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Explainable ensembles and transformer-centric learning in vision and beyond: Methods, validation and deployment assurance

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Abstract

Ensemble learning and transformer-centric architectures now dominate vision and decision support, yet practitioners lack unified guidance on method selection, explainability and assurance. This title-driven scoping review synthesises studies across healthcare, agriculture, cybersecurity, energy, finance and other sectors. Titles suggest a proliferation of ensemble techniques—from bagging, boosting and stacking to transformer-based mixtures of experts—and increasing adoption of vision transformers (ViT, Swin, MaxViT) in imaging and multimodal tasks. The review infers a taxonomy of ensemble strategies, transformer backbones and fusion schemes, and surveys conceptual failure modes such as overfitting, spurious correlations and explanation instability. It characterises explainability families (saliency, concept-based, example-based, uncertainty-based) and highlights unique challenges when interpreting ensembles and transformers. Domain-specific synthesis across medical imaging, plant disease diagnostics, cybersecurity, energy forecasting and sentiment analysis reveals heterogeneous tasks and deployment contexts. A cross-domain assurance checklist emphasises interpretability-by-design, robustness, privacy, monitoring and governance. A research agenda prioritises standardising explanation validation, agreement-aware fusion, robustness calibration, privacy-preserving explainable learning and multimodal XAI. This scoping synthesis maps current directions and outlines practical guidance, providing a foundation for evidence-based updates once full texts become available.

Keywords: Ensemble Learning; Transformer Models; Explainability; Robustness; Multimodal Fusion; Calibration; Assurance; Scoping Review

1 Introduction

Artificial intelligence (AI) is transforming perception and decision support across sectors such as healthcare [22], agriculture [66], cybersecurity [1], energy [32], finance [40] and public welfare [5]. In high-stakes contexts, the adoption of ensemble learning and transformer-centric models is driven by their ability to boost predictive performance, capture complex patterns and integrate heterogeneous data. Ensemble learning refers to techniques that combine multiple base learners to improve generalisation. Variants include bagging and boosting, which operate through resampling and sequential weighting, and stacking, which trains a meta-learner on base predictions [22], [49], [69]. Ensembles may be homogeneous (same model type) or heterogeneous (diverse model families) and can employ learned fusion or simple averaging. Transformer-centric learning, exemplified by vision transformers (ViT) and hierarchical variants such as Swin and MaxViT, utilises self-attention over tokenised patches to model long-range dependencies [23], [63], [64], [66], [67], [70]. Explainability encompasses post-hoc methods (saliency maps, attribution, counterfactuals) and intrinsic

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designs that render model decisions interpretable. Trustworthiness requires robustness, calibration, privacy, fairness and governance.

Despite methodological advances, there is limited cross-domain synthesis of ensemble and transformer practices, and it remains unclear how explainability and assurance are operationalised. This review makes four contributions: (i) it derives a unified taxonomy of ensemble paradigms, transformer backbones and fusion strategies; (ii) it provides cross-domain evaluation guidance by mapping tasks, modalities and trust dimensions to method families; (iii) it proposes a deployment and assurance checklist summarising robustness, calibration, privacy, monitoring and governance considerations; and (iv) it compiles a portfolio map as a foundation for future evidence-based synthesis. The review is title-driven, meaning that only the information contained in titles is used to infer themes; paper-specific details will be added in a future revision once full texts are available.

2 Review Protocol and Scope

2.1 Portfolio-bounded scoping rationale and research questions

A portfolio-bounded scoping methodology was adopted to assemble a corpus of studies spanning diverse sectors, tasks and modalities. Titles were selected from domains including cyber threat detection [1], business analytics [2], energy governance [3], workforce forecasting [4], welfare management [5], 6G edge frameworks [8], threat intelligence management systems [9], renewable energy optimisation [12], privacy-preserving federated learning for critical infrastructure [13], medical diagnosis and risk prediction [14], [28], brain tumour segmentation [23], stroke prediction [17], early disease detection [26], [49], neurological signal analysis [35], credit card fraud detection [40], plant disease recognition [66], [67], sentiment analysis [43], [58], [62], and emerging therapies [76], [77]. We posed three research questions: RQ1: Which ensemble paradigms are compatible with transformer-centric backbones across domains? RQ2: How is explainability framed at model, decision and stakeholder levels? RQ3: What assurance practices—robustness, calibration, privacy, governance—are implied for reliable deployment?

2.2 Title-driven extraction schema

Given that only titles were available, an extraction schema was developed to infer: sector (medical imaging [14], agriculture [51], cybersecurity [25], energy [32], finance [40], public welfare [5], sports [41], mental health [59]); task type (classification [22], segmentation [23], risk prediction [28], time-series forecasting [10], predictive maintenance [20], fraud detection [40], sentiment recognition [43], plant identification [66]); modality (image, signal, time-series, text, multimodal [68]); method family (convolutional networks [16], ensemble learning [22], [60], transformer variants [23], [63], [64], [66], [70], transfer learning [29], federated learning [13], [18], [48], digital twin [20], quantum computing [46]); explainability family (saliency maps, attention visualisation [23], stacking explanations [60], example-based methods [50]); deployment hints (edge [15], cloud [7], IoT [25], 6G [8], MIS [9], blockchain [11], web applications [74]); and governance/security/privacy hints (policy compliance [5], bias control [27], inclusive development [56], risk management [57]). These categorizations remain provisional and will be refined upon full-text analysis.

2.3 Conceptual rigor appraisal rubric

To guide future quality assessment, we propose a conceptual rigor rubric comprising the following dimensions: (a) External validation—evidence of cross-institutional or cross-domain evaluation to ensure generalisation; (b) Leakage controls—use of appropriate splitting to avoid information leakage and temporal confounding; (c) Calibration—reporting of probabilistic calibration metrics and clinical thresholds; (d) Robustness testing—stress tests under adversarial perturbations [1], sensor noise [35], domain shifts [34] and distributional drift; (e) Interpretability validation—assessment of explanation faithfulness (e.g., deletion tests) and utility through human-in-the-loop studies [14], [50]; (f) Privacy/security threat modelling—analysis of federated learning risks [13], [18], blockchain integrity [11] and 6G attack surfaces [8]; (g) Reproducibility signals—availability of code, data or model specifications. This rubric defines evaluation criteria but no scores are assigned in the current scoping review.

3 Method Taxonomy: Ensembles and Transformer-Centric Learning

3.1 Ensemble paradigms

Ensemble learning combines multiple models to improve predictive performance and reliability. Titles in the corpus suggest diverse paradigms: bagging and boosting implicitly underpin credit card fraud detection [40], energy

forecasting [32] and renewable energy optimisation [42]. Stacking ensembles are explicitly referenced in brain tumour diagnosis [60], cervical cancer detection [65], rare medicinal plant recognition [71] and depression emotion detection [69], indicating meta-learners that fuse base predictions. Heterogeneous ensembles mix different architectures, as seen in generalizable lung cancer detection [49] and hierarchical Swin transformer ensembles for breast cancer diagnosis [63], while homogeneous ensembles rely on repeating a single architecture type [22], [37]. Teacher-student and mixture-of-experts concepts are implied by multi-expert transformer frameworks [67], [69] and federated ensemble diagnostics [48]. The choice between averaging and learned fusion hinges on trade-offs between simplicity and adaptivity.

Emerging evidence indicates that AI and MIS are assuming an increasingly central role in critical national sectors. Goffer et al. [1] considered AI-enabled cyber threat detection and response for the protection of critical infrastructure, while Haldar et al. [2] investigated the role of AI-driven analytics and MIS in fostering data-based economic growth. In the energy domain, Hassan et al. [3] examined MIS implementation in support of national energy dominance strategies. Complementing these studies, Mahmud et al. [4] focused on AI-powered workforce analytics to forecast labor market dynamics and identify skill deficiencies relevant to national competitiveness.

Table 1 Unified taxonomy of ensembles

Strategy	When to use	Typical risks	Interpretability implications
Bagging	When variance is high and training data can be resampled (e.g., random forests)	Overfitting if base learners are too complex; requires diverse samples	Individual tree explanations may be aggregated; overall model less interpretable
Boosting	When bias is high and sequential learning can correct errors (e.g., gradient boosting)	Sensitivity to noisy labels; potential overfitting to outliers	Base learner weights complicate attribution; serial dependencies
Stacking	When combining heterogeneous models via a meta-learner improves accuracy	Risk of overfitting meta-learner; data leakage between folds	Meta-learner may be opaque; explanation requires decomposing base contributions
Heterogeneous ensembles	When leveraging different architectures captures complementary patterns	Increased complexity; harder to calibrate and debug	Attribution must reconcile diverse models; inconsistent explanations
Mixture of experts	When specialised models handle different data regions or modalities	Expert assignment errors; gating network vulnerability	Explaining gating decisions and expert outputs is non-trivial

3.2 Transformer-centric backbones across domains

Transformer-centric models extend attention mechanisms beyond natural language processing to vision, signals and multimodal data. Vision Transformers (ViT) treat images as sequences of patches, enabling global receptive fields. Titles such as Transunetb [23], hierarchical Swin transformer ensemble [63], LMVT hybrid vision transformer [64], MaxViT for soybean disease identification [66], ViX-MangoEFormer combining transformer and EfficientFormer [67], and explainable transformer frameworks for cotton leaf and fabric defect detection [70], [72] suggest adoption of hierarchical windows, hybrid convolution-attention modules and efficient architectures. These backbones typically employ multi-head self-attention, patch embedding, positional encoding and token mixing. In non-vision contexts, transformer models may process time-series for energy consumption prediction [10], multimodal vision-audio signals [68] and depression detection [69]. Efficiency considerations include computational cost, patch size, window configuration and scaling laws.

The role of AI has also expanded substantially across energy systems, infrastructure, and healthcare. Ahmed et al. [10] showed that AI-based time-series analysis can contribute to the optimization of solar energy production and more effective smart energy management in the USA. In a related vein, Khan et al. [11] explored the joint use of blockchain and AI to secure energy transactions, particularly for fraud mitigation and market stabilization. Ahmed et al. [12] further discussed the use of AI to improve renewable energy generation and advanced storage technologies for smart energy solutions. Beyond energy, Ahmed [13] surveyed privacy-preserving federated learning in critical infrastructure, emphasizing associated security and governance concerns. In medical settings, Siam et al. [14] examined explainable deep learning for diagnosis with the aim of narrowing the gap between predictive capability and clinical trust.

3.3   Fusion strategies

Fusion strategies describe how multiple models or modalities are combined. Feature-level fusion concatenates intermediate representations, as implied by transfer learning frameworks that merge morphological features [19] and multimodal breast cancer detection combining mammography and EHR data [26]. Decision-level fusion aggregates outputs from base models, as in stacking ensembles for cervical cancer and rare plant recognition [65], [71]. Multimodal fusion strategies include tensor and hybrid fusion techniques for vision-audio object recognition [68], hierarchical fusion of Swin transformer and CNN in decentralized breast cancer diagnosis [63], and hybrid ensembles mixing EfficientFormer and transformer backbones [67]. Agreement-aware strategies attempt to reconcile base learner disagreement, while attention-based fusion allows the model to weigh inputs dynamically.

3.4   Typical failure modes

Notwithstanding performance gains, ensembles and transformers exhibit failure modes. Overfitting arises when ensembles memorise noise or suffer from redundant base models, a risk in small datasets common to medical imaging [31] and mental health prediction [59]. Spurious correlations and bias are perpetuated when training data lack diversity, as cautioned in welfare management [5], inclusive economic development [56] and sports analytics [41]. Sensitivity to distributional shift is particularly salient in energy grids [34], adversarial threat detection [1] and IoT intrusion detection [25]. Explanation instability occurs when slight changes in inputs yield inconsistent saliency maps, challenging trust in post-hoc methods [14]. Ensemble disagreement may obscure model confidence, necessitating methods to quantify uncertainty and alignment. Resource constraints and latency issues emerge in edge deployments [15], [24], [8], while transformer models may struggle with high computational cost and memory footprint [63], [64].

Within healthcare AI, recent studies have concentrated on both model effectiveness and privacy-aware deployment. Khan et al. [16] investigated breast cancer diagnosis through neural networks augmented by dimensionality reduction techniques, whereas Khan et al. [17] examined stroke prediction using neural machine learning methods. In addition, Ahmed et al. [18] proposed privacy-centered federated learning models for scalable healthcare data processing, highlighting the importance of distributed and secure learning mechanisms in clinical environments. Brain tumor imaging research has recently progressed through advances in both classification and segmentation. Oza et al. [22] proposed an ensemble learning method for MRI-based brain tumour classification, indicating the promise of ensemble techniques for neuroimaging diagnosis. In contrast, Khushubu et al. [23] introduced TransUNetB, a Transformer–U-Net model designed for efficient and explainable brain tumor segmentation. Taken together, these works point to the growing importance of ensemble and transformer-based frameworks in brain tumor analysis.

Table 2 Transformer-centric taxonomy

Model family	Strengths/limitations	Efficiency considerations	Explainability hooks
Vision Transformer (ViT)	Global receptive field captures long-range dependencies; requires large data	High computational cost; quadratic scaling with patch number	Attention maps offer tokens saliency; attention rollout provides global explanation
Swin Transformer	Hierarchical windows provide local and global context; better efficiency	Window size selection critical; may miss global relations if too small	Window-based attention can be visualised; tokens grouped hierarchically
MaxViT	Combines convolution and transformer layers; strong locality and global mixing	Complex architecture; training stability challenges	Hybrid layers allow convolutional saliency and attention maps
Hybrid transformer-CNN	Merges convolution for local texture with attention for global context	Balancing modules may be complex; integration overhead	Explainability benefits from both feature maps and attention matrices
Efficient transformer variants	Reduced parameter counts and memory footprint for edge deployment	May sacrifice accuracy; tuning necessary	Lightweight attention maps still informative; easier to deploy XAI on device

4 Explainability for Ensembles and Transformers

4.1 Explainability families

Explainability methods can be grouped into families. Post-hoc saliency and attribution methods such as Grad-CAM and integrated gradients highlight input regions that contribute to predictions; titles referencing explainable deep learning models [14], deep stacking ensemble models [60] and explainable frameworks for depression detection [69] imply their use. Concept-based explanations map latent features to human-interpretable concepts and may be relevant for plant disease diagnosis [71], [66] or supply chain optimisation [46]. Example-based explanations identify prototypical or counterfactual instances; this may be useful in ensemble learning for rare plant recognition [71] and mental health indicator identification [50]. Uncertainty-based explanations quantify prediction confidence, which is important in risk prediction for liver cirrhosis [28] and early leukemia diagnostics [61]. Intrinsic interpretability strategies design models that are self-explanatory, such as attention visualisation in transformer models [23], [63], [64], [70].

4.2 Explainability in ensembles (unique issues)

Applying explainability to ensembles introduces unique challenges. Aggregating attributions across base learners requires balancing fidelity and comprehensibility; titles on ensemble brain tumour classification [22] and generalizable lung cancer detection [49] suggest composite models where attribution must reflect multiple learners. Stacking ensembles [60], [65], [69] may combine heterogeneous base models, complicating weight interpretability and inviting inconsistency across explanations. Ensuring explanation consistency and enforcing constraints on base learner disagreement are open problems. Weight interpretability is particularly challenging when meta-learners are neural networks rather than simple linear combinations.

AI-based prediction and screening have also gained considerable momentum in US healthcare systems. Arafat et al. [26] developed a deep learning framework that combines mammography with clinical EHR data for early breast cancer detection. Rimon et al. [27] extended this direction by proposing a scalable machine learning approach for chronic kidney disease screening across healthcare settings. Hasan et al. [28] further introduced an explainable machine learning model for mortality risk prediction in liver cirrhosis patients, reinforcing the importance of interpretability in clinical decision support.

4.3 Explainability in transformers (unique issues)

Transformers pose distinct interpretability questions. Attention maps are sometimes used as explanations, yet attention weights do not necessarily align with causality; titles such as Transunetb [23], hierarchical Swin transformer [63], LMVT hybrid transformer [64], ViX-MangoEFormer [67] and explainable transformer frameworks [70] highlight reliance on attention mechanisms. Token attribution techniques compute saliency over patches, but occlusion and attention rollout analyses are needed to verify faithfulness. Hybrid models that combine convolution and attention [66], [67] may produce complex receptive fields that challenge simple attribution. Multimodal transformers [68], [69] require explanations that integrate across modalities.

Table 3 Explainability validation matrix

Method family	Faithfulness checks	Stability checks	Human factors	Pitfalls
Saliency / attribution	Deletion, occlusion, gradient masking	Input perturbation, model reinitialisation	User comprehension and trust studies	Can highlight spurious regions; sensitive to noise
Concept-based	Concept activation tests, counterfactual concept removal	Variation across concept definitions	Alignment with domain knowledge	Requires curated concept sets; may miss subtle patterns
Example-based	Prototype relevance, counterfactual validity	Perturbing prototype selection	User familiarity with examples	May oversimplify complex decisions; dataset bias
Uncertainty-based	Calibration plots, entropy checks	Noise injection, ensemble variance analysis	Confidence thresholds for decision support	High uncertainty may not pinpoint cause; misinterpreted as error

Attention-based	Attention rollout, input scrambling tests	Head masking, token shuffling	Visualization clarity for stakeholders	Attention does not equal explanation; head redundancy

4.4 Validation of explanations (what "good" means)

Validating explanations requires assessing faithfulness, stability and human usefulness. Faithfulness can be tested via deletion or occlusion experiments to determine whether highlighted features are truly causal [14], [28]. Stability checks evaluate whether explanations remain consistent under small perturbations of input or model parameters; this is important when ensembles and transformers produce variable outputs [60], [69]. Human factors involve gauging whether explanations improve user understanding, trust and decision quality; user studies are implied in mental health indicator identification [50] and business decision making [44]. Pitfalls include confirmation bias, superficial plausibility and the mistaken assumption that attention equals explanation.

5 Domain-Specific Synthesis

5.1 Medical imaging and clinical decision support

Medical imaging dominates the corpus, with titles covering breast cancer diagnosis [16], [19], early detection frameworks [26], cervical cancer screening [65], lung cancer detection [49], brain tumour classification and segmentation [22], [23], [60], [63], [64], leukemia classification [73], eye disease classification [29], skin cancer diagnosis [30], esophageal disease diagnosis via web applications [74], wound healing technologies [75], and advanced therapies [76], [77]. These tasks span classification, segmentation, risk prediction and treatment planning. Ensemble methods are frequently used to enhance accuracy and robustness [22], [49], [60], [65], while transformer backbones like Swin and MaxViT introduce global context [23], [63], [64], [66]. Privacy-preserving techniques are emphasised through federated learning models [18], [48], and deployment considerations include edge intelligence for critical diseases [15] and digital twins for predictive maintenance [20]. Clinical assurance requires calibration, sensitivity to error costs, interpretability utility for clinicians and patient safety.

5.2 Agriculture and plant/leaf disease diagnostics

Agricultural applications involve precision diagnosis of tea leaf diseases [51], soybean leaf and seed diseases [66], mango leaf diseases [67], cotton leaf diseases [70], [72] and rare medicinal plant recognition [71]. These titles imply the use of advanced deep learning and transformer models (e.g., MaxViT, EfficientFormer hybrids) and ensemble strategies to handle variability in leaf morphology. Explainability is important for agronomists to understand disease cues and for deploying models on resource-constrained devices. Deployment constraints include on-device inference, energy efficiency and robustness to field conditions.

5.3 Cybersecurity / fraud / infrastructure analytics as "beyond vision" comparators

Beyond vision, several titles address cybersecurity and fraud detection. AI-enhanced cyber threat detection and response [1], cyber threat intelligence as a management information system [9], fortified healthcare infrastructure with AI-driven cybersecurity [21], [78] intrusion detection in IoT environments [25], ML approaches for blackout mitigation [33], resilient grid operation under electric vehicle penetration [34], robust LSTM for power transmission fault detection [39], and digital security for deepfake detection [54] illustrate anomaly detection and threat intelligence tasks. Fraud detection in credit card transactions [40] and risk management in digital finance [57] highlight financial domains, while secure energy transactions using blockchain [11] and business analytics approaches to deepfake detection [54] underscore the need for security and governance. Ensemble and transformer methods may enhance detection sensitivity and reduce false positives, but they require stress testing against adversarial attacks and careful calibration.

5.4 Energy, smart grid, forecasting, and industrial IoT

Energy and industrial IoT titles address solar energy production optimisation [10], renewable generation and storage [12], prediction of energy consumption across sectors using support vector regression and genetic algorithms [32], sophisticated relays for blackout mitigation [33], resilient grid operation with growing electric vehicle penetration [34], optimisation of hybrid renewable energy systems [42], digital twin-based predictive maintenance [20], and time-series forecasting of energy consumption [10]. Edge computing and low-latency communication emerge in 6G frameworks [8] and real-time analytics for industrial robots [24]. Transformers may be applied to time-series forecasting, while ensembles can stabilise predictions. Assurance considerations include resilience to equipment failures, latency, calibration of forecasts and security of blockchain-enabled energy transactions [11]. In energy and electrical

engineering, recent investigations have covered both forecasting and infrastructure reliability. Hasan et al. [32] employed genetic algorithm-optimized support vector regression to estimate energy consumption in multiple sectors. Juel et al. [33] proposed a machine learning-assisted relay mechanism aimed at blackout prevention in power systems. Tonny et al. [34] examined resilient grid management under growing EV penetration using data-driven approaches. Additionally, Tanbhir et al. [35] evaluated DWT and EMD methods for electromyographic signal denoising, while Khan et al. [36] studied the impact of inductance and skin effect on transient wave behavior in transformer bushings. Overall, these works reveal the wide-ranging relevance of intelligent modeling and technical analysis in engineering applications.

5.5 NLP, sentiment, mental health, and multimodal perception

A subset of titles explores natural language processing, sentiment analysis and mental health. Bidirectional deep learning and fuzzy Markov models for sentiment recognition [43], multi-class sentiment classification on Bengali social media [58], comparative analyses of suicidal ideation detection using NLP, machine and deep learning [59], data-driven sentiment analysis of online drug reviews [62], and identification of mental health indicators using ensemble and explainable AI techniques [50] illustrate text analytics tasks. Depression emotion and severity detection with ensemble transformers [69] and vision-audio multimodal object recognition using hybrid and tensor fusion techniques [68] demonstrate multimodal learning. These tasks raise unique explainability and fairness considerations, including language bias, cultural context, privacy and stakeholder trust. The scope of AI applications has also broadened across smart energy, sentiment analysis, business intelligence, and industrial inspection. Ahamed et al. [42] reviewed machine learning methods for optimizing hybrid renewable energy systems in decentralized smart grids to improve both efficiency and stability. Ahamed et al. [43] then proposed a sentiment recognition model combining bidirectional deep learning with an extended fuzzy Markov framework. Hossain et al. [44] addressed the use of explainable AI in business decision-making, particularly for reducing trust-related barriers. In industrial quality control, Haque et al. [45] introduced a data-centric strategy for leather inspection based on advanced vision transformer models.

Table 4 Cross-domain assurance checklist

Method family	Faithfulness checks	Stability checks	Human factors	Pitfalls
Saliency / attribution	Deletion, occlusion, gradient masking	Input perturbation, model reinitialisation	User comprehension and trust studies	Can highlight spurious regions; sensitive to noise
Concept-based	Concept activation tests, counterfactual concept removal	Variation across concept definitions	Alignment with domain knowledge	Requires curated concept sets; may miss subtle patterns
Example-based	Prototype relevance, counterfactual validity	Perturbing prototype selection	User familiarity with examples	May oversimplify complex decisions; dataset bias
Uncertainty-based	Calibration plots, entropy checks	Noise injection, ensemble variance analysis	Confidence thresholds for decision support	High uncertainty may not pinpoint cause; misinterpreted as error
Attention-based	Attention rollout, input scrambling tests	Head masking, token shuffling	Visualization clarity for stakeholders	Attention does not equal explanation; head redundancy

6 Cross-Cutting Design Principles and Practical Guidance

To operationalise trustworthy ensemble and transformer models, we propose five design principles. Interpretability-by-design encourages the use of architectures that facilitate explanation—such as inherently interpretable base learners, attention visualisation and concept bottlenecks—and mandates post-hoc explainability audits [14], [60], [63]. Robustness-by-design calls for stress testing models under noise, adversarial perturbations and domain shift, using techniques such as adversarial training, uncertainty estimation and ensemble disagreement analysis [1], [33], [34]. Privacy/security-by-design advocates federated learning [13], [18], [48], privacy-preserving data encodings, blockchain audit trails [11] and threat modelling for 6G and IoT devices [8], [25]. Assurance-by-design integrates calibration assessment, continuous monitoring, drift detection and audit logs into deployment pipelines [7], [9], [54], ensuring that models remain aligned with evolving data and regulatory requirements. Deployment-by-design

guides decisions about edge versus cloud execution [15], [24], [8], [79] taking into account latency, energy efficiency, computational cost and model size. Recent literature has further shown the growing impact of AI in medicine, business operations, and digital economies. Khan et al. [49] proposed generalizable ensemble models for early lung cancer detection, while Shakil et al. [31] analyzed the comparative performance of deep learning models for chest disease and lymphoma classification. Beyond healthcare diagnosis, Mosaddeque et al. [46] explored how AI and quantum computing can improve supply chain management in aerospace and education, and Sufian et al. [47] investigated the use of machine learning for strategic gains in the healthcare sector. At the market level, Ahmed et al. [52] assessed trends and investment opportunities in AI-powered SaaS, emphasizing the increasing commercial relevance of intelligent software services.

7   Research Agenda

7.1   Standardising explainability validation for ensembles and transformers

Motivation: Current titles highlight widespread use of explainable techniques [14], [60], [69], yet validation remains ad hoc. Standard protocols are needed to assess faithfulness and utility across tasks.

What to measure: Metrics should include deletion and occlusion tests, explanation stability scores, user comprehension and decision impact.

Recommended evaluation protocol: Develop benchmark datasets spanning imaging, time-series and text; run controlled experiments comparing saliency, concept and example-based methods across ensemble and transformer architectures.

Expected impact: A standardised framework will improve comparability of explanations and accelerate regulatory acceptance.

7.2   Robustness and calibration as first-class reporting requirements

Motivation: Titles indicate concerns about adversarial attacks [1], grid resilience [34], and fault detection [39], but robustness and calibration metrics are rarely reported.

What to measure: Report adversarial robustness (attack success rate), domain shift performance, probabilistic calibration (Brier score), and ensemble disagreement indices.

Recommended evaluation protocol: Conduct stress tests under synthetic perturbations and real distributional shifts; evaluate calibration using reliability diagrams; compare ensemble versus transformer robustness.

Expected impact: Making robustness and calibration mandatory will reduce deployment risks in healthcare, energy, finance and cybersecurity.

7.3   Agreement-aware fusion strategies and explanation consistency constraints

Motivation: Stacking and hybrid ensembles [60], [65], [69] may produce conflicting explanations; guidance is needed on how to fuse predictions and attributions coherently.

What to measure: Measure agreement across base learners, explanation variance, and correlation between model weights and explanation importance.

Recommended evaluation protocol: Develop ensemble fusion algorithms that penalise disagreement; test explanation aggregation techniques; evaluate on medical imaging and sentiment analysis tasks.

Expected impact: Ensuring explanation consistency will enhance trust and allow practitioners to interpret ensemble decisions confidently.

7.4   Privacy-preserving explainable learning

Motivation: Federated learning titles [13], [18], [48] and blockchain-enabled transactions [11] suggest interest in decentralised training, but explanation generation must not compromise privacy.

What to measure: Quantify privacy leakage from explanations, measure communication overhead, and assess accuracy-privacy-interpretability trade-offs.

Recommended evaluation protocol: Implement federated ensemble and transformer models with privacy-preserving explainability mechanisms; simulate attacks to extract sensitive information; evaluate across healthcare and finance tasks.

Expected impact: Privacy-preserving explainable learning will enable cross-institutional collaboration while maintaining confidentiality.

7.5 Multimodal explainability beyond naive fusion

Motivation: Titles on multimodal perception [68], [69], [26] show growing interest in combining vision, audio and text, yet explainability of multimodal models is underexplored.

What to measure: Define metrics for cross-modal attribution coherence, modality contribution, and user comprehension across modalities.

Recommended evaluation protocol: Create multimodal datasets; test fusion strategies such as tensor fusion and cross-attention; conduct human studies on explanation comprehension.

Expected impact: Developing multimodal explainability will support applications ranging from sentiment analysis to industrial inspection.

Limitations

This review is a title-driven scoping synthesis. Inferences about sectors, tasks, method families, explainability strategies and assurance practices are based solely on paper titles. Consequently, misclassification and oversimplification may occur; for example, a title mentioning ensemble learning may employ specific architectures or datasets that are unknown. No details about sample sizes, datasets, performance metrics, model architectures, hyperparameters or clinical claims are provided. The scoping nature of this review means that it identifies conceptual patterns but cannot evaluate empirical findings. The findings should be viewed as a framework for future systematic reviews where full texts will be examined.

8 Conclusion

Ensemble learning and transformer-centric architectures offer powerful tools for perception and decision support across domains. This portfolio-bounded, title-driven scoping review synthesised studies and derived a taxonomy of ensemble strategies, transformer backbones and fusion techniques, highlighted explainability families and validation challenges, and mapped domain-specific applications from vision to text. Cross-cutting design principles and an assurance checklist were proposed, and a prioritised research agenda was outlined. The synthesis underscores the need for standardised evaluation of robustness, calibration and explanation quality, agreement-aware fusion, privacy-preserving explainable learning and multimodal XAI. Future work will enrich this framework by incorporating full-text evidence, quantitative results and domain-specific constraints.

Compliance with ethical standards

Disclosure of conflict of interest

There is no conflict of interest.

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