Journal of Medical and Health Studies (JMHS)
ISSN: 2710-1452
DOI: 10.32996/jmhs
Journal Homepage: www.al-kindipublisher.com/index.php/jmhs

JMHS
AL-KINDI CENTER FOR RESEARCH AND DEVELOPMENT

| REVIEW ARTICLE

Human-Centered Artificial Intelligence for Healthcare, Education, Business, and Assistive Technologies

Mst Rafia Jannat
Department of Information System Management, Stanton University, Los Angeles, CA 90036, USA
Corresponding Author: Mst Rafia Jannat, **E-mail**: rafiajannat14112000@gmail.com

| ABSTRACT
Artificial intelligence increasingly mediates consequential human decisions across healthcare, education, business, assistive technologies, digital health, and organizational management. Yet the dominant evaluation paradigm—predictive accuracy—inadequately captures the properties most relevant to human welfare: interpretability, usability, accessibility, fairness, privacy, and the quality of human-AI collaboration. Human-centered AI reframes AI development as a socio-technical design discipline in which model outputs must support—rather than supplant—human expertise, judgment, and agency. This structured critical review synthesizes an eight-axis human-centered taxonomy covering domain, function, data modality, architecture family, design concern, deployment pathway, evidence role, and evidence maturity. Seven human-centered domains are examined: healthcare and biomedical decision support, education and adaptive learning, assistive technologies and accessibility, neuro-affective and mental-health AI, business and organizational decision-making, human-facing IoT and smart infrastructure, and cybersecurity and trustworthy digital systems. Synthesis reveals that while AI architectures have advanced substantially across vision transformers, hybrid ensembles, graph neural networks, and federated systems, human-centered design properties—validated explainability, inclusive design, privacy-preserving deployment, affective ambiguity management, and governance accountability—remain inconsistently addressed. An eleven-direction research agenda emphasizes human-centered evaluation, user-driven validation, fairness-aware design, accessible deployment, and governance-ready AI systems across all critical domains.

| KEYWORDS

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

| ARTICLE INFORMATION

ACCEPTED: 15 April 2026 **PUBLISHED:** 24 May 2026 **DOI:** 10.32996/jmhs.2026.7.8.3

1. Introduction

The integration of artificial intelligence into systems that directly serve human needs—clinical diagnosis, educational support, financial access, communication assistance, workforce management, and public safety—has created a new imperative: AI systems must be designed not merely to be accurate, but to be usable, accessible, trustworthy, interpretable, and accountable to the people they affect. This imperative defines human-centered AI: an approach to AI design in which the measurement of system value includes not only model performance on benchmark tasks, but the system's capacity to support human decision-making, respect human dignity, and operate within ethical and social constraints.

Across healthcare, AI increasingly influences clinical decisions that affect patient safety and treatment quality. Systems supporting cancer diagnosis [10, 32, 45], clinical risk assessment [7, 38], and diabetes management [5] must be interpretable to clinicians, safe for patients, and compliant with privacy regulations. In education, AI-powered adaptive feedback systems [9] and digital health platforms for students with autism spectrum disorder [1] must support learners without undermining teacher agency or exposing sensitive developmental data. In business and organizational settings, credit scoring [8], workforce retention analytics [52], and enterprise information systems [17] must be auditable, fair, and aligned with organizational governance. In assistive technologies, sensor-based devices [2], emotion-recognition systems [6, 25, 48, 64], and voice biomarker screening [3] must be accessible, reliable, and respectful of the neurodiversity of the users they serve.

This review constructs a human-centered AI taxonomy and evidence map synthesizes cross-domain evidence of human-centered AI application and gaps, and identifies the research directions most consequential for advancing AI as a genuinely human-serving technology. Figure 1 illustrates the central framing of the review: AI systems in healthcare, education, business, assistive technologies, and digital infrastructure should not be evaluated only by predictive performance.

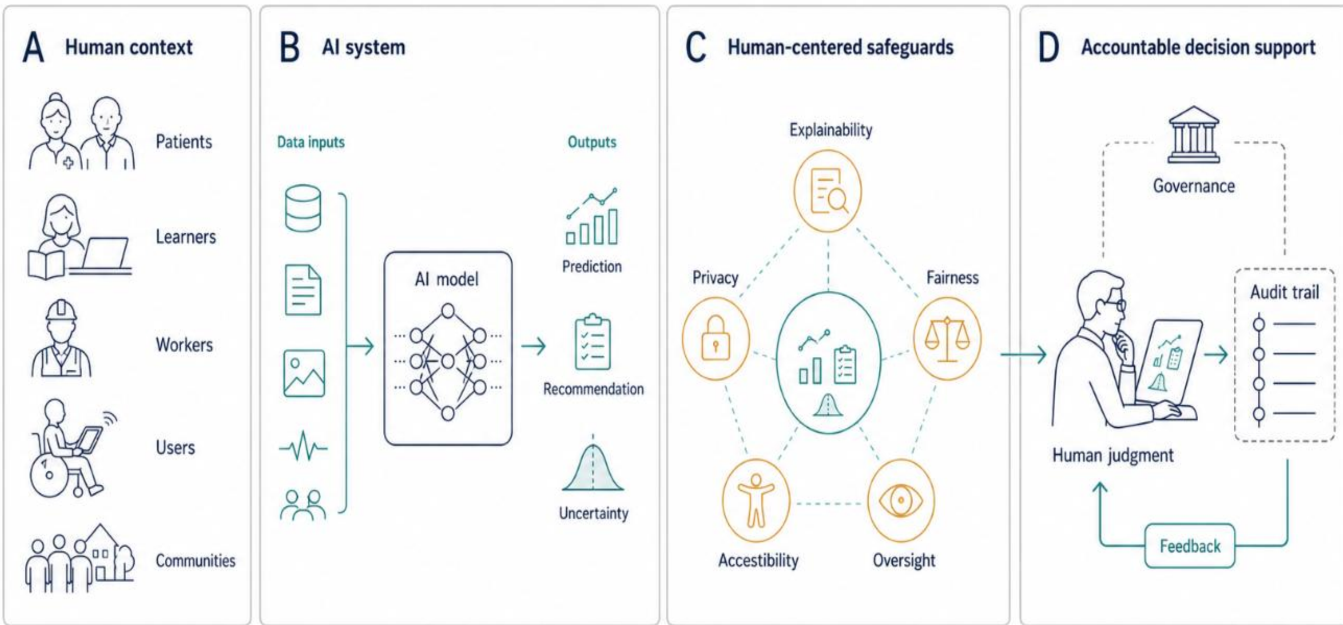

Figure 1. Human-centered AI as socio-technical decision support.

2. Review Scope and Human-Centered Taxonomic Framework

The corpus was assembled to provide balanced representation across human-centered AI domains, architecture families, data modalities, deployment pathways, and design concerns. An eight-axis taxonomy organizes the evidence.

Axis 1 classifies by human-centered domain: healthcare and biomedical decision support, education and adaptive learning, assistive technologies and accessibility, neuro-affective and mental-health AI, business and organizational decision-making, human-facing IoT and smart infrastructure, and cybersecurity and trustworthy digital systems. Axis 2 classifies by human-centered function: screening and early detection, clinical decision support, learning personalization, communication and accessibility support, emotion and behavior understanding, risk assessment, strategic decision support, workflow automation, privacy-preserving collaboration, and safety and governance. Axis 3 classifies by data modality across nine categories. Axis 4 identifies the architecture family. Axis 5 records the dominant human-centered design concern: interpretability, usability, accessibility, personalization, privacy, fairness, human oversight, accountability, trust calibration, or safety. Axis 6 classifies the deployment pathway. Axis 7 assigns the evidence role. Axis 8 identifies the evidence maturity concern.

A methodological note governs this taxonomy: papers are not labeled as human-centered unless their titles support that classification. Papers representing agricultural AI, industrial monitoring, infrastructure, or cybersecurity are classified as deployment-context, infrastructure, or trustworthiness evidence and cited accordingly. Table 1 summarizes the taxonomy used to code the reviewed studies across domain, function, modality, architecture, design concern, deployment pathway, evidence role, and maturity.

Table 1. Human-centered AI taxonomy used for evidence coding.

Axis	Coding dimension	Main categories	Human-centered relevance
Axis 1	Application domain	Healthcare; education; assistive AI; mental-health AI; business AI; IoT/infrastructure; cybersecurity	Defines the human and organizational context affected by AI.
Axis 2	Function	Screening; decision support; personalization; accessibility support; risk assessment; workflow automation; governance	Clarifies how AI supports human activity and decision-making.
Axis 3	Data modality	Image; text; tabular data; voice; EEG; facial/behavioral data; IoT signals; multimodal data	Indicates privacy, consent, and interpretability requirements.
Axis 4	Architecture family	ML; deep learning; transformers; ensembles; GNNs; Bayesian AI; generative AI; federated AI	Links model design to explainability, robustness, privacy, and deployment

Axis	Coding dimension	Main categories	Human-centered relevance
			feasibility.
Axis 5	Design concern	Interpretability; usability; accessibility; privacy; fairness; oversight; accountability; safety	Identifies the main human-centered requirement.
Axis 6	Deployment pathway	Offline prototype; web; mobile/edge; IoT; cloud; federated; enterprise workflow; real-world deployment	Shows whether the system is experimental or deployment oriented.
Axis 7	Evidence role	Application; method; deployment; privacy; explainability; governance; trustworthiness	Clarifies the contribution of each study.
Axis 8	Evidence maturity	Conceptual; proof of concept; internal validation; robustness testing; external validation; user validation; monitored deployment	Distinguishes early evidence from deployment-ready evidence.

3. Conceptual Foundations of Human-Centered AI

3.1 From Model-Centered AI to Human-Centered AI

The dominant AI research paradigm has historically been model-centered: systems are evaluated by their performance on benchmark datasets, and improvement is measured by accuracy gains on held-out test sets. Human-centered AI challenges this paradigm by asking a different question: does the system support the humans who use it? A cancer classifier that achieves high accuracy but cannot explain its predictions to an oncologist is not clinically deployable. A credit scoring model that achieves high AUC but produces unfair outcomes for protected groups is not organizationally acceptable. A sentiment analysis system that processes workforce behavioral data without explicit consent is not ethically sound. The trustworthy AI framework for high-stakes decision support [56] provides a cross-domain articulation of this shift: accuracy is necessary but insufficient for trustworthy deployment, which requires explainability, robustness, privacy, security, and governance as co-equal requirements.

3.2 Human-Centered AI as Decision Support

A defining principle of human-centered AI is that AI should support rather than replace human expertise, judgment, and agency. In healthcare, clinical decision support for heart disease prediction [7] and diabetes management [5] illustrate AI as a tool that provides evidence to clinicians rather than autonomous clinical decisions. In education, the adaptive feedback system for learner improvement [9] positions AI as a supplement to teacher oversight rather than a substitute for it. In business, automated risk assessment in agile project management [37] illustrates AI that coordinates human stakeholder decisions rather than displacing them. The question of full autonomy in underwater robotics [39] directly addresses the limits of autonomous decision-making: even in industrial contexts, the framing as a realistic prospect question reflects genuine governance uncertainty that extends to clinical, educational, and organizational AI.

3.3 Personalization, Accessibility, and Inclusion

Personalization is a fundamental human-centered design property that distinguishes systems designed for generic users from those designed for specific individuals with specific needs. Personalized ML models for Parkinson's disease screening via voice biomarkers—accounting for age, gender, and linguistic variability [3] exemplify clinical personalization: the model adapts to individual vocal characteristics that demographic variation would otherwise conflate. The AI-powered digital health platform for students with autism spectrum disorder [1] extends personalization to therapeutic and educational contexts, where individual variation in communication, sensory sensitivity, and learning style demands adaptive system design. Credit scoring for financially underserved businesses [8] illustrates the inclusion dimension : AI systems designed to serve populations historically excluded from mainstream financial services must incorporate alternative data sources and fairness constraints that generic credit models do not address.

3.4 Interpretability, Trust, and Accountability

Interpretability in human-centered AI is not an aesthetic preference but a functional requirement: human decision-makers must be able to understand, verify, and where necessary override AI recommendations. The comparative analysis of explainable ML models for cancer classification [45] and the ensemble transformer with post-hoc explanations for depression emotion and severity detection [14] illustrate two different explainability approaches, comparative feature attribution and post-hoc transformer explanation—both motivated by the need to make model outputs auditable by domain experts. The explainable deep stacking ensemble for brain tumor diagnosis [20] and the Swin Transformer with XAI for cervical cell classification with web-based screening [63] demonstrate that explainability can be integrated into deployment pathways. Critically, explainability must be validated: attention maps and saliency overlays are informative but do not constitute causal explanations, and trust in AI systems should be calibrated rather than maximized.

3.5 Privacy and User-Sensitive Data

Human-centered AI operates over some of the most sensitive categories of personal data: medical images, facial expressions, EEG signals, voice recordings, behavioral traces, workforce analytics, and digital communication records. The multimodal privacy-preserving cancer diagnosis framework [58] and the privacy-preserving behavior analytics for workforce retention [52, 77] directly address the tension between data-driven personalization and the privacy rights of data subjects. The distributed edge-cloud-6G federated learning framework for secure and auditable decision support [71] provides the architectural response to this tension at scale: enabling collaborative AI without centralizing sensitive raw data. The facial expression database of ASD children [6] illustrates a data resource where the subjects are particularly vulnerable and the ethical obligations of the researchers and system developers are correspondingly heightened.

3.6 Human-Centered Deployment

Human-centered AI deployment must be evaluated not only at the model level but at the system level: does the deployment pathway support the intended users in the intended context? Web-based deployment of breast cancer classification [10] and cervical cell screening [63] makes clinical AI accessible to healthcare systems without specialized computational infrastructure. The IoT-based smart healthcare medical box for elderly people [13] illustrates deployment designed for users who may have limited digital literacy. The AI-driven solar financing system for rural clinics and health small businesses [44] addresses the intersection of technological deployment and economic access in low-resource healthcare settings. Across all these deployments, the user interface, maintenance model, and governance structure are human-centered design properties as important as the underlying model architecture.

4. Architecture Families for Human-Centered AI

4.1 Conventional Machine Learning and Structured Analytics

Conventional machine learning, logistic regression, random forests, gradient-boosted trees, and LSTM networks applied to structured and tabular data, provides the most directly interpretable architecture family for human-centered applications. Clinical decision support for heart disease prediction from structured patient data [7] illustrates the deployment value of interpretable feature-level attribution: clinicians can examine which risk factors drove a prediction and exercise professional judgment about whether to act on it. In business, retail demand forecasting with LSTM and gradient boosting [34], market trend forecasting with external factor integration [24], e-commerce pricing optimization [15], and small-business ML for customer retention and financial forecasting [12] represent structured analytics where feature-level explainability is directly compatible with organizational audit requirements. Credit scoring for financially underserved businesses [8] introduces fairness as a design requirement alongside interpretability. Market basket analysis for healthcare service bundling [38] bridges clinical and business decision support. Multi-class sentiment classification on Bengali social media [78] illustrates multilingual NLP analytics.

4.2 Deep Learning and Transfer Learning

Deep learning enables human-centered AI in domains where structured analytics cannot match the representational complexity of image, signal, and sequence data. Transfer learning for sleep stage classification under data-constrained conditions [65] illustrates the clinical relevance of pre-trained feature extractors in physiological monitoring contexts. The bidirectional Elman neural network for facial emotion recognition [64] extends deep sequence modeling to affective computing, where temporal dynamics of facial expression are clinically and socially significant. Lightweight deep learning for concrete crack characterization via acoustic-emission signals [54] demonstrates that deep learning can be compressed for industrial edge deployment. Lightweight ResNeXt for aquaculture disease diagnosis [23] and advanced deep learning for tea leaf disease [60] provide agricultural domain evidence. Multichannel CT lung cancer analysis for imbalanced data [29] addresses the class-imbalance challenge directly relevant to medical screening quality.

4.3 Transformer and Attention-Based Models

Transformer architectures have become the dominant model family for image-based human-centered decision support across healthcare and agricultural domains. The hierarchical Swin Transformer ensemble for breast cancer with decentralized deployment [32] and the Swin Transformer for cervical cell classification with XAI and web deployment [63] demonstrate attention-based architectures combined with explicit explainability and accessible deployment pathways. The LMVT hybrid vision transformer for lung cancer with XAI [69] and the hybrid vision transformer for prostate cancer in MRI [40] illustrate oncological imaging applications. The ensemble transformer with post-hoc explanations for depression emotion and severity detection [14] extends transformer-based AI to mental health contexts. The MaxViT soybean disease model [62, 76] and MaizeFormerX lightweight cross-scale ViT with XAI for maize disease [36] demonstrate agricultural precision AI. The FuseAttenX attention-enhanced deep learning for business strategy optimization [31] illustrates transformer-based enterprise analytics. Critically, attention maps in all these systems provide visual communicability but should not be presented as validated causal explanations without additional formal evaluation.

4.4 Hybrid, Ensemble, and Multimodal Systems

Hybrid and ensemble architectures improve representational diversity and support richer post-hoc explanation strategies, at the cost of increased system complexity. The explainable deep stacking ensemble for brain tumor diagnosis [20] and the stacking ensemble-based breast cancer classifier with real-time web deployment [10] illustrate post-hoc XAI combined with ensemble diversity. The hybrid multi-modal emotion recognition framework using InceptionV3DenseNet [42] addresses the modality-fusion dimension of affective computing AI. The vision-audio multimodal object recognition system via hybrid tensor fusion [26] provides cross-modal evidence for industrial and assistive perception. The explainable AI hybrid deep learning framework for skin cancer [72] and the explainable transformer for skin lesion classification [73] extend hybrid XAI to dermatological decision support. The accelerated cervical cancer stacking ensemble with XAI [16] demonstrates stacking in gynecological oncology.

4.5 Graph Neural Networks and Knowledge-Graph Reasoning

Graph neural networks and knowledge-graph systems provide structurally auditable reasoning that is directly compatible with human-centered accountability requirements. The GNN-enhanced gas-pipeline monitoring system is relevant as deployment-context evidence [57]. Knowledge-graph and NLP integration for heuristic reasoning [21] demonstrates symbolic AI that produces human-readable, entity-linked reasoning chains, a form of explainability that neither attention maps nor post-hoc attribution methods can match. The AddManBERT knowledge-graph construction for additive manufacturing design support [61] illustrates knowledge-structured engineering decision support. These architectures are particularly relevant in human-centered contexts where domain experts need to trace and validate AI reasoning rather than simply accept a probability score.

4.6 Bayesian, Physics-Guided, and Uncertainty-Aware AI

The physics-guided Bayesian neural network for sensor fault detection in wind turbines [43] illustrates the most principled human-centered property of this architecture family: the ability to express calibrated uncertainty that supports human oversight. In safety-critical contexts, including clinical diagnosis, industrial monitoring, and autonomous systems a model that cannot communicate its own confidence limitations cannot responsibly support human decision-making. Trust calibration, helping users understand not only what a model predicts but how reliable that prediction is a fundamental human-centered design requirement that Bayesian and uncertainty-aware architectures address directly.

4.7 Generative, Agentic, and Enterprise AI

Generative AI in enterprise information systems [17] and automated risk assessment AI in agile project management [37] represent the generative and agentic AI cluster relevant to organizational human-centered AI. Generative systems introduce hallucination risk—the production of fluent but factually incorrect outputs, that is particularly dangerous in human-facing contexts where users may overtrust authoritative-sounding AI responses. AI-enabled management information systems for economic resilience and governance [22] and AI-driven business analytics for IT strategy position AI within organizational governance frameworks. The AI-driven digital transformation analytics [53] illustrates enterprise AI at the strategic planning level. Governance, accountability, and the allocation of decision responsibility between AI systems and human stakeholders are the defining human-centered design challenges at this architectural level.

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

Privacy-preserving and federated architectures are essential infrastructure for human-centered AI in healthcare, education, and workforce contexts where the sensitivity of personal data creates legal, ethical, and trust obligations. The distributed edge-cloud-6G federated learning framework for secure and auditable decision support [71] provides the architectural foundation for privacy-respecting multi-institutional AI. The multimodal privacy-preserving cancer diagnosis framework [58] demonstrates clinical multimodal AI under privacy constraints. Privacy-preserving behavior analytics for workforce retention [52, 77] demonstrates organizational privacy-preserving analytics. The intelligent cybersecurity framework for ML-driven data protection [41] and AI as a strategic engine for digital resilience [28] address the security layer that protects users in human-facing digital systems. The resilience-by-design framework [49] provides the governance architecture for trustworthy cross-domain human-facing AI. Table 2 summarizes how major architecture families differ in their human-centered strengths, limitations, and deployment implications.

Table 2. Architecture families and human-centered design implications.

Architecture family	Main strength	Main limitation	Human-centered implication
Conventional ML	Transparent feature-based reasoning	Limited for complex images, signals, and multimodal data	Useful where auditability and interpretability are priorities
Deep learning	Strong pattern learning from images, signals, and sequences	Opaque and sensitive to dataset shift	Requires XAI, calibration, and robustness testing
Transformers	Captures global context and long-range dependencies	Attention is not a validated explanation	Needs explanation validation and external testing
Hybrid and ensemble models	Combines complementary model strengths	Higher complexity and lower transparency	Requires clear justification and simplified reporting
GNNs and knowledge graphs	Models relationships and traceable reasoning paths	Depends on graph quality and domain knowledge	Useful for auditable, relationship-aware decision support
Bayesian and uncertainty-aware AI	Communicates prediction uncertainty	More difficult to implement and validate	Supports trust calibration and safe human oversight
Generative and agentic AI	Enables flexible interaction and workflow automation	Risk of hallucination and unclear accountability	Requires human review, audit trails, and governance controls
Federated and privacy-preserving AI	Enables collaboration without centralizing raw data	Non-IID data and site-level bias may reduce reliability	Needs site-wise validation, privacy governance, and monitoring

5. Domain-Specific Human-Centered Synthesis

Figure 2. Conceptual risk–sensitivity map for human-centered AI domains.

5.1 Healthcare and Biomedical Decision Support

Healthcare is the domain where human-centered AI requirements are most stringent and most consequential. Cancer detection applications—spanning skin cancer [72, 73], lung cancer [29, 69], breast cancer [10, 32], cervical cancer [16, 63], brain tumor [20], kidney disease [18], prostate cancer [40], and cytological cancer classification [45]—collectively represent the domain where explainability and privacy are most consistently integrated alongside accuracy. The comparative XAI analysis for cytological cancer classification [45] provides systematic evidence that different explanation methods produce different attributions, a finding directly relevant to clinical trust calibration. The privacy-preserving multimodal cancer diagnosis framework [58] addresses the privacy requirement that multicenter clinical AI demands. Heart disease prediction from structured data [7] and the AI-integrated healthcare information system for diabetes management [5] represent structured data clinical AI where interpretability is directly compatible with clinical audit. Market basket analysis for healthcare service bundling [38] extends human-centered clinical AI to service delivery optimization. The IoT smart healthcare medical box for elderly people [13] illustrates human-centered deployment for a vulnerable user population. Figure 2 positions major application domains according to the sensitivity of the data they process and the potential consequence of AI-supported decisions. Neural network models combined with dimensionality reduction and optimized architectural design have improved breast cancer diagnosis from clinical and morphological features [80], [81], while neural machine learning approaches have also been explored for stroke-risk prediction in healthcare settings [82]. Beyond predictive modeling, privacy-preserving federated learning has been proposed to support scalable healthcare data processing without centralized data sharing [83]. Related advances in digital twins and AI-enabled cybersecurity further indicate the relevance of intelligent systems for predictive maintenance in industrial IoT environments and the protection of healthcare and essential infrastructure [84], [86]. In parallel, explainable deep learning has emerged as a key requirement for translating AI-based diagnostic models into clinically trustworthy decision-support systems [85].

5.2 Education, Learning, and Adaptive Support

Education represents a human-centered domain where personalization, feedback quality, and ethical use of learner data are primary design concerns. The AI-powered digital health platform for students with autism spectrum disorder [1] is the most comprehensive human-centered educational AI system in the corpus: it integrates adaptive learning, therapeutic accessibility, and data-driven personalization for a population with specific and variable communication and learning needs. The adaptive feedback system for learner improvement [9] illustrates AI as a pedagogical support tool that enhances rather than replaces the feedback loop between learner and teacher. The ethical concerns specific to educational AI are heightened by the developmental vulnerability of student populations: data minimization, purpose limitation, parental consent, and teacher oversight are governance requirements that many current educational AI systems do not yet fully address.

5.3 Assistive Technologies and Accessibility

Assistive AI represents the most directly human-centered application domain in the corpus: every system in this cluster is designed to directly extend human capability for individuals who face communication, sensory, motor, or cognitive challenges. The flex-sensor hand glove for deaf and mute people [2] provides motor-assisted communication support for individuals with speech and hearing disabilities. ASD classification systems using facial grid-wise emotion features and dual-branch visual transformation [25, 48] and the ASD facial expression database [6] address detection and representation of affective states in a population where conventional emotion-recognition assumptions may not apply. The iris detection and recognition system [67] extends biometric accessibility to identification contexts. The tDCS model [33] addresses neuro-modulation as a clinical support technology. Voice biomarker-based Parkinson's screening with personalization [3] illustrates disease-detection AI designed to accommodate the linguistic and demographic variability of a patient population. All assistive AI systems carry the obligation to avoid false positives that may lead to misclassification of behavior, incorrectly interpreted emotional states, or inappropriate clinical referrals.

5.4 Neuro-Affective, Behavioral, and Mental-Health AI

Neuro-affective AI operates on the most ambiguous and sensitive human signals: facial expressions, EEG activity, voice characteristics, and behavioral patterns that may or may not reflect the internal states they are assumed to index. The facial emotion recognition systems represented in this corpus, a bidirectional Elman neural network [64], a hybrid deep belief optimization system [46], and the hybrid multi-modal InceptionV3DenseNet framework [42] illustrate multiple architectural approaches to a problem whose ground-truth ambiguity is not resolved by any architecture. The multimodal EEG analysis framework [11] and the ensemble transformer with post-hoc XAI for depression emotion and severity detection [14] extend the affective computing domain to physiological signals with direct clinical implications. Suicidal ideation detection via NLP [4] is a critical mental health application where false negatives carry catastrophic consequences and model confidence calibration is ethically non-negotiable. Data-driven drug review sentiment extraction [30] and Bengali social media sentiment classification [78] illustrate text-based mental health and social analytics. Privacy-preserving behavior analytics for workforce retention [52, 77] addresses behavioral analytics in organizational contexts where consent and purpose-limitation are primary ethical concerns.

5.5 Business, Enterprise, and Organizational Decision-Making

Business and organizational AI illustrates the widest diversity of human-centered design requirements: from financial fairness in credit scoring [8] through strategic transparency in generative enterprise AI [17] to workforce dignity in behavior analytics [52]. Credit scoring for financially underserved businesses [8] introduces fairness and access as primary design requirements—the AI must not perpetuate historical exclusion patterns. Predictive project risk analytics [27] and automated risk assessment in agile project management [37] illustrate governance-structured organizational AI. Retail demand forecasting [34], e-commerce pricing [15], customer satisfaction analytics in hospitality [66], and small-business management ML [12] represent the operational forecasting cluster. Blockchain and ML in supply chain management [50, 75] introduces distributed trust infrastructure alongside predictive AI. Market trend forecasting with external factors [24] and market basket analysis for healthcare bundling [38] complete the structured business analytics cluster. AI-enabled MIS for economic resilience and governance [22], AI-driven business analytics for IT strategy, and digital transformation analytics [53] address the strategic and governance layer. The conceptual AI-ERP integration framework for dark factories [79] illustrates the governance challenges of autonomous organizational environments.

5.6 Human-Facing IoT, Infrastructure, and Sustainability Systems

Human-facing IoT and infrastructure AI illustrates how technical systems designed for infrastructure monitoring ultimately serve human needs, energy access, healthcare continuity, communication reliability, and food security. The IoT-based solar micro-grid battery monitoring system [19] and smart energy metering [35] address energy reliability for communities served by these infrastructures. The smart healthcare medical box for elderly patients [13] illustrates IoT healthcare extended to a vulnerable user population. AI-driven smart agriculture for crop yield optimization [68] and AI-driven solar financing for rural clinics [44] address sustainability and access in low-resource settings. The wireless mesh network routing algorithm [55] and MANET routing protocol simulation [59, 74] address the communication infrastructure that enables digital access. HAPs communications optimization [70] extends this to airborne infrastructure. The resilience-by-design framework [49] provides the systemic governance lens for AI that serves interdependent human and technical systems. The lightweight explainable transformer for cotton leaf diagnostics [51] and lightweight maize disease ViT [36] illustrate agricultural AI designed for field-user accessibility.

5.7 Cybersecurity, Privacy, and Trustworthy Digital Systems

Cybersecurity AI serves human-centered purposes by protecting users, preserving privacy, and maintaining the trustworthiness of digital systems that humans rely on. The intelligent cybersecurity ML framework for data protection and threat intelligence [41] addresses the adversarial security environment in which all human-facing AI operates. AI as a strategic engine for data security and digital communication resilience [28] positions security at the organizational governance level. The distributed edge-cloud-6G federated learning framework [71] provides the security architecture for privacy-preserving human-centered AI at scale. The trustworthy AI framework for high-stakes decision support [56] provides the cross-domain accountability framework that must underpin all human-facing AI. The resilience-by-design framework [49] addresses the systemic interdependency of security, sustainability, and health in AI systems that serve human communities.

6. Cross-Domain Challenges for Human-Centered AI

6.1 Defining Human Benefit Beyond Predictive Accuracy

Human benefit in AI systems cannot be reduced to predictive accuracy. A facial emotion recognition system [46, 64] that achieves high accuracy on a benchmark facial expression dataset may still harm users by systematically misclassifying expressions from underrepresented demographics, by pathologizing emotional variability, or by triggering inappropriate clinical referrals. A credit scoring model [8] that achieves high AUC may perpetuate historical exclusion if its training data reflects discriminatory lending patterns. The trustworthy AI framework [56] establishes that human benefit must be evaluated across multiple dimensions: interpretability, robustness, fairness, privacy, governance, and evidence maturity. Human-centered AI evaluation frameworks must therefore assess these properties systematically, not as afterthoughts to model development.

6.2 User-Sensitive Data, Privacy, and Consent

Human-centered AI operates over categories of data that carry heightened ethical and legal obligations. Medical images [32, 58, 63], facial expressions [6, 25, 42, 46], EEG signals [11], voice biomarkers [3], behavioral analytics [52, 77], and digital communication records [41, 71] are subject to medical privacy regulations, informed consent requirements, and data minimization principles that many current AI development pipelines do not systematically address. The privacy-preserving behavior analytics systems [52, 77] and the multimodal privacy-preserving cancer diagnosis framework [58] illustrate technical approaches to privacy-preserving deployment. The distributed federated learning framework [71] provides the architectural infrastructure for privacy-preserving collaboration. However, technical privacy mechanisms do not substitute for ethical consent processes, transparent data governance, and meaningful data subject rights.

6.3 Interpretability, Explanation, and Trust Calibration

The explainability requirements of human-centered AI differ fundamentally across user populations and decision contexts. Clinical oncologists reviewing cancer imaging AI [20, 32, 45] require explanations that map to anatomically meaningful features. Teachers reviewing adaptive learning AI [9] require explanations that describe learning progress in pedagogically meaningful terms. Business managers reviewing enterprise risk AI [37, 47] require audit trails that satisfy governance and compliance standards. The comparative explainable ML analysis [45] and the ensemble transformer with post-hoc XAI [14] illustrate systematic approaches to explanation that address specific audiences. Critically, trust calibration—ensuring that users neither overtrust nor undertrust AI recommendations—is a human-centered design property that depends on presenting uncertainty alongside predictions, and that requires user evaluation studies to validate.

6.4 Personalization, Fairness, and Inclusion

Personalization and fairness are potentially complementary but require deliberate design to avoid conflict. Personalizing Parkinson's screening for age, gender, and linguistic variability [3] improves clinical accuracy by reducing demographic confounds. Personalizing credit scoring for underserved small businesses [8] improves financial access by incorporating alternative data that mainstream models exclude. The ASD digital health platform [1] personalizes therapeutic support for learners whose needs are not served by standard educational AI. Risks of bias arise when personalization reproduces historical discrimination, when training datasets underrepresent specific demographic groups, or when system designers fail to test for differential performance across protected groups. Fairness-aware design requires not only technical debiasing methods but organizational processes for identifying affected communities, testing for differential impact, and establishing accountability mechanisms.

6.5 Workflow Integration and Human Oversight

Human-centered AI deployment requires integration into existing workflows, roles, and accountability structures that pre-date the AI system. Clinical decision support [7, 63] must align with clinical information system architectures and professional responsibilities. The adaptive feedback system [9] must align with pedagogical frameworks and teacher roles. Enterprise risk assessment AI [37] must align with project management governance structures and stakeholder accountability. The question of full autonomy in underwater robotics [39] illustrates the governance challenge that applies across all human-centered AI: the degree of autonomy appropriate for a given system depends not only on technical capability but on the accountability and oversight structures within which the system operates.

6.6 Accessibility and Assistive Deployment

Accessible deployment of AI requires attention to physical device design, interface usability, computational resource requirements, network connectivity, and maintenance models. The hand glove assistive device [2] requires physical robustness and motor compatibility. The IoT smart healthcare medical box [13] requires interface design appropriate for elderly users with varying digital literacy. The AI-driven solar financing system for rural clinics [44] must function in contexts with limited infrastructure and professional technical support. Lightweight models, MaizeFormerX [36], lightweight ResNeXt [23], and lightweight DL for acoustic-emission analysis [54], demonstrate that computational efficiency is an accessibility property, enabling AI deployment in resource-constrained contexts where heavyweight models cannot be operated.

6.7 Robustness, Safety, and Evidence Maturity

Evidence maturity in human-centered AI requires not only technical performance evaluation but user-centered validation, external validation on independent populations, and post-deployment monitoring. Affective AI systems [11, 14, 42, 46] face the additional challenge of affective ambiguity: the ground truth for emotional state recognition is inherently uncertain, and systems trained on acted or laboratory-collected expressions may not generalize to naturalistic settings. The physics-guided Bayesian neural network [43] addresses robustness through uncertainty quantification. Distribution shifts the divergence of deployment data from training data, is particularly consequential in healthcare [58, 63], behavioral analytics [52, 77], and business forecasting [24, 34] contexts where populations and conditions change over time.

6.8 Governance and Accountability

Human-centered AI governance requires explicit allocation of responsibility, transparent audit trails, clear role definitions, and mechanisms for affected individuals to seek redress. The trustworthy AI framework [56] and the resilience-by-design framework [49] provide cross-domain governance principles. The AI-enabled MIS for economic resilience and governance [22] and the digital transformation analytics [53] illustrate organizational-level AI governance requirements. Generative and agentic AI systems [17, 37] introduce new governance challenges: when an AI system generates strategic recommendations or initiates decision workflows autonomously, the allocation of accountability between the AI, the developer, the operator, and the human overseer must be explicitly specified and legally grounded.

7. Future Research Directions

Future research on human-centered AI should move beyond accuracy-centered evaluation toward multidimensional frameworks that jointly assess interpretability, usability, fairness, privacy, accessibility, robustness, and predictive performance [56, 49]. Deployment claims in healthcare, education, and assistive contexts should also require user-centered validation involving clinicians, teachers, learners, patients, caregivers, and end users, with evaluation based on user acceptance, clinical utility, learning outcomes, and practical usability [45, 9, 1]. Furthermore, accessible and inclusive AI should be designed for diverse populations, including linguistic minorities, elderly users, disabled individuals, and neurodiverse communities, with evaluation through demographic parity, accessibility compliance, and cross-population performance testing [3, 2, 1, 78]. Privacy-preserving approaches should be expanded for digital health, assistive technologies, workforce analytics, and mental-health AI, using federated or distributed methods while monitoring privacy budgets, federated utility loss, and consent compliance [52, 58, 71, 77].

Explainability research should prioritize trust calibration by validating explanation methods for specific users such as clinicians, educators, business managers, and assistive-technology users [14, 20, 45, 56]. Human-in-the-loop and human-on-the-loop systems should incorporate oversight mechanisms triggered by uncertainty, with assessment based on decision quality, override frequency, and outcome differences with and without AI support [39, 43, 56]. Moreover, fairness-aware AI remains essential in credit scoring, clinical decision support, and educational AI, requiring auditing protocols for disparate impact, demographic parity gaps, and fairness–accuracy trade-offs [8, 3, 7]. Lightweight and edge-deployable assistive systems should be optimized for embedded, IoT, and mobile settings while preserving accessibility, latency, energy efficiency, and real-world usability [2, 13, 36, 54]. Finally, governance-ready AI should include audit trails, accountability assignment, compliance mechanisms, hallucination detection, factual verification, and human approval for enterprise, generative, and agentic systems [17, 37, 22, 17, 56]. Human-centered AI research should also establish evidence maturity levels that distinguish conceptual prototypes from internally validated, externally tested, user-evaluated, and governance-ready systems [56, 45, 3].

8. Limitations of the Review

The synthesis is thematic, architectural, human-centered, and deployment-level rather than quantitative. Specific user-study findings, usability scores, fairness analyses, performance metrics, dataset characteristics, validation protocols, deployment environments, and statistical evidence could not be extracted from titles alone. The review should be interpreted as a structured human-centered evidence map and taxonomic analysis rather than a quantitative meta-analysis or systematic review. Full paper-level extraction would be required to support meta-analytic comparisons of explanation quality, user acceptance, fairness properties, accessibility features, deployment environments, or governance mechanisms. The curated corpus may not comprehensively represent all active human-centered AI research threads; participatory design, AI ethics by design, disability-inclusive AI, global South perspectives, and legal AI accountability are underrepresented. Not every paper in the corpus is explicitly human-centered; papers are classified by their contribution to the broader human-centered AI landscape rather than mislabeled. The eight-axis taxonomy is one defensible organization; alternative frameworks emphasizing different human-centered properties may yield complementary insights.

9. Conclusion

This structured critical review has examined human-centered AI across seven domains—healthcare and biomedical decision support, education and adaptive learning, assistive technologies and accessibility, neuro-affective and mental-health AI, business and organizational decision-making, human-facing IoT and smart infrastructure, and cybersecurity and trustworthy digital systems, using an eight-axis human-centered taxonomy. The synthesis reveals a landscape in which AI architectures have advanced substantially, but the properties most directly relevant to human benefit—validated explainability, inclusive and accessible design, privacy-preserving deployment, affective ambiguity management, fairness-aware modeling, and governance accountability, remain inconsistently addressed. Healthcare AI demonstrates the most consistent XAI integration, while neuro-affective and mental-health AI carries the most acute combination of sensitivity, ambiguity, and privacy obligation. Business and organizational AI is advancing toward governance-aware deployment, but generative and agentic systems introduce accountability challenges that current governance frameworks are not yet equipped to address. Assistive and educational AI show the highest human-centered design specificity but the least systematic evidence of user evaluation.

The path toward genuinely human-centered AI requires treating human benefit as a first-class design requirement from the earliest phase of system development. Usable, accessible, explainable, privacy-preserving, fair, robust, human-supervised, and governance-aware AI systems are not merely safer or more compliant than conventional AI, they are the only kind of AI system that can responsibly serve the healthcare decisions, learning journeys, communication needs, financial access, and organizational capabilities that define human flourishing across the diverse contexts in which AI is increasingly deployed.

Funding: This research received no external funding.
Conflicts of Interest: The authors declare no conflict of interest.

References

[1] Haque S, Islam MS, Islam MI, Islam MS, Khan R, Tarafder MTR, Mohammad N. Enhancing adaptive learning, communication, and therapeutic accessibility through the integration of artificial intelligence and data-driven personalization in digital health platforms for students with autism spectrum disorder. Journal of Posthumanism. 2025;5(8):737-756. doi:10.63332/joph.v5i8.3255.
[2] Al Mamun A, Polash MSJK, Alamgir FM. Flex sensor based hand glove for deaf and mute people. International Journal of Computer Networks and Communications Security. 2017;5(2):38-48.
[3] Ghosh BP, Bhuiyan MS, Bishnu KK, Mahmud FU, et al. Personalized machine learning models for Parkinson's disease screening via voice biomarkers: Accounting for age, gender, and linguistic variability. The International Medicine. 2025 Dec.
[4] Haque R, Islam N, Islam M, Ahsan MM. A comparative analysis on suicidal ideation detection using NLP, machine, and deep learning. Technologies. 2022;10(3):57. doi:10.3390/technologies10030057.
[5] Lucky KY, Haque S, Al-Samad K, Akter R, Faruq O, Azim KS, et al. AI-powered healthcare information systems securing diabetes management through integrated technology solutions and enhanced patient care delivery. Vascular and Endovascular Review. 2025;8(11s):465-476.
[6] Alamgir FM, Saif SMH, Hossain SM, Al Hadi A, Alam MS. Facial Expression Database of Autism Spectrum Disorder Children. European Chemical Bulletin. 2023;12(Special Issue 4):21109-21120. doi:10.48047/ecb/2023.12.Si4.1851.
[7] Rashid SU, Siddiqui MIH, Mahmud FU, Rahman MS, Kabir AA, Shammah RS. Machine learning based clinical decision support for heart disease prediction using structured patient data. Journal of Computer Science and Technology Studies. 2024;6(1):340-350. doi:10.32996/jcsts.2024.6.1.36.
[8] Mithun MM, Tanim SH, Tarannum R. Developing AI-Powered Credit Scoring Models Leveraging Alternative Data for Financially Underserved US Small Businesses. Repository Antis Publisher. 2025 Oct 18:699254.
[9] Qadir HM, Khan RA, Rasool M, Sohaib M, Shah MA, Hasan MJ. An adaptive feedback system for the improvement of learners. Scientific Reports. 2025;15:17242. doi:10.1038/s41598-025-01429-w.
[10] Jashim FB, Refat FR, Karim MH, Mahmud FU, Sakib AH. Stacking ensemble-based breast cancer classification: Enhancing diagnostic accuracy with deep learning and real-time web deployment. International Journal of Science and Research Archive. 2025;15(2):1417-1431. doi:10.30574/ijsra.2025.15.2.1502.
[11] Majumdar J, Apu MH, Rahman M, Zaman T, Hassan MM. Multimodal EEG analysis of neural synchrony in minimal phrase processing using machine learning. Conference paper; 2025 Nov.

[12] Naznin R, Sarkar MAI, Asaduzzaman M, Akter S, Mou SN, Miah MR, Sajal A. Enhancing small business management through machine learning: A comparative study of predictive models for customer retention, financial forecasting, and inventory optimization. International Interdisciplinary Business Economics Advancement Journal. 2024;5(11):21-32.

[13] Al-Mahmud O, Khan K, Roy R, Alamgir FM. Internet of Things (IoT) based smart health care medical box for elderly people. In: 2020 International Conference for Emerging Technology (INCET). IEEE; 2020. doi:10.1109/INCET49848.2020.9153994.

[14] Islam S, Haque R, Khan MA, Mohiuddin AB, Siddiqui MIH, Limon ZH, Khushbu KG, Swapno SMMR, Ahmed MR, Appaji A. Ensemble transformer with post-hoc explanations for depression emotion and severity detection. iScience. 2026;29(2):114605. doi:10.1016/j.isci.2025.114605.

[15] Chowdhury MS, Shak MS, Devi S, Miah MR, Al Mamun A, Ahmed E, Hera SAA, Mahmud F, Mozumder MSA. Optimizing e-commerce pricing strategies: A comparative analysis of machine learning models for predicting customer satisfaction. The American Journal of Engineering and Technology. 2024;6(09):6-17. doi:10.37547/tajet/Volume06Issue09-02.

[16] Siddiqui MIH, Khan S, Limon ZH, Rahman H, Khan MA, Al Sakib A, et al. Accelerated and accurate cervical cancer diagnosis using a novel stacking ensemble method with explainable AI. Informatics in Medicine Unlocked. 2025;56:101657. doi:10.1016/j.imu.2025.101657.

[17] Haque S, Islam H, Sharmin F, Joy SI, Naher K, Rimi NN, et al. Generative Artificial Intelligence in Enterprise Information Systems: Transforming Business Intelligence and Strategic Decision Support Processes. International Journal of Interdisciplinary Cultural Studies, ISSN:2327-008XE-ISSN:2327-2554. 2025;20(2):1754–63. doi:10.18848/8P0S2E25

[18] Ahmed S, Miah MR, Shakil MR, Linkon AA, Siddiqui MIH, Malik AH. Global-local attention modeling for reliable multiclass kidney disease classification from CT images. Journal of Medical and Health Studies. 2026;7(5):36-45. doi:10.32996/jmhs.2026.7.5.6.

[19] Mahamud S, Hossain MS, Hassan MM, Maruf MY, Rafi MAH, et al. IoT based wireless battery monitoring system for enhanced solar micro-grid performance in Bangladesh. In: Arefin MS, Kaiser MS, Bhuiyan T, Based MA, Ray K, editors. Proceedings of the 3rd International Conference on Big Data, IoT and Machine Learning. BIM 2025. Lecture Notes in Networks and Systems, vol. 1798. Cham: Springer; 2026. p. 474-489. doi:10.1007/978-3-032-15346-3_33.

[20] Haque R, Khan MA, Rahman H, Khan S, Siddiqui MIH, Limon ZH, Swapno SMMR, Appaji A. Explainable deep stacking ensemble model for accurate and transparent brain tumor diagnosis. Computers in Biology and Medicine. 2025;191:110166. doi:10.1016/j.compbiomed.2025.110166.

[21] Haruna A, Noman K, Li Y, Makanda ILD, Zubair A, Hasan MJ, Alhassan AB. Facilitating heuristic reasoning by utilizing knowledge graph and natural language processing. Knowledge-Based Systems. 2026;334:115153. doi:10.1016/j.knosys.2025.115153.

[22] Shakil MR, Hasan M, Tarek MIH, Polash FI, Meem EJ. AI-enabled management information systems for economic resilience and organizational performance: Analytics, governance, cyber risk and decision automation. World Journal of Advanced Engineering Technology and Sciences. 2026;18(3):294-307. doi:10.30574/wjaets.2026.18.3.0156.

[23] Masum AKM, Khan MFI, Mahmud FU, Hassan MM, Khaliluzzaman M. Improving aquaculture disease diagnosis with lightweight ResNeXt architectures. In: 2025 3rd International Conference on Artificial Intelligence, Blockchain, and Internet of Things (AIBThings); 2025. doi:10.1109/AIBThings66987.2025.11296219.

[24] Hossain MS, Khan A, Das P, Haque MSU, Kamruzzaman F, Akter S, Ahmed A, Miah MR. Enhanced market trend forecasting using machine learning models: A study with external factor integration. International Interdisciplinary Business Economics Advancement Journal. 2025;6(1):5-12. doi:10.55640/business/volume06issue01-02.

[25] Alamgir FM, Zaman T, Hossain MS, Hassan MM, Alam MS. ASDnet: Classification model for individuals with autism spectrum disorder using facial grid-wise expressions features and dual-branch visual transformation. Biomed Signal Process Control. 2026 Jul 1;120:109999. doi:10.1016/J.BSPC.2026.109999.

[26] Ahmed MR, Haque R, Rahman SMA, Reza AW, Siddique N, Wang H. Vision-audio multimodal object recognition using hybrid and tensor fusion techniques. Information Fusion. 2026;126:103667. doi:10.1016/j.inffus.2025.103667.

[27] Tanim SH, Ahmad MS, Mithun MMU, Tarannum R, Refat FR, Sunny MNM. Leveraging predictive analytics for risk identification and mitigation in project management. Journal of Information Systems Engineering and Management. 2025;10(43s):1041-1052. doi:10.52783/jisem.v10i43s.8523.

[28] Faruq O, Chowdhury S, Al-Samad K, Akter R, Haque S, Shimu F, Mambetaliev A. Artificial Intelligence as the Strategic Engine of Data Security, Analytics, and Digital Communication for a Resilient Digital Future. Interdisciplinary Journal of Information, Knowledge, and Management (IJIKM). 2025;20(2):846-66.

[29] Sohaib M, Hasan MJ, Zheng Z. A multichannel analysis of imbalanced computed tomography data for lung cancer classification. Measurement Science and Technology. 2024;35(8):085401. doi:10.1088/1361-6501/ad437f.

[30] Haque R, Laskar SH, Khushbu KG, Hasan MJ, Uddin J. Data-driven solution to identify sentiments from online drug reviews. Computers. 2023;12(4):87. doi:10.3390/computers12040087.

[31] Mahmud FU, Rahman A, Khan MA, Bishnu KK, Eva AA, Maua J. FuseAttenX: Leveraging attention-enhanced deep learning for business strategy optimization. In: 2025 IEEE 4th International Conference on Computing and Machine Intelligence (ICMI). 2025. doi:10.1109/ICMI65310.2025.11141140.

[32] Ahmed MR, Rahman H, Limon ZH, Siddiqui MIH, Khan MA, Pranta ASUK, Haque R, Swapno SMMR, Cho YI, Abdallah MS. Hierarchical Swin transformer ensemble with explainable AI for robust and decentralized breast cancer diagnosis. Bioengineering. 2025;12(6):651. doi:10.3390/bioengineering12060651.

[33] Sourav MSU, Rahman A, Al Mamun A, Alamgir FM. Standard transcranial direct current stimulation (tDCS) model. International Journal of Computer Networks and Communications Security. 2017;5(12):264-270.

[34] Shak MS, Mozumder MSA, Hasan MA, Das AC, Miah MR, Akter S, Hossain MN. Optimizing retail demand forecasting: A performance evaluation of machine learning models including LSTM and gradient boosting. The American Journal of Engineering and Technology. 2024;6(09):67-80. doi:10.37547/tajet/Volume06Issue09-09.

[35] Haque MM, Choudhury ZH, Tejesh GS, Alamgir FM. IoT based smart energy metering system for power consumers. In: 2019 2nd International Conference on Innovation in Engineering and Technology (ICIET). IEEE; 2019. doi:10.1109/ICIET48527.2019.9290661.

[36] Rahman MM, Gony MN, Ullah MS, Shuvra SMK, et al. MaizeFormerX: A lightweight vision transformer with cross-scale attention for explainable maize leaf disease diagnosis. Scientific Reports. 2026. doi:10.1038/s41598-026-44550-0.

[37] Haque S, Chowdhury S, Faruq O, Akter R, Joy MSI, Munny MA, Shimu F. Automated risk assessment and collaborative decision-making AI applications in agile project management and stakeholder engagement. International Journal of Advances in Signal and Image Sciences. 2026;12(1):915-923. doi:10.29284/v2jv8q59.

[38] Rimon RH, Nurujjaman, Mithun MMU. Market basket analysis for healthcare services to identify bundled care offerings. Frontiers in Computer Science and Artificial Intelligence. 2025;4(3):44-67.

[39] Rohan A, Tolie HF, Hasan MJ, Kannan S. Full autonomy in underwater robotics systems: A realistic prospect?. Engineering Applications of Artificial Intelligence. 2025 Dec 22;162:112638. doi:10.1016/j.engappai.2025.112638.

[40] Debnath J, Mohiuddin AB, et al. Hybrid vision transformer model for accurate prostate cancer classification in MRI images. In: 2025 International Conference on Electrical, Computer and Communication Engineering (ECCE). IEEE; 2025. doi:10.1109/ECCE64574.2025.11013952.

[41] Shimu F. Intelligent cybersecurity framework: Machine learning-driven data protection and threat intelligence integration for modern digital communications. International Journal of Applied Mathematics. 2025;38(8s):620-632. doi:10.12732/ijam.v38i8s.595.

[42] Alamgir FM, Alam MS. Hybrid multi-modal emotion recognition framework based on InceptionV3DenseNet. Multimedia Tools and Applications. 2023;82:40375-40402. doi:10.1007/s11042-023-15066-w.

[43] Khan MDA, Rahman A, Mahmud FU, Bishnu KK, Nabil HR, Mridha MF, et al. A physics-guided Bayesian neural network for sensor fault detection in wind turbines. IEEE Open Journal of the Computer Society. 2025;6:931-942. doi:10.1109/OJCS.2025.3577588.

[44] Tanim SH, Mithun MMU, Tarannum R. Sustaining vital care in disasters: AI-driven solar financing for rural clinics and health small businesses. American Journal of Technology Advancement. 2025;2(9):123-153. doi:10.31149/ajta.v2i9.2528.

[45] Siddiqui MIH, Rahman MS, Kabir AA, Mahmud FU, Rashid SU, Shammah RS. Comparative analysis of explainable machine learning models for cancer classification using cytological features. Journal of Medical and Health Studies. 2023;4(5):110-150. doi:10.32996/jmhs.2023.4.5.14.

[46] Alamgir FM, Alam MS. An artificial intelligence driven facial emotion recognition system using hybrid deep belief rain optimization. Multimedia Tools and Applications. 2023;82:2437-2464. doi:10.1007/s11042-022-13378-x.

[47] Karshiboev A, Al-Samad K, Tarafdar MTR, Rimi NN, Islam MS, Papel MSI. Artificial intelligence for risk and decision assessment in agile IT projects: A thematic analysis and dynamic structuration framework approach. International Journal of Advances in Signal and Image Sciences. 2026;12(1):387-410. doi:10.29284/9k2nx425.

[48] Alamgir FM, Zaman T. Classification model for autism spectrum disorder individuals: Utilizing facial grid-wise emotion features and dual-branch visual transformation. In: 2024 IEEE International Conference on Power, Electrical, Electronics and Industrial Applications (PEEIACON). IEEE; 2024. doi:10.1109/PEEIACON63629.2024.10800506.

[49] Shakil MR, Hasan M, Tarek MIH, Polash FI, Meem EJ. Resilience-by-design: AI for security, sustainability and health in interdependent systems. World Journal of Advanced Engineering Technology and Sciences. 2026;18(3):254-267. doi:10.30574/wjaets.2026.18.3.0153.

[50] Rahman T, Uddin MK, Hosen MM, Bhattacharjee B, Taluckder MS, Mou SN, Akter P, Hossain MS, Miah MR, Rahman MM. Blockchain applications in business operations and supply chain management by machine learning. International Journal of Computer Science & Information System. 2024;9(11):17-30. doi:10.55640/ijcsis/Volume09Issue11-03.

[51] Rahman Swapno SMM, Sakib A, Uddin Khondakar Pranta AS, Hossain A, Debnath J, Al Noman A, et al. Explainable transformer framework for fast cotton leaf diagnostics and fabric defect detection. iScience. 2026 Feb 20;29(2):114411. doi:10.1016/j.isci.2025.114411

[52] Hussain TS, Tarannum R, Md Manarat Uddin M. Privacy-preserving behavior analytics for workforce retention approach. American Journal of Engineering, Mechanics and Architecture. 2023;1(9):188-215.

[53] Faruq O, Islam MI, Islam MS, Tarafder MTR, Rahman MM, Islam MS, Mohammad N. Re-imagining digital transformation in the United States: Harnessing artificial intelligence and business analytics to drive IT project excellence in the digital innovation landscape. Journal of Posthumanism. 2025;5(9):333-354. doi:10.63332/joph.v5i9.3326.

[54] Habib MA, Hasan MJ, Kim JM. A lightweight deep learning-based approach for concrete crack characterization using acoustic emission signals. IEEE Access. 2021 Jul 26;9:104029-50. doi:10.1109/ACCESS.2021.3099124.

[55] Alamgir FM, Ahmed F, Miah M, Munna HM, Barua S. A novel routing algorithm for inter-group load balancing in wireless mesh networks. In: 2018 21st Saudi Computer Society National Computer Conference (NCC). IEEE; 2018. doi:10.1109/NCG.2018.8593192.

[56] Shakil MR, Hasan M, Tarek MIH, Polash FI, Meem EJ. Trustworthy AI for high-stakes decision support across critical sectors. World Journal of Advanced Engineering Technology and Sciences. 2026;18(3). doi:10.30574/wjaets.2026.18.3.0152.

[57] Hasan MJ, Noman K, Navid WU, Li Y, Haruna A, Ashfak K. Intelligent diagnosis of gas pipeline condition through multivariate analysis of acoustic emission signal-based imaging. Nondestructive Testing and Evaluation. 2025. doi:10.1080/10589759.2025.2456088.

[58] Kabir AA, Mahmud FU, Rahman MS, Rashid SU, Siddiqui MIH, Shammah RS. Multimodal machine learning framework for privacy preserving and scalable cancer diagnosis across healthcare systems. Journal of Adaptive Learning Technologies. 2024;1(6).

[59] Ahmed F, Alamgir FM. Simulation-based proportional study of routing protocols for MANET. International Journal of Computer Networks and Communications Security. 2017;5(12):28-36.

[60] ZakirHossain M, Khan MM, Thapa S, Uddin R, Meem EJ, Niloy SK, et al. Advanced deep learning techniques for precision diagnosis of tea leaf diseases. In: 2025 IEEE International Conference on Emerging Technologies and Applications (MPSec ICETA); 2025. doi:10.1109/MPSecICETA64837.2025.11118779.

[61] Haruna A, Noman K, Li Y, Wang X, Hasan MJ, Alhassan AB. AddManBERT: A combinatorial triples extraction and classification task for establishing a knowledge graph to facilitate design for additive manufacturing. Advanced Engineering Informatics. 2025;67:103578. doi:10.1016/j.aei.2025.103578.

[62] Pranta ASUK, Fardin H, Debnath J, Hossain A, Sakib AH, Ahmed MR, Haque R, Reza AW, Dewan MAA. A novel MaxViT model for accelerated and precise soybean leaf and seed disease identification. Computers. 2025;14(5):197. doi:10.3390/computers14050197.

[63] Shakil MR, Malik AH, Siddiqui MIH, Ahmed S, Miah MR, Linkon AA. Swin Transformer-driven cervical cell classification with explainable AI and web-based screening. Journal of Medical and Health Studies. 2026;7(5):25-35. doi:10.32996/jmhs.2026.7.5.5.

[64] Alamgir FM, Alam MS. A novel deep learning-based bidirectional Elman neural network for facial emotion recognition. International Journal of Pattern Recognition and Artificial Intelligence. 2022;36(10):2252016. doi:10.1142/S0218001422520164.

[65] Mahmud FU, Rahman H, Limon ZH, Khan MA, Jashim FB. Transfer learning approach for sleep stage classification with limited training data. International Journal of Science and Research Archive. 2025;15(2). doi:10.30574/ijsra.2025.15.2.1506.

[66] Talukder T, Masud SB, Miah MR, Hera A, Faruque MO. An examination of how social media participation and customer satisfaction affect the likelihood that a business will make another transaction in the hospitality sector. Open Access Library Journal. 2025;12:1-15. doi:10.4236/oalib.1112802.

[67] Biswas R, Uddin J, Hasan MJ. A new approach of iris detection and recognition. International Journal of Electrical and Computer Engineering. 2017;7(5):2530-2536. doi:10.11591/ijece.v7i5.pp2530-2536.

[68] Riipa MB, Saha S, Ferdousmou J, Khatoon R, Mohammad N, Hossain M. AI-driven smart agriculture: Optimizing crop yield and sustainability in the U.S. In: 2025 5th International Conference on Electrical, Computer and Energy Technologies (ICECET); 2025; Paris, France. doi:10.1109/ICECET63943.2025.11472088.

[69] Debnath J, Uddin Khondakar Pranta AS, Hossain A, Sakib A, Rahman H, Haque R, Ahmed MR, Reza AW, Swapno SMMR, Appaji A. LMVT: A hybrid vision transformer with attention mechanisms for efficient and explainable lung cancer diagnosis. Informatics in Medicine Unlocked. 2025;57:101669. doi:10.1016/j.imu.2025.101669.

[70] Adnan BM, Chakma S, Alam MMJ, Alamgir FM. Performance simulation and comparison in High Altitude Platforms communications systems under PSK, DPSK, QAM and FSK modulation schemes and AWGN, Rician and Rayleigh communication channels. In: 2016 IEEE 7th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON); 2016; Vancouver, BC. p. 1-11. doi:10.1109/IEMCON.2016.7746080.

[71] Shakil MR, Hasan M, Tarek MIH, Polash FI, Meem EJ. Distributed intelligence and privacy-preserving deployment: Edge-cloud-6G-federated learning for secure, auditable decision support. World Journal of Advanced Engineering Technology and Sciences. 2026;18(3):268-279. doi:10.30574/wjaets.2026.18.3.0154.

[72] Al Sakib A, Swapno SMMR, Ahamed F, Mohiuddin AB, Bhuiyan MIH, Khan S, Khushbu KG, Haque R, Alahmadi TJ, Moni MA. Explainable AI-driven hybrid deep learning framework for accurate skin cancer diagnosis. Digital Health. 2026;12:20552076261438923. doi:10.1177/20552076261438923.

[73] Linkon AA, Shakil MR, Ahmed S, Miah MR, Malik AH. Explainable transformer-based skin lesion classification from clinical images. Journal of Medical and Health Studies. 2026;7(5):46-55. doi:10.32996/jmhs.2026.7.5.7.

[74] Ahmed F, Alamgir FM. Simulation-based proportional study of routing protocols for MANET. International Journal of Computer Networks and Communications Security. 2017;5(12):28-36.

[75] Rahman T, Uddin MK, Hosen MM, Bhattacharjee B, Taluckder MS, Mou SN, Akter P, Hossain MS, Miah MR, Rahman MM. Blockchain applications in business operations and supply chain management by machine learning. International Journal of Computer Science & Information System. 2024;9(11):17-30. doi:10.55640/ijcsis/Volume09Issue11-03.

[76] Pranta ASUK, Fardin H, Debnath J, Hossain A, Sakib AH, Ahmed MR, Haque R, Reza AW, Dewan MAA. A novel MaxViT model for accelerated and precise soybean leaf and seed disease identification. Computers. 2025;14(5):197. doi:10.3390/computers14050197.

[77] Hussain TS, Tarannum R, Md Manarat Uddin M. Privacy-preserving behavior analytics for workforce retention approach. American Journal of Engineering, Mechanics and Architecture. 2023;1(9):188-215.

[78] Haque R, Islam N, Tasneem M, Das AK. Multi-class sentiment classification on Bengali social media comments using machine learning. International Journal of Cognitive Computing in Engineering. 2023;4:21-35. doi:10.1016/j.ijcce.2023.01.001.

[79] Islam MS, Islam MI, Mozumder AQ, Khan MTH, Das N, Mohammad N. A conceptual framework for sustainable AI-ERP integration in dark factories: Synthesising TOE, TAM, and IS success models for autonomous industrial environments. Sustainability. 2025;17(20):9234. doi:10.3390/su17209234.

[80] Khan MA, Parveen R, Ahmed I, Milon MH, Khan TA. High-Accuracy Breast Cancer Diagnosis Using Neural Networks and Dimensionality Reduction Techniques. In2025 IEEE 19th International Conference on Open Source Systems and Technologies (ICOSST) 2025 Dec 1 (pp. 1-6). doi:10.1109/ICOSST69113.2025.11315291.

[81] Raja MR, Milon MH, Ahmed I, Papel MS, Khan MA, Islam MZ. Optimizing Neural Architectures for Accurate Diagnosis of Breast Cancer from Morphological Features. In2025 3rd International Conference on Cyber Resilience (ICCR) 2025 Jul 3 (pp. 1-6). doi:10.1109/ICCR67387.2025.11292567.

[82] Khan MA, Papel MS, Milon MH, Ahmed I, Islam MZ, Raja MR. Optimizing Stroke Prediction in Healthcare with Neural Machine Learning Algorithms. In2025 3rd International Conference on Cyber Resilience (ICCR) 2025 Jul 3 (pp. 1-7). doi:10.1109/ICCR67387.2025.11292555.

[83] Ahmed I, Papel MS, Raja MR, Islam MZ, Khan MA, Milon MH. Privacy-First Federated Learning Models for Scalable Healthcare Data Processing. In2025 3rd International Conference on Cyber Resilience (ICCR) 2025 Jul 3 (pp. 1-6). doi:10.1109/ICCR67387.2025.11291736.

[84] Milon MH, Rahman MM, Papel MS, Raja MR, Semi MM, Tarafder MT. Digital Twin Technology for Predictive Maintenance in Industrial Iot Environments: Enhancing Operational Efficiency and Asset Longevity. In2025 3rd International Conference on Business Analytics for Technology and Security (ICBATS) 2025 May 1 (pp. 1-8). doi:10.1109/ICBATS66542.2025.11258212.

[85] Siam MA, Ahmed I, Khan MA, Islam MA, Milon MH, Ahamed A, Islam MZ. Explainable Deep Learning Models for Medical Diagnosis: Bridging the Gap between AI and Healthcare. In2025 3rd International Conference on Business Analytics for Technology and Security (ICBATS) 2025 May 1 (pp. 1-7). doi:10.1109/ICBATS66542.2025.11258368.

[86] Islam MZ, Siam MA, Ahmed I, Khan MA, Islam MA, Milon MH. Fortifying Healthcare and Essential Infrastructure with AI-Driven Cybersecurity Technologies. In2025 International Conference on Metaverse and Current Trends in Computing (ICMCTC) 2025 Apr 10 (pp. 1-9). doi:10.1109/ICMCTC62214.2025.11196395.