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| REVIEW ARTICLE

Explainable Deep Learning and Transformer Models for Applied AI: A Review Across Medical, Agricultural, Industrial, and Business Domains

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| ABSTRACT

Explainable deep learning and transformer models are increasingly applied to consequential decisions in healthcare, agriculture, industry, business, smart infrastructure, and human-centered AI. Their widespread adoption is motivated not by architectural novelty alone, but by the recognition that deep representations must be interpretable, auditable, and trustworthy in domains where model outputs influence patient diagnoses, crop management, infrastructure safety, organizational strategy, and accessibility. This review identifies and critically examines direct explainable AI evidence—spanning post-hoc interpretability in oncological imaging, attention-based explanation in transformer-based disease classifiers, visual XAI in lightweight agricultural transformers, and ensemble post-hoc analysis in affective computing—alongside transformer evidence across Swin, MaxViT, EfficientFormer, and hybrid vision transformer architectures. It situates these within a broader applied-AI ecosystem including conventional ML baselines, graph neural networks, Bayesian physics-guided models, privacy-preserving systems, and enterprise AI. Synthesis reveals that while explainability mechanisms have diversified across visual, attentional, post-hoc, and knowledge-structured approaches, explanation validity, the degree to which explanations faithfully represent model reasoning—is rarely formally evaluated. A ten-direction research agenda addresses this gap alongside robustness, privacy, edge deployment, human oversight, and governance-aware reporting.

| KEYWORDS

Explainable AI, deep learning, Vision transformers; Post-hoc interpretability; medical AI, agricultural AI, applied AI, trustworthy AI

| ARTICLE INFORMATION

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1. Introduction

The rapid adoption of deep learning and transformer architectures across applied AI domains has been accompanied by growing recognition that predictive performance is a necessary but insufficient criterion for responsible deployment. In healthcare, a deep learning model that classifies tumors with high accuracy but cannot explain its predictions to oncologists is not clinically deployable; regulatory frameworks and professional standards require that AI recommendations be accompanied by intelligible justifications. In agriculture, a transformer-based disease classifier that cannot communicate its diagnostic reasoning to agronomists with varying technical literacy may fail to be adopted, regardless of benchmark accuracy. In industrial monitoring, a neural fault detector that cannot explain which sensor patterns triggered an alarm cannot support the maintenance engineer decisions that downstream safety requires. Across all these domains, the gap between model capability and trustworthy deployment is mediated by explainability. Figure 1 distinguishes model prediction from explanation generation and explanation validation. Transformer architectures have become particularly prominent in applied AI because their self-attention mechanisms offer a visual communication tool—attention maps that is often presented as an explanation of model reasoning. Vision transformers [5, 42, 65], Swin Transformer-based systems [5, 42], MaxViT models [31], EfficientFormer-enhanced ensembles [29], cross-scale attention ViTs [39], global–local attention models [16], and hybrid vision transformers [28, 65] collectively represent the dominant architectural trend in image-based applied AI. However, the review of explainability literature consistently reveals that attention visualization and saliency maps should not be treated as validated causal explanations without additional formal evaluation, a methodological distinction that is central to this review's critical contribution.

This review examines explainable deep learning and transformer models as part of a broader applied-AI ecosystem that includes conventional machine learning baselines [50, 13, 18], graph neural network reasoning [74, 35, 37], Bayesian physics-guided models [22], privacy-preserving systems [56, 27, 4], enterprise and governance AI [53, 68, 21], and the IoT and infrastructure deployment contexts [7, 44, 34] within which many of these systems must ultimately operate. The seven-axis taxonomy and evidence map provided in this review enable structured analysis of where explainability is strongest, where it remains superficial, and where the most consequential research gaps lie.

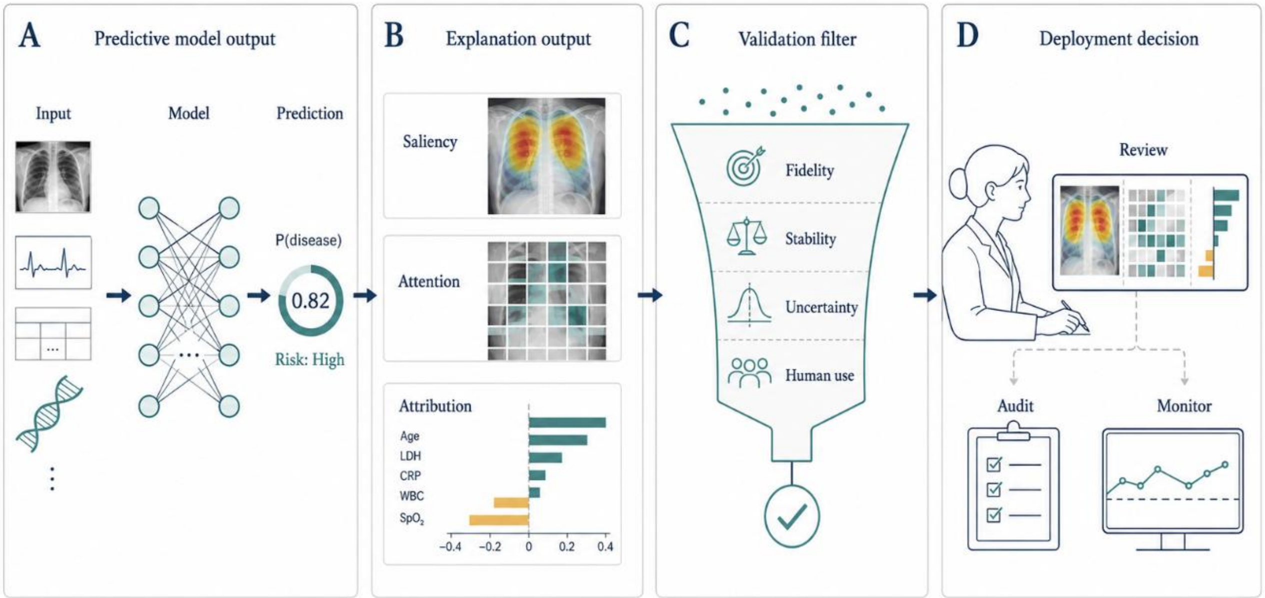

Figure 1: From predictive AI to trustworthy explanation evidence.

2. Review Scope and Taxonomic Framework

A seven-axis taxonomy organizes the evidence-by-evidence role, model family, explainability function, data modality, application domain, decision-support function, and deployment or evidence concern. Axis 1 distinguishes: direct explainable deep learning evidence, direct transformer or attention-model evidence, hybrid or ensemble deep learning evidence, comparative machine-learning evidence, domain application evidence, deployment-context evidence, and governance, privacy, or trustworthiness evidence. Axis 2 spans twelve model families from conventional ML through CNNs, transfer learning, recurrent models, vision transformers, transformer variants, attention-enhanced architectures, hybrid systems, graph neural networks, Bayesian models, generative AI, and federated systems. Axis 3 records the explainability function: visual explanation, attention-based explanation, post-hoc interpretability, feature-level explanation, model transparency, knowledge-graph reasoning, decision auditability, human-readable decision support, or not explicitly explainability-focused. Axes 4–7 classify modality, domain, decision-support function, and deployment concern respectively. A critical taxonomic principle governs this review: papers are not labeled as explainable or transformer-based unless their titles explicitly support that classification. Papers representing conventional ML, IoT systems, knowledge graphs, cybersecurity, business analytics, or broader AI governance are classified according to their actual evidence role—comparative ML, deployment context, governance, or domain evidence, and cited accordingly. Table 1 summarizes the classification scheme used to organize the reviewed literature by evidence role, model family, explanation function, modality, domain, decision-support purpose, and deployment concern.

Table 1. Classification framework for explainable applied AI.

Dimension	Categories	Synthesis purpose
Evidence role	Direct XAI; transformer/attention; hybrid/ensemble; comparative ML; domain evidence; deployment/governance evidence	Defines each paper's contribution type
Model family	ML; CNN; transfer learning; ViT/Swin/MaxViT; hybrid Transformer; ensemble; GNN; Bayesian; federated; generative AI	Groups studies by architecture
Explainability function	Saliency; attention; post-hoc attribution; feature importance; knowledge graph; audit trail; human-readable support	Identifies how explanations are produced

Dimension	Categories	Synthesis purpose
Data modality	Image; tabular; text; signal; graph; IoT stream; multimodal data	Links explanation needs to input structure
Application domain	Medical; agriculture; industrial; business; assistive AI; IoT/infrastructure; cybersecurity	Captures domain-specific requirements
Decision-support function	Screening; diagnosis; localization; prediction; grading; forecasting; monitoring; recommendation; audit	Connects model output to practical use
Deployment/evidence concern	Validity; robustness; calibration; privacy; fairness; security; edge feasibility; human oversight; reproducibility	Assesses deployment readiness

3. Conceptual Foundations of Explainable Deep Learning and Transformer Models

3.1. Why Explainability Matters in Applied Deep Learning

Explainability in applied deep learning is not an aesthetic preference but a functional requirement driven by the consequences of model outputs. In healthcare, a misclassified tumor prediction that cannot be explained cannot be corrected by a clinician who lacks insight into the model's reasoning. In agriculture, an unexplained disease diagnosis cannot guide a farmer's treatment decision. In industry, an unexplained fault alert cannot distinguish a true anomaly from a sensor artifact. In business, an unexplained credit denial cannot be appealed under fairness regulations. The trustworthy AI framework for high-stakes decision support [68] establishes that explainability is one of several co-equal trustworthiness requirements, alongside robustness, privacy, security, and governance that must be addressed jointly for responsible AI deployment.

3.2. Explainability Types and Their Limits

The explainability landscape encompasses multiple distinct mechanisms with different strengths, limitations, and appropriate audiences. Visual explanation methods, gradient-weighted class activation mapping, occlusion sensitivity, and patch-based saliency—produce image overlays that communicate which input regions influenced a prediction. These methods are widely used in medical imaging [17, 76] and agricultural AI [29, 39, 66], but their fidelity—the degree to which the highlighted region represents the actual decision mechanisms not guaranteed and may vary across inputs, model versions, and visualization parameters. Attention-based explanation, available natively in transformer architectures [16, 42, 65], provides a structured view of which input tokens or patches the model attended to, but attention weights do not constitute causal explanations and should not be presented to clinicians or regulators as such without additional validation. Post-hoc interpretability methods, SHAP, LIME, and their variants—provide approximate local explanations for individual predictions and are architecture-agnostic, making them applicable to stacking ensembles [57, 58, 76] and hybrid systems [17]. Knowledge-graph reasoning [35, 37, 74] provides a structurally auditable explanation that is entity-linked and domain-traceable, offering a qualitatively different form of accountability that post-hoc attribution cannot match.

3.3. Transformer Models and Attention Mechanisms

Transformer architectures process inputs as sequences of tokens or patches and compute multi-head self-attention over all pairs, capturing long-range dependencies that convolutional architectures address less naturally. Vision transformers adapt this paradigm to image inputs by dividing images into non-overlapping patches. Swin Transformer variants [5, 42] introduce hierarchical windowed attention to improve computational efficiency while preserving multi-scale feature representation, making them well-suited to high-resolution medical and agricultural images. MaxViT [31] combines multi-axis attention with convolutional layers to address the quadratic attention cost of standard ViTs. EfficientFormer-based ensembles [29] prioritize inference efficiency alongside representational richness, relevant for field-deployable agricultural AI. Cross-scale attention ViTs [39] and global-local attention models [16] illustrate architectural customizations that address specific decision-support requirements—fine-grained crop pathology and multi-class lesion discrimination, respectively. Hybrid vision transformers [28, 65] combine convolutional feature extraction with transformer-based context modeling, potentially offering the best-of-both-worlds tradeoff between local feature sensitivity and global dependency modeling. The critical caution for all transformer architectures is that attention maps, however visually communicable, do not constitute validated causal explanations and must be supplemented by formal explainability evaluation in high-stakes applied settings.

3.4. Explainable AI Across Applied Domains

Explainability requirements differ systematically across application domains, reflecting differences in audience, consequences, and regulatory context. In medical imaging, clinicians require explanations that map to anatomically meaningful regions and pathological features, and that support differential diagnosis rather than merely confirming a model's prediction. In agriculture, explanations must be actionable by field users with varying technical literacy, communicating which leaf regions or spectral features indicate disease. In industrial monitoring, explanations must support maintenance decision-making by identifying which sensor patterns or spatial regions triggered a fault alert. In business analytics, explanations must support audit trails and fairness assessment. In cybersecurity, explanations must identify which behavioral patterns or network features contributed to a threat classification. In assistive AI, explanations must be accessible to users, caregivers, and clinical supervisors simultaneously.

3.5. From Explainable Outputs to Trustworthy Deployment

Explainability is a necessary but insufficient component of trustworthy deployment (See Figure 2). The trustworthy AI framework [68] positions explainability alongside robustness, privacy, security, fairness, governance, and evidence maturity as co-equal requirements. Robustness concerns preservation of model reliability, including explanation reliability, under distribution shift, adversarial perturbation, and sensor degradation. Privacy-preserving deployment [4, 27, 56] must protect sensitive input data during both training and inference, which may constrain the explanation mechanisms available. Uncertainty quantification addressed most rigorously by the physics-guided Bayesian neural network [22], enables AI systems to communicate their own epistemic limitations, supporting human oversight decisions about when to trust and when to escalate. Evidence maturity, the degree to which AI system claims are supported by rigorous external validation, is the governance property most consistently under addressed across the applied-AI corpus.

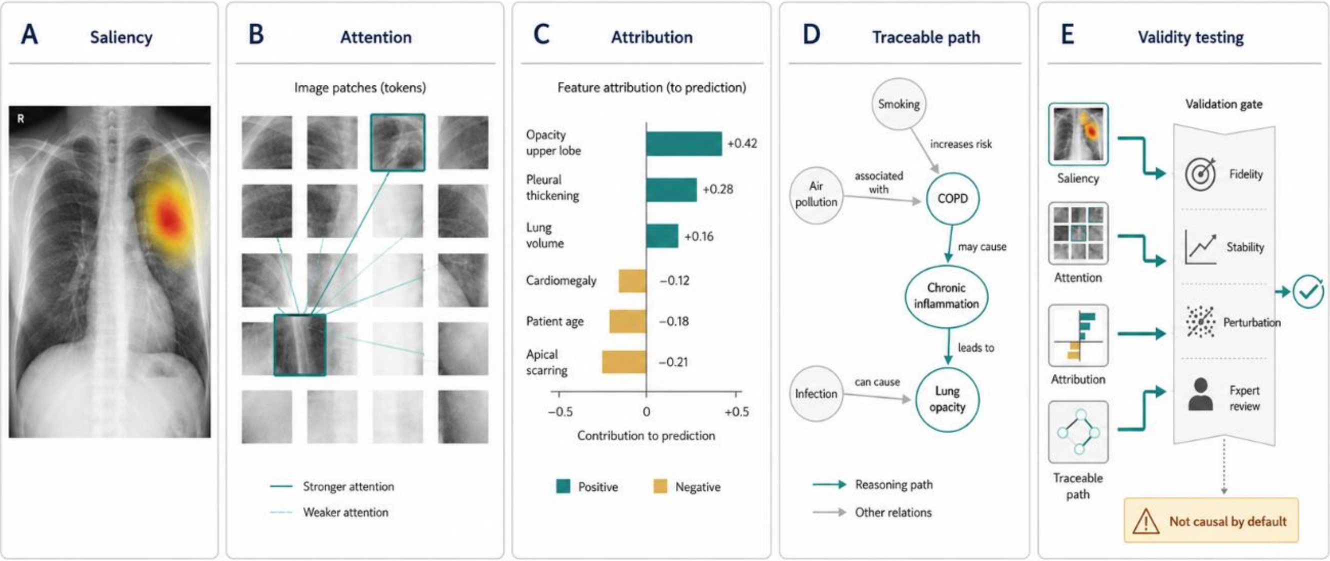

Figure 2: Explanation output is not explanation validity.

4. Architecture Families

4.1. Conventional Machine Learning and Interpretable Structured Analytics

Conventional machine learning constitutes the interpretability benchmark against which deep learning and transformer models must be measured: feature-level attribution is well-understood, computationally inexpensive, and compatible with regulatory audit requirements. Clinical decision support for heart disease prediction from structured patient data [50] and personalized ML for Parkinson's disease screening via voice biomarkers [59] illustrate the continued deployment relevance of structured ML in medical contexts. In business analytics, retail demand forecasting using LSTM and gradient boosting [18], market trend forecasting with external factor integration [13], e-commerce pricing optimization [70], and small-business management ML for customer retention and financial forecasting [9] demonstrate that conventional ML architecture serves as the operational baseline for enterprise decision support. Credit scoring for financially underserved businesses [10] provides evidence for ML fairness challenges in financial AI. Market basket analysis for healthcare service bundling [15] bridges business and health analytics. The interpretability advantage of conventional ML is substantive: global feature importance scores provide directly auditable decision factors that post-hoc methods applied to deep models only approximate.

4.2. CNN-Based Deep Learning and Transfer Learning

CNN-based architectures and their transfer-learned variants provide domain-specific feature representations that conventional ML cannot match for image and signal data but introduce explanation requirements that exceed what feature importance can provide. Transfer learning for sleep stage classification under limited data conditions [8] and early leukemia diagnostics incorporating image processing and transfer learning [77] illustrate the data-efficiency advantage of pre-trained CNNs in medical contexts. The explainable AI hybrid deep learning framework for skin cancer [17] explicitly integrates post-hoc XAI with CNN feature learning—one of the clearest examples of explanation being designed into the architecture rather than added afterward. Facial emotion recognition via a bidirectional Elman neural network [41] and a hybrid deep belief optimization system [32] extend CNN-based representation learning to affective computing. The lightweight deep learning approach for concrete crack characterization via acoustic-emission signals [26] demonstrates CNN adaptability for edge-deployable industrial monitoring. The multichannel CNN analysis of imbalanced CT data for lung cancer [25] illustrates both the modality capacity of CNNs and the class imbalance challenge that makes explanation particularly important in medical triage contexts.

4.3. Transformer and Attention-Based Models

The transformer architecture family encompasses the largest cluster of direct XAI evidence in the corpus, with explicit explainability integration across medical and agricultural domains. The Swin Transformer with XAI and web-based screening for cervical cell classification [42] provides the clearest example of transformer architecture combined with web deployment and formal explainability: attention visualization and post-hoc methods are jointly applied to support clinical screening. The hierarchical Swin Transformer ensemble for breast cancer with decentralized deployment [5] extends this to federated clinical settings with explicit XAI. The explainable transformer for skin lesion classification [30] and the LMVT hybrid vision transformer for lung cancer with XAI [65] illustrate oncological applications. The hybrid vision transformer for prostate cancer in MRI [28] provides attention-based explanation in a multi-parametric imaging context. The global-local attention model for kidney disease classification from CT images [16] demonstrates dual-scale attention for multi-class renal lesion discrimination. In precision agriculture, MaizeFormerX lightweight cross-scale attention ViT with XAI [39], the MaxViT soybean disease model [31], the ViX-MangoEFormer ensemble with XAI [29], and the explainable transformer for cotton leaf diagnostics [66] constitute a lightweight agricultural transformer cluster where explainability, efficiency, and field deployability are jointly optimized. The dual-branch visual transformation models for ASD classification with XAI [51, 78] extend transformer-based XAI to assistive AI. FuseAttenX attention-enhanced deep learning for business strategy optimization [45] illustrates transformer attention applied to enterprise analytics. The ensemble transformer with post-hoc XAI for depression emotion and severity detection [57] demonstrates explainable transformer AI in mental health contexts.

4.4. Hybrid, Ensemble, Stacking, and Multimodal Deep Learning

Hybrid and ensemble architectures improve generalization and provide richer post-hoc explanation opportunities, but at the cost of increased explanation complexity. The explainable deep stacking ensemble for brain tumor diagnosis [76] and the stacking ensemble-based breast cancer classifier with real-time web deployment [52] demonstrate ensemble diversity combined with post-hoc XAI in oncological imaging. The stacking ensemble with XAI for cervical cancer diagnosis [58] and the ensemble transformer with post-hoc explanations for depression detection [57] extend this pattern to gynecological and psychiatric contexts. The hybrid multi-modal emotion recognition framework using InceptionV3DenseNet [40] and the vision-audio multimodal object recognition system via hybrid tensor fusion [75] illustrate multimodal fusion architectures whose explanations must address not only what was predicted but which modality was most influential. A critical observation about ensemble and hybrid systems is that post-hoc explanation methods applied to the ensemble's final output may not accurately reflect the reasoning of individual base learners, and explanation methods designed for single models may produce misleading attributions in stacking architectures. Neural network–based diagnostic models combined with dimensionality reduction techniques have shown potential for improving breast cancer detection by extracting discriminative patterns from complex biomedical data [80]. AI also plays a growing role in safeguarding healthcare and essential infrastructure, where intelligent cybersecurity systems can support threat detection, risk monitoring, and resilience against attacks targeting sensitive medical and operational systems [81].

4.5. Graph Neural Networks and Knowledge-Graph Reasoning

Graph neural networks and knowledge-graph architectures provide structurally auditable explanations that are qualitatively different from saliency-based or attention-based methods: entity-linked reasoning chains that domain experts can trace without technical AI knowledge. The GNN-enhanced acoustic-emission gas-pipeline monitoring system [74] provides fault localization grounded in the physical sensor network topology. Knowledge-graph and NLP integration for heuristic reasoning [35] and the AddManBERT knowledge-graph construction for additive manufacturing design support [37] demonstrate that symbolic knowledge graphs can be integrated with neural language models to produce reasoning chains that are both expressive and auditable by engineering professionals. The gas-pipeline diagnosis system using acoustic-emission imaging [3] provides the domain context within which GNN-based explanation is most consequential—safety-critical infrastructure where false negatives carry severe physical consequences and fault localization must be both accurate and traceable.

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

The physics-guided Bayesian neural network for sensor fault detection in wind turbines [22] represents the most principled form of explainable AI in the corpus for safety-critical applications: physical priors constrain model behavior under novel inputs, and Bayesian inference provides calibrated uncertainty estimates that quantify model confidence as a deployable probability distribution rather than an uncalibrated softmax score. The explanation value of this architecture is epistemic: when the model's uncertainty is high, it communicates that the prediction should be reviewed by a human expert rather than acted upon autonomously. This uncertainty-aware explanation is arguably more valuable than a high-confidence saliency map in safety-critical industrial contexts, because it directly supports the human oversight mechanism that safety accountability requires.

4.7. Generative, Enterprise, Distributed, and Privacy-Preserving AI

Infrastructure-level deployment contexts—federated learning, edge-cloud systems, enterprise information systems, and cybersecurity frameworks—determine whether explainable deep learning and transformer models can be practically deployed at scale. The distributed edge-cloud-6G federated learning framework for secure and auditable decision support [56] provides the deployment architecture for privacy-preserving AI at scale. Privacy-preserving behavior analytics for workforce retention [27] demonstrates operational differential privacy in organizational analytics. The multimodal privacy-preserving cancer diagnosis framework [4] illustrates the tension between privacy constraints and multimodal explainability: protecting data across institutions may limit the explanation mechanisms available. Generative AI in enterprise information systems [53] introduces accountability challenges specific to generative models, whose explanations cannot be evaluated using the same post-hoc attribution methods applicable to discriminative classifiers. The intelligent cybersecurity ML framework [43] and AI as a strategic engine for digital resilience [21] address the security layer of AI deployments, within which explanation auditability is itself a security property. AI-driven business analytics for IT strategy [47] and AI-enabled MIS for governance [19] illustrate the enterprise deployment layer where explanation must satisfy organizational governance requirements as well as technical accountability.

5. Domain-Specific Synthesis

5.1. Medical and Biomedical AI

The medical domain provides the densest cluster of direct XAI evidence in the corpus, reflecting both the intensity of clinical AI research and the stringency of explanation requirements in patient-facing decision support. Explainable XAI architectures span skin cancer [17, 30], lung cancer [25, 65], breast cancer [5, 52], cervical cancer [42, 58], brain tumor [76], leukemia [77], prostate cancer [28], kidney disease [16], and cytological cancer classification [1]. The comparative explainable ML analysis for cancer cytology [1] provides the most methodologically rigorous XAI comparison in the corpus, systematically evaluating multiple explanation methods on the same classification task. The ensemble transformer with post-hoc XAI for depression emotion and severity detection [57] extends medical XAI into affective computing, where ground truth ambiguity makes explanation calibration particularly challenging. Heart disease prediction from structured data [50] and Parkinson's screening via voice biomarkers [59] illustrate conventional ML baselines in clinical contexts. The multimodal privacy-preserving cancer diagnosis framework [4], the AI-integrated healthcare information system for diabetes management [67], and market basket analysis for healthcare service bundling [15] complete the healthcare application synthesis. The web-based Swin Transformer cervical screening tool [42] demonstrates the deployment pathway—web interface, real-time inference, and integrated explanation output—that most oncological AI systems aspire to but few have achieved.

5.2. Agricultural and Environmental AI

Agricultural AI illustrates the evolutionary pressure toward lightweight, explainable, and field-deployable transformer systems where explanation must be accessible to domain users with varying technical backgrounds. MaizeFormerX lightweight cross-scale attention ViT with XAI [39], the MaxViT soybean disease model [31], the ViX-MangoEFormer ensemble with XAI [29], the explainable transformer for cotton leaf diagnostics [66], lightweight ResNeXt for aquaculture disease [61], and advanced deep learning for tea leaf disease [63] constitute the agricultural AI cluster. The explicit XAI mandate in [29, 39, 66] reflects the field-user deployment context: an explanation that identifies the specific leaf region or color change indicating disease is more actionable for a farmer than a classification probability. AI-driven smart agriculture for crop yield optimization [72] and AI-driven solar financing for rural health businesses [38] address the systemic sustainability dimension, connecting agricultural AI with rural health infrastructure and resource management.

5.3. Industrial Monitoring and Cyber-Physical Systems

Industrial monitoring AI requires explanation mechanisms that can communicate fault evidence to maintenance engineers and support safety-critical decision-making under time pressure. The GNN-enhanced gas-pipeline monitoring system [74] and the multivariate acoustic-emission imaging system for gas-pipeline diagnosis [3] represent two approaches to pipeline fault explanation—graph-relational reasoning and imaging-based feature attribution—in the same application domain. The lightweight deep learning system for concrete crack characterization via acoustic-emission signals [26] demonstrates edge-deployable DL for structural health monitoring. The physics-guided Bayesian neural network for wind-turbine sensor fault detection [22] provides the most principled uncertainty-aware explanation in the industrial cluster. The vision-audio multimodal object recognition system via tensor fusion [75] contributes multimodal evidence for industrial perception. The question of full autonomy in underwater robotics [11] directly engages the human oversight axis: even if an autonomous system's perception model provides XAI outputs, the deployment decision about whether a robot can act on those outputs without human review is a governance question that XAI alone cannot resolve.

5.4. Business, Enterprise, and Organizational Analytics

Business AI explanation requirements are driven by governance, fairness, and audit trail obligations rather than professional interpretability standards. Credit scoring ML for financially underserved businesses [10] introduces fairness-critical explanation requirements: credit applicants may have legal rights to explanation that must be satisfied by the AI system's output. Predictive project risk analytics [60], automated risk assessment AI in agile project management [12], and AI for IT project risk [2] illustrate governance-structured business AI contexts where decision trails must be auditable. Market basket analysis for healthcare bundling [15], customer satisfaction analytics [48], retail demand forecasting [18], and small-business ML [9] represent the operational forecasting cluster. The attention-enhanced deep learning system FuseAttenX for business strategy optimization [45] illustrates hybrid attention-based analytics in enterprise AI. Blockchain and ML in supply chain management [6], generative AI in enterprise information systems [53], AI-enabled MIS for governance [19], digital transformation analytics [64], and AI-ERP integration conceptual framework [33] address the governance and enterprise integration layer. AI-driven business analytics for IT strategy [47] and predictive analytics for project risk [60] complete the business evidence synthesis.

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

Assistive AI explanation requirements reflect the dual audience of technical developers and non-technical users, caregivers, and clinical supervisors. ASD classification via dual-branch ViT with XAI [51, 78] and ASDnet [51] demonstrate transformer-based XAI for developmental assessment. The ASD facial expression database [69] provides the foundational modality resource. The AI-powered digital health platform for ASD students [24] and the adaptive feedback system for learner improvement [23] illustrate human-in-the-loop deployment contexts where explanation must be accessible to educators and therapists. The multimodal EEG neural synchrony analysis [20] and the standard tDCS model [62] address neuro-affective and clinical neuroscience AI. Facial emotion recognition systems [32, 41] and the hybrid InceptionV3DenseNet multimodal framework [40] span multiple CNN evolutionary stages in affective signal processing. Suicidal ideation detection using NLP [36] and Bengali social media sentiment classification [54] illustrate text-based human-centered AI where explanation is ethically critical. Drug review sentiment extraction [14] and the flex sensor hand glove for deaf and mute individuals [73] extend the assistive AI domain. The iris detection and recognition system [46] addresses biometric identification in accessibility contexts.

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

Smart infrastructure AI operates in hardware-constrained, real-time, and distributed environments where explanation must be computationally efficient and actionable for infrastructure operators. IoT-based wireless battery monitoring for solar micro-grids [34], smart energy metering [44], and the smart healthcare medical box for elderly patients [7] represent IoT-embedded monitoring applications where AI explanation must function within strict latency budgets. Wireless mesh network routing optimization [49] and MANET routing protocol simulation [71] address network-layer decision support. High-altitude platform communications optimization [79] extends infrastructure AI to airborne systems with dynamic channel conditions. In these contexts, the explanation requirement is not clinical or agricultural interpretability but operational transparency: infrastructure operators need to understand why an AI system flagged a condition or recommended an action, so they can verify the flag before taking consequential action.

5.7. Cybersecurity, Privacy, and Distributed Intelligence

Cybersecurity AI explanation requirements are shaped by adversarial risk: in a threat-detection context, explaining a model's reasoning may inadvertently reveal the features that adversaries can learn to evade. The intelligent cybersecurity ML framework [43] addresses this tension between explainability and security. AI as a strategic engine for data security and digital communication resilience [21] positions security explanation at the organizational governance level. Privacy-preserving behavior analytics for workforce retention [27] demonstrates operational differential privacy in organizational contexts. The distributed edge-cloud-6G federated learning framework [56] provides the deployment architecture for privacy-preserving AI, within which explanation auditability must be maintained across distributed nodes. The resilience-by-design framework [55] and the trustworthy AI framework [68] address the governance layer that determines when, how, and to whom AI explanations must be provided across cybersecurity and distributed intelligence contexts.

6. CROSS-DOMAIN CHALLENGES

6.1. Explanation Validity and Overinterpretation

The most pervasive challenge in applied explainable deep learning is the overinterpretation of explanation outputs. Attention maps in Swin Transformer [5, 42] and cross-scale ViT [39] systems show which spatial regions the model attended to, but attention weights are not causal, a model may attend to a diagnostically irrelevant background region and produce a correct prediction for unrelated reasons. Gradient-based saliency maps in hybrid DL skin cancer systems [17] are sensitive to input preprocessing and normalization choices that may not reflect genuine diagnostic reasoning. Post-hoc SHAP values stacking ensembles [57, 76] approximate local decision boundaries but may not accurately attribute importance in high-dimensional feature spaces where correlations are complex. The comparative explainable ML analysis [1] and the trustworthy AI framework

[68] both implicitly address this challenge, motivating the need for formal explanation validity testing as a standard component of applied XAI evaluation.

6.2. Robustness, Imbalance, and Distribution Shift

Robust challenges in medical AI include class imbalance in cancer screening datasets [25] and cross-scanner distribution shift in multi-site imaging studies [5, 65]. Agricultural AI faces seasonal illumination variability and growth-stage differences that may shift the feature distribution from training to field deployment [29, 39, 66]. Industrial sensor networks experience sensor degradation and novel fault patterns that fall outside training distributions [22, 74]. Business forecasting models face economic regime changes that alter the relationship between input features and target variables [13, 18]. The physics-guided Bayesian neural network [22] addresses robustness through physical priors; no other architecture in the corpus provides comparable formal robustness guarantees. The resilience-by-design framework [55] addresses systemic robustness at the infrastructure level.

6.3. Data Heterogeneity and Multimodal Evidence

Data heterogeneity presents alignment and quality challenges that affect both model training and explanation coherence. Medical imaging data [25, 28, 65] requires standardized preprocessing that may differ across imaging sites. Physiological signals [20, 22, 59] have different temporal dynamics than imaging data, making cross-modal fusion technically demanding. The hybrid multimodal emotion recognition framework [40] and vision-audio tensor fusion system [75] illustrate architectures that attempt modality alignment, but the explanation challenge, which modality drove the fused prediction is not resolved by current post-hoc methods. Business datasets [10, 13, 18] span heterogeneous sources whose integration requires domain-specific feature engineering that conventional ML handles explicitly but deep learning may obscure.

6.4. Privacy, Security, and Federated Deployment

Privacy-preserving deployment introduces constraints that directly affect explainability: if model inference is distributed across federated nodes [56], centralized explanation generation is architecturally impossible, and explanation methods must be adapted to operate on local data without compromising privacy. The multimodal privacy-preserving cancer diagnosis framework [4] illustrates this tension. Privacy-preserving behavior analytics [27] demonstrates differential privacy in organizational contexts. The cybersecurity deployment context [43] adds adversarial risk: explanation outputs may reveal discriminative features that adversaries can learn to evade. The resilience-by-design framework [55] and the distributed intelligence framework [56] provide the governance architecture within which privacy-preserving explainability must operate.

6.5. Computational Complexity and Deployment Feasibility

Transformer architecture faces a fundamental computational tension: standard self-attention scales quadratically with sequence length, making full-resolution image processing computationally prohibitive for IoT and edge deployment. The lightweight cross-scale ViT for maize disease [39], the MaxViT soybean model [31], and the EfficientFormer-based mango disease ensemble [29] address this through architectural efficiency innovations. Lightweight ResNeXt for aquaculture [61] and lightweight DL for concrete crack characterization [26] demonstrate that edge deployability can be achieved with CNN compression. Web-based Swin Transformer deployment [42] and stacking ensemble web deployment [52] demonstrate that cloud-hosted inference can satisfy real-time requirements for medical screening, though at the cost of network latency and data transmission privacy risks.

6.6. Human Oversight, Accountability, and Governance

Explainable AI must ultimately support human oversight rather than substitute for it. The question of full autonomy in underwater robotics [11] illustrates the governance boundary: even a fully explainable AI system should not act autonomously in safety-critical contexts without human review, because explanation fidelity cannot be guaranteed under novel conditions. The trustworthy AI framework [68] and the resilience-by-design framework [55] embed human oversight as a design requirement. Generative AI in enterprise information systems [53] and AI-enabled MIS for governance [19] illustrate the organizational governance layer where AI accountability extends to board-level decision audit. In agentic AI systems for project management [12], the allocation of accountability between AI and human stakeholders must be explicitly documented.

6.7. Reproducibility and Evidence Maturity

The explainable deep learning corpus reveals significant variability in evaluation rigour. The comparative explainable ML analysis [1] and the personalized ML for Parkinson's screening [59] represent among the most systematic evaluation designs in the corpus, comparative, stratified, and modality-specific but remain within single-institution datasets. External validation on independent multi-site datasets, ablation of explanation components, and calibration analysis are rarely reported. Reproducibility standards for XAI should require reporting of the specific explanation method used, the validation protocol for fidelity testing, the software implementation version, and the sensitivity of the explanation output to input perturbations. These standards do not yet exist in mature form across any application domain. Table II summarizes how explanation needs differ across application domains according to the intended user, decision type, explanation format, and deployment concern.

Domain	Users	Decision context	Explanation need	Main concern
Medical AI	Clinicians; radiologists	Screening; diagnosis; triage	Anatomical saliency; uncertainty	Clinical validity
Agricultural AI	Farmers; agronomists	Disease detection; treatment guidance	Leaf-region evidence	Field usability
Industrial AI	Engineers; operators	Fault detection; safety alerts	Sensor/fault attribution	Reliability
Business AI	Managers; auditors	Risk scoring; forecasting	Feature contribution; audit trail	Accountability
Assistive AI	Caregivers; educators; users	Behavioral assessment; support planning	Human-readable rationale	Accessibility
IoT/infrastructure	Operators; administrators	Monitoring; anomaly alerts	Alert rationale; trend evidence	Latency
Cybersecurity AI	Security analysts; privacy teams	Threat detection; incident response	Behavioral evidence; evidence trace	Adversarial risk

7. Future Research Directions

Future research should prioritize formal validation of XAI outputs by developing fidelity metrics and protocols for attention, saliency, and post-hoc explanations, particularly in medical and agricultural AI, using explanation fidelity scores, perturbation sensitivity, and user-comprehension studies [1,68]. Transformer-specific audits are also needed to evaluate attention heads, cross-scale attention, and global–local attention through fidelity, consistency, and clinical usability measures [5,16,42]. Cross-domain benchmarks should jointly assess accuracy, explanation validity, robustness, and governance readiness across medical, agricultural, and industrial applications, supported by multi-domain leaderboards, explanation-validity indices, and governance-compliance scores [68]. Future work should further optimize XAI-integrated transformers for edge, IoT, and mobile deployment, with evaluation based on latency, memory use, and explanation fidelity at the edge [39,29,66,26]. Robustness should be strengthened by integrating Bayesian uncertainty and post-deployment drift monitoring, assessed through calibration error, out-of-distribution detection, and drift-alert latency [22,55]. For multimodal and hybrid systems, explanation methods must attribute predictions to specific modalities and interactions using cross-modal fidelity, modality-dropout stability, and user-comprehension testing [40,75,57]. Privacy-preserving and federated XAI should enable explanation generation without centralizing sensitive data, while reporting privacy budget, federated explanation utility, and communication efficiency [4,27,56]. Human-in-the-loop evaluation should test whether explanations improve expert decision quality, adoption, and agreement in medical, agricultural, and industrial settings [11,68]. Finally, governance-aware reporting standards and evidence maturity levels are needed to specify explanation methods, fidelity tests, validation protocols, computational requirements, and progression from proof-of-concept to externally validated and deployment-validated XAI systems [68,55,1,68].

8. Limitations of the review

The synthesis is thematic, methodological, explainability-oriented, architectural, and deployment-level rather than quantitative. Specific performance metrics, explanation methods and their fidelity scores, dataset characteristics, 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 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 explanation quality, model performance, or deployment feasibility. The curated corpus may not comprehensively represent all active explainable deep learning and transformer research; video-based transformers, large language model XAI, multi-agent explanation systems, and natural language–image grounding are underrepresented. Not every paper in the corpus is explicitly about explainable AI or transformers; papers representing conventional ML, IoT deployment, business analytics, cybersecurity, and governance are classified as comparative, domain, deployment, or governance evidence and used accordingly rather than mislabeled.

9. Conclusion

This structured critical review has examined explainable deep learning and transformer models across seven application domains—medical and biomedical AI, agricultural and environmental AI, industrial monitoring and cyber-physical systems, business and enterprise analytics, human-centered and assistive AI, smart infrastructure and IoT, and cybersecurity and distributed intelligence. The synthesis reveals a field in which transformer architectures—Swin, MaxViT, EfficientFormer, hybrid ViT, cross-scale attention, and global-local attention variants—have rapidly become the dominant image classification paradigm across medical oncology and precision agriculture, with explicit XAI integration increasingly treated as an architectural requirement rather than a post-research addition. Post-hoc explanation methods applied to stacking ensembles, hybrid deep learning, and multimodal fusion systems extend the XAI mandate to more complex architectures, while graph neural networks and knowledge-graph reasoning provide the most structurally auditable explanation mechanisms available. Conventional ML baselines remain essential as interpretability benchmarks, and Bayesian physics-guided architectures provide the most principled uncertainty-aware explanation for safety-critical industrial systems. The path toward trustworthy explainable AI in real-world applied settings requires resolving the critical gap identified throughout this review: the systematic absence of explanation validity testing. Explanation outputs, whether visual saliency, attention maps, or post-hoc attributions—are routinely reported without formal evaluation of whether they faithfully represent model reasoning, generalize across inputs, or are useful to the intended audience. Closing this gap requires developing formal explanation fidelity metrics, transformer-specific interpretability audit protocols, cross-domain XAI benchmarks, and governance-aware reporting standards that create a shared language of explanation accountability across medical, agricultural, industrial, business, and infrastructure domains. Privacy-preserving and federated explainable AI, lightweight and edge-deployable transformer models, and human-in-the-loop explanation evaluation frameworks are the architectural and evaluation frontiers on which progress is most urgently needed. The ultimate goal is AI systems whose predictions are not only accurate but whose explanations are genuinely trustworthy—validated, reproducible, and meaningful to the humans who must act on them.

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