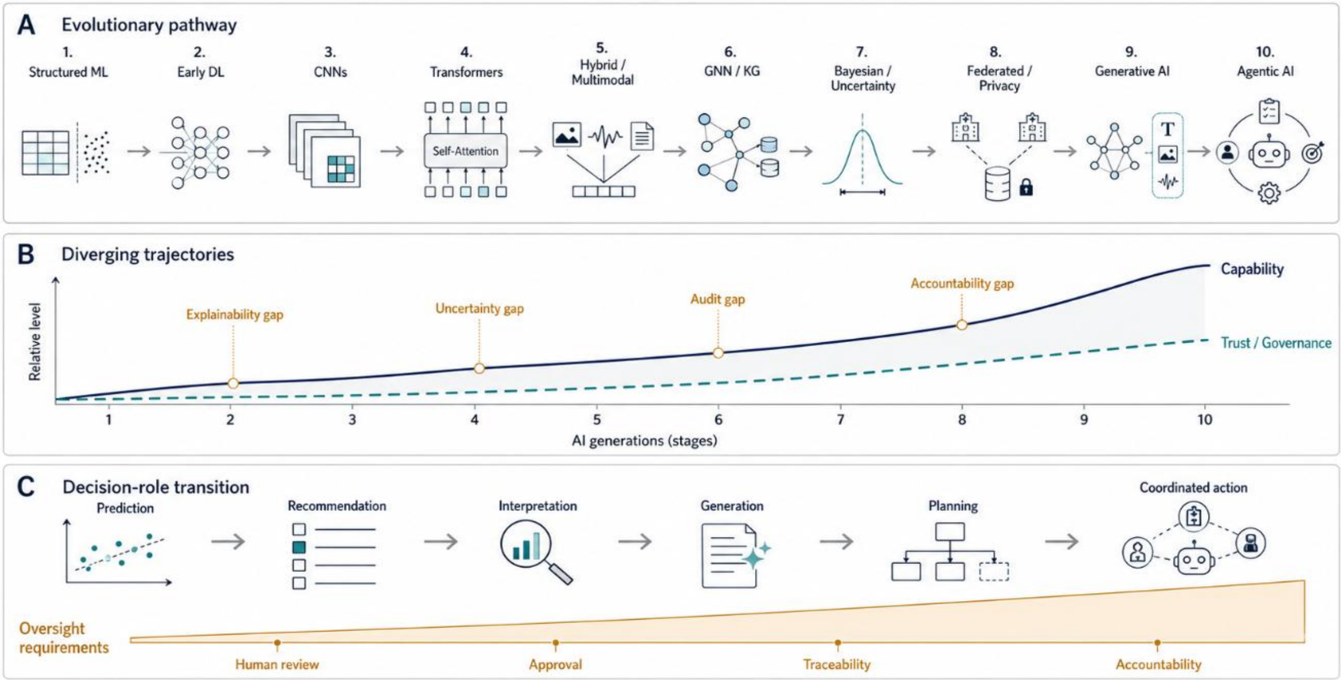

Figure 1: Capability progression and governance lag across successive generations of AI decision systems.

3.9. Agentic and Collaborative Decision Systems

Agentic AI, systems in Figure 1 that pursue goals, decompose tasks, use tools, and collaborate with human or AI agents across workflow steps—represents the emerging frontier of the evolutionary arc. Automated risk assessment and collaborative decision-making AI in agile project management [68] exemplifies the agentic pattern: AI that initiates and coordinates decision workflows rather than responding to individual queries. AI for risk and decision in agile IT projects with thematic analysis [36] and the conceptual frameworks for sustainable AI-ERP integration in dark factories [28, 57] illustrate agentic AI embedded in autonomous industrial and organizational environments. The question of full autonomy in underwater robotics [2] directly addresses the human oversight axis within agentic systems: the framing as an open prospect reflects the genuine difficulty of establishing accountable governance conditions for unsupervised autonomous decision-making in unstructured environments. AI-enabled MIS for economic resilience and decision automation [15] represents the organizational agentic frontier, where AI not only analyzes but initiates governance actions. The evolutionary challenge at this stage is not architectural capability—agentic systems can already perform impressive multi-step reasoning and coordination—but accountability: when an agentic AI system initiates a consequential decision across multiple workflow steps, the allocation of responsibility between the AI, the developer, the operator, and the human overseer must be explicitly defined, auditable, and legally grounded.

4. Cross-domain Application Synthesis

4.1. Healthcare and Biomedical Decision Systems

Healthcare is the domain where the full evolutionary arc from conventional ML to transformer-based and multimodal decision systems is most visibly expressed. At the conventional ML stage, heart disease prediction from structured patient data [29] remains a clinically deployable decision-support tool. The CNN and transfer learning stage is represented by early leukemia diagnostics incorporating image processing and transfer learning [60] and the multichannel CNN analysis of imbalanced CT lung cancer data [37]. The transformer stage encompasses the hybrid ViT for lung cancer [17], Swin Transformer cervical screening with web deployment [4], hierarchical Swin Transformer ensemble for breast cancer [24], hybrid ViT for prostate cancer in MRI [67], global-local attention for kidney disease [53], and the explainable transformer for skin lesion classification [59]. The explainable ML stage for cytological cancer classification [61] and the explainable AI hybrid deep learning framework for skin cancer [73] provide comparative XAI evidence. The stacking ensemble stage is represented by brain tumor diagnosis [63] and breast cancer web deployment [65]. The multimodal privacy-preserving stage is represented by the cancer diagnosis framework [66]. The ensemble XAI stage for depression and severity detection [70] extends the healthcare application boundary into mental health. The accelerated cervical cancer stacking ensemble with XAI [20] and the AI-integrated healthcare information system for diabetes management [5] complete the sector synthesis. Parkinson's screening via personalized voice biomarker ML [13] illustrates the voice modality extension of clinical AI. Across all these evolutionary stages, the shared deployment requirement is that explainability must increase in rigor as model complexity increases—a requirement that has not been consistently met.

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

Assistive and human-centered AI illustrates a different evolutionary pressure: rather than optimizing representational power, the dominant evolutionary push is toward accessibility, personalization, ethical oversight, and the sensitive handling of vulnerable user populations. ASD classification using dual-branch visual transformation [25] and ASDnet [45] represent transformer-based classification at the current technological frontier, while the ASD facial expression database [54] provides the foundational data resource that makes this evolution possible. The AI-powered digital health platform for ASD students [69] illustrates the agentic frontier of assistive AI: personalized, adaptive, and responsive to individual therapeutic trajectories. Multimodal EEG neural synchrony analysis [11] and the standard tDCS model [58] address neuromodulation and brain-computer interface AI with direct clinical safety implications. Facial emotion recognition systems—including the bidirectional Elman NN [62], hybrid deep belief optimization [47], and InceptionV3DenseNet hybrid [30]—span multiple evolutionary stages of deep learning for affective computing. Suicidal ideation detection using NLP and deep learning [43] and Bengali social media sentiment classification [34] represent NLP-based human-centered AI where calibrated uncertainty and ethical oversight are deployment-critical. The adaptive feedback system for learner improvement [50], the flex sensor hand glove for deaf and mute individuals [72], and iris detection and recognition [33] extend the sector to education, physical accessibility, and biometric AI. Online drug review sentiment extraction [42] bridges health information and text-based human-centered AI.

4.3. Industrial Monitoring, Cyber-Physical Systems, and Robotics

Industrial monitoring AI illustrates the evolutionary shift from statistical signal processing toward graph-based relational reasoning and physics-guided uncertainty, with safety rather than performance as the primary deployment driver. Gas-pipeline condition diagnosis via acoustic-emission signal imaging [49] and GNN-enhanced gas-pipeline monitoring [21] represent sequential evolutionary stages in the same application domain: the GNN approach adds relational topology to what the imaging approach treats as a signal classification problem. The lightweight deep learning approach for concrete crack characterization via acoustic-emission signals [8] represents edge-deployable CNN inference for structural health monitoring. The physics-guided Bayesian neural network for wind-turbine sensor fault detection [12] is the most evolutionarily advanced system in the industrial cluster, combining physical priors with probabilistic inference to support uncertainty-aware maintenance decisions. Vision-audio multimodal object recognition via tensor fusion [74] extends the multimodal evolutionary stage to industrial perception. The question of full autonomy in underwater robotics [2] engages the agentic frontier of industrial AI, where the accountability and governance conditions for autonomous decision-making without human oversight remain unsettled.

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

Smart infrastructure AI illustrates the evolutionary transition from rule-like monitoring and simulation toward real-time connected, edge-aware, and scalable intelligent systems. IoT-based wireless battery monitoring for solar micro-grids [35] and smart energy metering [16, 48] represent the IoT monitoring evolutionary stage in energy infrastructure. The IoT-based smart healthcare medical box for elderly patients [44] extends IoT AI to health monitoring. Wireless mesh network routing [22] and MANET routing protocol simulation [40] address network-layer decision support at the infrastructure management evolutionary stage. High-altitude platform communications optimization [56] extends infrastructure AI to airborne communication systems where dynamic channel conditions demand real-time adaptive optimization. The evolutionary observation for this domain is that smart infrastructure AI is structurally constrained by hardware: processor capability, memory footprint, power budget, and communication bandwidth define the deployable model family, independent of the performance available from larger architectures. Evolutionary progress in this domain is therefore driven by model compression and efficient architecture research rather than by scaling.

4.5. Agriculture, Environment, and Sustainability

Agricultural AI has evolved rapidly from task-specific CNNs toward lightweight, explainable, and sustainability-oriented transformer-based systems. Advanced deep learning for tea leaf disease precision diagnosis [79] and lightweight ResNeXt for aquaculture disease [32] represent early DL stages in crop and aquaculture pathology. The MaxViT soybean disease model [27], MaizeFormerX lightweight cross-scale ViT [51], the ViX-MangoEFormer ensemble with XAI for mango disease recognition, and the explainable transformer for cotton leaf diagnostics [9] represent the transformer evolutionary stage in precision agriculture, with an explicit mandate for explainability accessible to field users. AI-driven smart agriculture for crop yield optimization [26] addresses the systemic sustainability dimension. The AI-driven solar financing for rural clinics and health businesses [38] extends agricultural sustainability AI to rural health financing—a systems-level application that connects agricultural infrastructure with health system resilience. The resilience-by-design framework [78] provides the overarching cross-sectoral sustainability and resilience lens.

4.6. Business, Enterprise, and Organizational Decision Systems

Business AI exhibits the widest evolutionary span in the corpus, from conventional structured ML through generative and agentic architectures. Conventional ML forms the operational foundation: retail demand forecasting [41], credit scoring [3], market trend forecasting [23], small-business ML [64], e-commerce pricing optimization [6], predictive project risk analytics [55], and customer satisfaction analytics [76] each represent mature, deployment-ready ML applications. Market basket analysis for healthcare service bundling [52] bridges health and business analytics. Blockchain and ML in supply chain management [52] introduces distributed ledger trust mechanisms alongside predictive AI. The attention-enhanced deep learning system FuseAttenX for business strategy [46] and AI-driven business analytics for IT strategy [10] represent the transformer evolutionary stage in enterprise analytics. The generative AI stage is represented by [1] and digital transformation AI [7]. The agentic stage is represented by automated risk assessment and collaborative AI in agile project management [68] and AI for agile IT risk and decision [36]. Enterprise integration frameworks [28, 57] and AI-enabled MIS for governance and decision automation [15] address the governance layer of this evolutionary transition.

4.7. Cybersecurity, Privacy, and Distributed Intelligence

Cybersecurity AI illustrates the evolutionary shift from reactive rule-based detection toward proactive, distributed, privacy-preserving, and governance-aware intelligent systems. The intelligent cybersecurity ML framework for data protection and threat intelligence [14] represents the ML-driven security stage. AI as a strategic engine for data security, analytics, and digital communication resilience [19] positions security AI at the organizational governance level. Privacy-preserving behavior analytics for workforce retention [18] operationalizes differential privacy in organizational analytics, an evolutionary step with broad cross-sector applicability. The distributed edge-cloud-6G federated learning framework for secure and auditable decision support [71] represents the architectural frontier of the privacy-preserving distributed AI evolutionary stage. Trustworthy AI for high-stakes decision support across critical sectors [77] provides the cross-sector governance framework that underpins all evolutionary stages in high-stakes deployment. The resilience-by-design framework [78] addresses the interdependency of security, sustainability, and health resilience a systemic framing that neither pure ML security nor isolated infrastructure AI can address alone. Table 2 compares how different application sectors express the broader transition from task-specific machine learning toward foundation and agentic decision intelligence.

Table 2. Cross-domain distribution of AI decision-system evolution.

Domain	Dominant AI stages	Main decision function	Deployment priority	Key gap
Healthcare and biomedical AI	ML, CNNs, transformers, ensembles, multimodal/federated AI	Diagnosis, screening, grading, prediction	Validation, privacy, explainability, calibration	External validation and uncertainty reporting
Human-centered and assistive AI	DL, transformers, NLP, multimodal AI, adaptive platforms	Personalization, affective assessment, communication support	Ethics, accessibility, safety, fairness	Human-subject and long-term usability evaluation
Industrial monitoring and robotics	Lightweight DL, GNNs, Bayesian/physics-guided AI, autonomy	Fault diagnosis, monitoring, maintenance support	Reliability, safety, uncertainty, real-time response	Scalable uncertainty-aware and accountable autonomy
Smart infrastructure, IoT, and energy	IoT monitoring, edge-aware AI, simulation/optimization	Monitoring, routing, energy management	Latency, power, bandwidth, hardware efficiency	Secure edge intelligence and federated monitoring
Agriculture and sustainability	CNNs, lightweight DL, transformers, explainable field AI	Disease diagnosis, yield optimization, sustainability support	Robustness, interpretability, edge feasibility	Seasonal/geographic validation and field usability
Business and enterprise AI	Structured ML, forecasting, attention models, generative/agentic AI	Forecasting, strategy support, risk assessment, automation	Traceability, governance, accountability	Workflow-level validation and responsibility allocation
Cybersecurity and distributed intelligence	ML security, privacy-preserving analytics, federated/edge-cloud AI	Threat detection, secure analytics, distributed decision support	Privacy, resilience, auditability, attack resistance	Privacy accounting and poisoning-defense standards

5. Challenges in the transition toward foundation and agentic decision systems

5.1. From Task-Specific Models to Generalizable Systems

The dominant evolutionary pattern in the corpus, specialized models trained on narrow datasets for single-domain classification tasks are antithetical to the generalizability ideal of foundation models. A maize disease classifier [51] and a gas-pipeline fault detector [21] may both use transformer architectures, but they operate in disjoint representation spaces, have incompatible output formats, and have been validated on domain-specific benchmarks that do not transfer. Generalizing across these contexts requires not merely larger pre-trained models but structured approaches to domain adaptation, knowledge transfer, and workflow alignment that the current literature does not yet provide. The transition toward generalizable AI decision systems requires shared intermediate representations, cross-domain evaluation protocols, and deployment frameworks that can accommodate domain-specific fine-tuning without catastrophic forgetting. Neural machine learning approaches have supported stroke prediction and early risk assessment [82], while neural-network-based diagnostic models, including dimensionality reduction strategies and optimized architectures, have demonstrated promise for breast cancer classification using morphological and clinical features [81], [80]. In parallel, AI-driven cybersecurity techniques are gaining importance for protecting healthcare and essential infrastructure by improving threat detection, system robustness, and continuity of critical services [83].

5.2. Explanation, Auditability, and Interpretability Across Model Generations

Each evolutionary stage has introduced more powerful representations alongside more complex explanation requirements. Conventional ML [29, 13] offers straightforward feature-level attribution. CNN-based systems [37, 60] use gradient-based saliency that is visually communicable but not causally validated. Transformer-based systems [4, 17, 24] provide attention maps that are frequently presented as explanations but lack the formal properties of causal attribution. Ensemble and stacking systems [63, 65, 70] require explanation methods that account for inter-learner interactions. Knowledge-graph systems [21, 31, 39] provide structurally auditable reasoning chains but require costly domain maintenance. Generative AI systems [1, 7, 10] may generate fluent explanatory text that is factually unreliable. Agentic systems [68, 15] must explain multi-step decision sequences across coordinated agents. The evolutionary trajectory of explainability has not kept pace with the evolutionary trajectory of representational power, a misalignment that is most consequential in healthcare [73, 77] and safety-critical industrial contexts [12].

5.3. Data Heterogeneity, Multimodality, and Evidence Integration

Each evolutionary stage handles data heterogeneity differently. Conventional ML is adapted to single structured tables. CNNs operate on standardized image formats. Transformers extend to sequences and patches but require careful handling of cross-domain distribution differences. Multimodal systems [30, 66, 74] must manage intra-modal quality differences and handle cases where one modality is unavailable at inference time as shown in Figure 2. The multimodal privacy-preserving cancer diagnosis framework [66] illustrates that privacy constraints can be applied across modalities without unified data, but the performance-privacy tradeoff requires domain-specific calibration. As AI systems evolve toward broader integration of clinical images, genomic sequences, electronic health records, and wearable sensor streams, heterogeneity management will become the central data engineering challenge.

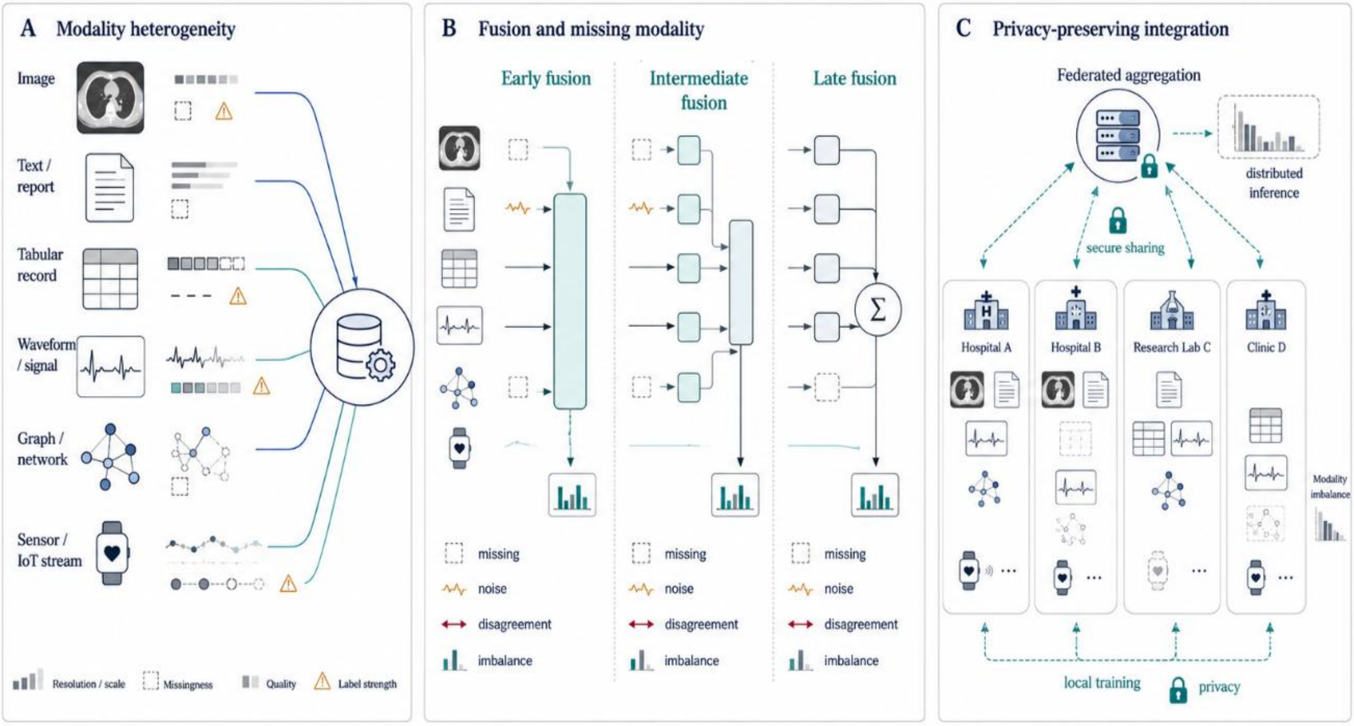

Figure 2: Multimodal heterogeneity and privacy-preserving integration in advanced decision systems.

5.4. Privacy, Security, and Distributed Learning

Privacy and security requirements have grown more complex at each evolutionary stage. Conventional ML on centralized tabular data faces data governance challenges [3, 18]. CNN training on medical images faces patient privacy obligations [66]. Federated learning [71] addresses data sovereignty but introduces model poisoning and communication interception risks. Edge deployment [8, 32, 51] reduces data transmission exposure but requires inference on hardware that may be tampered with. Generative AI [1, 7] introduces prompt injection and output manipulation risks. Agentic systems [68, 15] that access external tools and APIs introduce attack surfaces that do not exist in isolated classifiers. The trustworthy AI framework [77] and the resilience-by-design approach [78] provide high-level governance principles, but sector-specific privacy and security standards for each evolutionary stage remain underdeveloped.

5.5. Real-Time Feasibility, Scalability, and Resource Constraints

The evolutionary arc toward larger, more expressive architectures is in direct tension with the deployment reality of resource-constrained environments. Lightweight ResNeXt [32], lightweight deep learning for acoustic-emission analysis [8], and

MaizeFormerX lightweight ViT [51] all explicitly address this tension. IoT systems [16, 35, 44, 48] and HAPs communications [56] impose hardware constraints that no amount of architectural innovation can overcome without model compression. The evolutionary challenge is that as foundation models and agentic systems grow in scale, the deployment gap between state-of-the-art models and resource-constrained field hardware widens rather than narrows. Efficient architecture research—knowledge distillation, quantization, pruning, and hardware-aware neural architecture search—must advance in parallel with the scaling trend.

5.6. Robustness, Uncertainty, and Model Monitoring

Robustness to distribution shift is an evolutionary challenge that becomes more complex as models become more expressive. CNN classifiers face cross-scanner and cross-site medical imaging shifts [37, 66]. Agricultural models face seasonal and geographic variability [9, 27, 51]. Industrial models face sensor degradation and novel fault patterns [12, 21, 49]. Business forecasting models face economic regime changes [23, 41]. The physics-guided Bayesian neural network [12] provides the most evolutionary mature robustness mechanism in the corpus, but its application remains limited to a single industrial domain. Uncertainty reporting, expressing model confidence as a calibrated probability rather than a softmax score is a prerequisite for responsible deployment at every evolutionary stage but is consistently underrepresented in literature.

5.7. Human Oversight, Autonomy, and Accountability

The appropriate level of AI autonomy is an evolutionary function of both technological capability and maturity. At the conventional ML stage, AI provides ranked feature lists that clinicians interpret [29]. At the transformer stage, AI provides classification probabilities with visual explanations that clinicians review [4, 73]. At the agentic stage, AI initiates multi-step workflows, coordinates stakeholders, and may act before human review is possible [68, 15]. The question of full autonomy in underwater robotics [2] represents the agentic frontier in industrial systems. The trustworthy AI framework [77] explicitly addresses the conditions under which different levels of autonomy are defensible. The key evolutionary principle is that accountability mechanisms must scale with autonomous capability: as AI systems become more agentic, governance frameworks must become more specific, auditable, and legally grounded, not merely more aspirational.

5.8. Evidence Maturity and Reproducibility

Evidence maturity the degree to which AI system claims are supported by rigorous, reproducible, externally validated evidence varies dramatically across evolutionary stages and domains. Conventional ML for heart disease prediction [29] can be evaluated against established clinical cohorts. Transformer-based skin lesion classification [59] requires dermoscopy-specific benchmarking. Privacy-preserving federated cancer diagnosis [66] requires multi-institutional federated evaluation. Agentic risk assessment [68] requires organization-level workflow deployment studies that do not currently exist in standardized form. The absence of shared evidence maturity standards analogous to clinical trial phases but extended across all evolutionary stages and domains—is a governance gap with direct consequences for the responsible deployment of AI decision systems.

6. Future Research Directions

Future research should advance evolution-aware evaluation frameworks that assess AI decision systems across developmental stages and deployment domains, using benchmarks that jointly measure accuracy, explainability, robustness, privacy, and governance readiness through multi-stage leaderboards, cross-domain transferability scores, and governance compliance indices [77]. Domain-specific foundation-model adaptation is also needed for healthcare, industrial, and agricultural AI, with fine-tuning protocols that quantify adaptation accuracy, catastrophic forgetting, and deployment readiness [17, 51]. For generative and agentic AI, future work should establish hallucination detection, audit-trail mechanisms, and accountability frameworks, evaluated through hallucination rate, audit completeness, and responsibility assignment [1, 68]. Similarly, human-in-the-loop and human-on-the-loop systems require systematic assessment across autonomy levels, including agentic collaboration, by comparing decision quality with and without AI, override frequency, and clinician or operator outcome differences [2, 15]. Further progress depends on multimodal and graph-enhanced decision intelligence, including principled modality fusion and knowledge-graph integration for clinical and industrial AI, assessed through modality-dropout robustness, knowledge-graph coverage, and cross-modal explanation coherence [30, 31, 66, 74]. Federated and privacy-preserving foundation-style learning should be scaled to multi-institutional and multi-sector settings with formal privacy accounting, considering privacy budget, federated utility loss, and communication efficiency under 6G constraints [18, 66, 71]. Explanation validation should move beyond attention by developing fidelity metrics for attention-based, post-hoc, and GNN explanations, supported by user comprehension and regulatory acceptance measures [4, 21, 73]. Robust deployment also requires Bayesian and physics-guided uncertainty monitoring with drift detection, evaluated through calibration error, OOD detection, and drift-alert latency [12, 78].

Finally, lightweight edge-deployable transformers and GNNs should be optimized for latency, memory, and accuracy–efficiency trade-offs [8, 32, 51], while governance-aware reporting standards and agentic-AI evidence maturity levels should formalize reporting completeness, reproducibility, external validation, and accountability documentation [77, 68, 2].

7. Limitations of the review

The synthesis is therefore thematic, architectural, evolutionary, and deployment-level in nature rather than quantitative. Specific performance metrics, dataset characteristics, sample sizes, computational requirements, validation protocols, deployment environments, user studies, and statistical evidence could not be extracted from titles alone. The review should be interpreted as a structured evolutionary 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 needed to support meta-analytic comparisons of evolutionary stage, deployment feasibility, or explanation quality. The curated corpus may not comprehensively represent all evolutionary threads; large-scale foundation model deployments, reinforcement learning from human feedback, multi-agent system theory, and legal AI are not well represented. The ten-stage evolutionary taxonomy is one defensible organization of the evidence space; alternative taxonomies emphasizing different architectural transitions may yield complementary insights.

8. Conclusion

This structured critical review has mapped the evolutionary arc of AI decision systems across ten architectural stages from conventional machine learning and structured analytics through early deep learning, CNN-based domain systems, transformer and attention-based models, hybrid ensembles, graph neural networks, Bayesian physics-guided architectures, federated and privacy-preserving systems, generative enterprise AI, and emerging agentic decision frameworks, applied to seven application domains. The synthesis reveals that representational capability has advanced dramatically: vision transformers, graph neural networks, and multimodal fusion systems have substantially expanded what AI can perceive, reason about, and communicate in healthcare, industry, agriculture, business, and cybersecurity. At the same time, the deployment-critical properties of validated explainability, calibrated uncertainty, privacy-preserving inference, governance-aligned accountability, and maturity have advanced more slowly, creating a widening gap between what AI decision systems can do architecturally and what they can be trusted to do responsibly in high-stakes settings.

The transition toward foundation and agentic AI represents the most consequential evolutionary horizon in this trajectory, and also the most challenging governance frontier. Generative AI systems that synthesize strategic recommendations and agentic systems that coordinate multi-step decision workflows require accountability frameworks of a fundamentally different character than those developed for discriminative classifiers. The research agenda for this transition must be built on four pillars: trustworthy and validated explainability that scales from CNNs to agentic chains; privacy-preserving and federated learning that enables collaborative intelligence without data centralization; robustness and uncertainty quantification that signals model limitations before deployment failures occur; and governance-aware reporting standards that create a shared language of evidence maturity across domains, evolutionary stages, and regulatory contexts. Progress on these fronts will determine whether the remarkable representational advances documented in this review translate into AI decision systems that are genuinely trustworthy, equitable, and beneficial across the full range of human consequential decisions.

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