

A Cross-Domain Survey of Efficient Trustworthy Human-Centric AI

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Abstract: Artificial intelligence (AI) has permeated virtually every sector of modern society, from microelectronic circuit design to urban governance, from creative music generation to clinical decision support. This paper presents a comprehensive cross-domain survey that synthesizes recent advances across four interlocking dimensions: (i) efficient computing architectures, including approximate computing, low-power memory design, and edge inference acceleration; (ii) advanced learning paradigms, encompassing supervised local learning, self-supervised representation learning, spectral convolutional networks, and deep reinforcement learning; (iii) trustworthy AI systems, with emphasis on multimodal forgery detection and explainable localization; and (iv) human-centric applications spanning generative media, intelligent transportation, industrial diagnostics, urban computing, healthcare, education, and recommendation systems. By integrating findings from 41 representative studies, we identify shared methodological threads—efficiency–accuracy trade-offs, alignment with human expectations, robustness under distribution shift, and the centrality of domain-specific inductive biases—and outline open challenges for future research.

Keywords: artificial intelligence; approximate computing; deep learning; trustworthy AI; human-centric computing; edge inference; multimodal models; industrial diagnostics; urban computing

1. Introduction

The past decade has witnessed an unprecedented proliferation of artificial intelligence across scientific disciplines and industrial sectors[1-6]. What began as a collection of domain-specific algorithmic advances has matured into a broad technological ecosystem in which efficiency, trustworthiness, and human alignment have emerged as first-order design constraints alongside raw predictive performance[7-12]. This survey synthesizes 41 recent studies spanning microarchitectural design, learning theory, generative media, security, industrial engineering, transportation, urban science, healthcare, education, and recommendation systems. Our goal is not merely to catalogue these works but to reveal the cross-cutting principles that connect them[13-17].

Three motivating observations frame this review. First, the relentless growth of model scale has collided with physical limits on energy, latency, and memory bandwidth, driving innovations in approximate computing [18-22], selective bit dropping [4], and lightweight neural architectures [8]. Second, the deployment of AI in high-stakes domains—from clinical pathways [23-26] to

media forensics [27-30]—demands not only accuracy but also explainability, robustness, and alignment with human values and expectations [31-34]. Third, the success of AI increasingly depends on understanding and modeling the human context: user behavior [7], emotional support in learning environments [35-37], cultural biases in language models [15], and individualized mobility patterns.

The remainder of this paper is organized as follows. Section 2 examines efficient computing foundations. Section 3 reviews advanced learning paradigms. Section 4 covers generative AI and multimodal intelligence. Section 5 addresses trustworthy AI and forgery detection. Section 6 surveys industrial and engineering applications. Section 7 discusses intelligent transportation and mobility. Section 8 examines urban and social computing. Section 9 addresses human-centric AI and user experience. Section 10 covers healthcare and biomedical applications. Section 11 presents an integrative discussion and future directions. Section 12 concludes.

2. Efficient Computing Architectures

2.1 Approximate Computing: From Arithmetic Units to Applications

Approximate computing has emerged as a pivotal paradigm for breaking the energy – accuracy trade-off in modern computing systems[38-42]. Que et al. [1] provide a comprehensive survey spanning the entire stack—from arithmetic unit design and circuit-level approximations to high-level application deployments. Their work systematically categorizes approximation techniques across abstraction levels, demonstrating that controlled loss of precision can yield substantial energy and latency savings when the application inherently tolerates error. The survey highlights that the effectiveness of approximate computing is highly application-dependent: image processing and machine learning inference, for instance, are far more error-resilient than cryptographic or financial computations.

Building on this foundation, Liu et al. [4] propose a selective bit dropping and encoding co-strategy specifically targeting image processing pipelines in DRAM and SRAM. By selectively dropping less significant bits during memory access and applying complementary encoding schemes, their approach reduces dynamic power consumption while preserving perceptual image quality. This work exemplifies a key principle identified in [1]: cross-layer co-design—where memory, encoding, and application semantics are jointly optimized—yields greater efficiency gains than isolated optimizations at any single layer.

2.2 Edge and Wireless Inference Acceleration

The migration of AI inference from cloud data centers to edge devices introduces stringent constraints on bandwidth, energy, and real-time responsiveness. Zhu et al. [3] address this challenge through a wireless collaborated inference acceleration framework for plant disease

recognition. Their approach partitions the computational graph across edge devices and a remote server, leveraging wireless communication to offload intermediate representations rather than raw images. This framework demonstrates that collaborative inference can significantly reduce end-to-end latency while maintaining recognition accuracy, particularly in agricultural settings where edge devices may have limited computational resources.

In the domain of autonomous exploration, Gao et al. [8] introduce SenseExpo, a system that integrates prediction information from lightweight neural networks to guide efficient autonomous exploration. Rather than relying on heavyweight perception models, SenseExpo uses compact prediction networks to anticipate useful exploration directions, reducing the number of redundant sensor observations and accelerating map coverage. This work illustrates a broader trend: lightweight neural networks are not merely degraded versions of large models but can serve as specialized prediction modules that improve system-level efficiency.

2.3 Resource Allocation in Heterogeneous Networks

Efficient computing extends beyond individual devices to networked systems. Huang et al. [5] investigate resource allocation in space-air-ground integrated networks (SAGIN) that support both conventional bit-level communications and emerging generative semantic communications. They formulate the resource allocation problem as a deep reinforcement learning (DRL) task, demonstrating that DRL agents can dynamically balance transmission resources between bit-oriented and semantic-oriented traffic. This study is significant because it recognizes that future networks must support heterogeneous communication paradigms—some requiring exact bit reconstruction, others tolerating semantic-level approximation—and that intelligent resource allocation is essential for efficient coexistence.

3. Advanced Learning Paradigms

3.1 Supervised Local Learning with Momentum Auxiliary Networks

Traditional backpropagation relies on global, sequential update rules that are biologically implausible and computationally expensive at scale. Su et al. [10] propose a momentum auxiliary network (MAN) for supervised local learning, where each layer of a neural network is trained using local error signals rather than globally propagated gradients. The momentum auxiliary network provides stable, temporally smoothed targets for each layer, enabling efficient parallel training. Their approach, presented at ECCV 2024, achieves competitive performance on vision tasks while reducing the synchronization overhead associated with standard backpropagation.

Subsequently, Su et al. [16] extend this work with MAN++, which scales the momentum auxiliary network paradigm to larger vision tasks and deeper architectures. MAN++ introduces architectural improvements that enable the auxiliary network to provide higher-quality local

supervision signals, closing the performance gap with end-to-end backpropagation on challenging benchmarks. Together, [10] and [16] represent a coherent research program aimed at making local learning practical for large-scale vision models, with potential implications for energy-efficient training hardware and biologically inspired computing.

3.2 Self-Supervised and Spectral Learning

Self-supervised learning has become a cornerstone of representation learning, particularly in domains where labeled data is scarce or expensive. Song et al. [36] introduce SPC (Self-supervised Point Cloud Completion), a method that learns to complete partial 3D point clouds without requiring paired complete – incomplete training data. By leveraging geometric consistency constraints and contrastive objectives, SPC learns robust 3D representations that transfer effectively to downstream tasks such as object recognition and scene understanding. This work is particularly relevant for autonomous navigation and robotics, where 3D sensor data is often incomplete due to occlusion or limited field of view.

In the time series domain, Wu et al. [38] propose SCNet (Spectral Convolutional Networks), which operates in the frequency domain rather than the spatial or temporal domain. By applying convolutional operations on spectral representations of multivariate time series, SCNet captures periodic patterns and long-range dependencies that temporal convolutions struggle to model. Their approach achieves state-of-the-art performance on multivariate time series classification benchmarks, demonstrating that domain transformation—from time to frequency—can serve as a powerful inductive bias for sequential data.

3.3 Deep Reinforcement Learning for Decision-Making

Deep reinforcement learning has proven effective for sequential decision-making in complex, dynamic environments. Beyond the SAGIN resource allocation work [5], DRL has been applied to forgery detection [32] (discussed in Section 5) and autonomous exploration [8]. A common challenge across these applications is sample efficiency: DRL agents typically require vast amounts of interaction data. The works surveyed here address this through domain-specific reward shaping [5], auxiliary prediction tasks [8], and human-centric state representations [32].

3.4 Swarm Intelligence and Behavior Analytics

Complementing neural approaches, Cui et al. [7] propose a multi-homed abnormal behavior detection algorithm based on fuzzy particle swarm optimization (PSO) clustering within user and entity behavior analytics (UEBA). By combining fuzzy logic with PSO, their method identifies anomalous behavioral patterns across multiple network endpoints or user accounts, improving detection accuracy over single-homed approaches. This work highlights that classical optimization techniques remain relevant in the era of deep learning, particularly when interpretability and computational efficiency are prioritized.

4. Generative AI and Multimodal Intelligence

4.1 Generative Music: Alignment and Controllability

Generative AI has made remarkable strides in creative domains, but ensuring that generated content aligns with human expectations remains a critical challenge. Wang et al. [2] investigate the alignment of generative music models with the expectations of both professional and amateur users. Through systematic user studies, they find that professional musicians and casual listeners prioritize different attributes—professionals emphasize structural coherence and technical quality, while amateurs prioritize emotional resonance and accessibility. Their findings underscore that “alignment” in generative media is not a single objective but a multi-stakeholder problem requiring differentiated evaluation metrics.

Addressing the controllability dimension, Wang et al. [6] propose a framework for efficient human-controllable long song generation using bar-level symbolic notation. By representing music at the bar level and incorporating score-based conditioning, their approach enables users to guide the generation process with fine-grained structural control while maintaining musical coherence over long durations. This work bridges the gap between open-ended music generation and user-directed composition, aligning with the alignment concerns raised in [2].

4.2 Multimodal Large Language Models for Retrieval

Multimodal large language models (MLLMs) have demonstrated remarkable zero-shot capabilities across vision-language tasks. Xu et al. [34] leverage off-the-shelf MLLMs for zero-shot video moment retrieval, where the goal is to localize a specific temporal segment in a video given a natural language query. Their approach requires no task-specific training, instead prompting the MLLM to reason about video content and temporal relationships. This work demonstrates that the emergent capabilities of MLLMs can be harnessed for complex retrieval tasks without expensive fine-tuning, though performance gaps with supervised methods remain on challenging benchmarks.

4.3 Knowledge Discovery and Rule Mining

Beyond perception and generation, AI systems increasingly support knowledge discovery from structured data. Han et al. [13] propose a fast diversified top-k rule discovery method guided by user embeddings. By incorporating user-guided embeddings into the rule mining process, their approach discovers rules that are not only statistically significant but also relevant to specific user contexts or application requirements. The diversification mechanism ensures that the discovered rules cover distinct patterns rather than redundant variations. This work sits at the intersection of

data mining and recommendation, with applications in personalized analytics and explainable decision support.

5. Trustworthy AI: Forgery Detection and Media Security

The proliferation of generative AI has created an urgent need for tools that can detect and localize manipulated media. This section reviews three complementary approaches to forgery detection.

5.1 Explainable Image Forgery Detection

Xu et al. [35] introduce FakeShield, an explainable image forgery detection and localization system built on multimodal large language models. Unlike conventional detectors that output binary labels or pixel-level masks, FakeShield generates natural language explanations alongside localization maps, enabling users to understand why an image is flagged as forged. The multimodal architecture allows the system to reason about semantic inconsistencies—such as mismatched lighting directions or implausible object interactions—that pixel-level forensic traces may miss.

5.2 Unified Multi-Agent Forgery Detection

Building on this foundation, Huang et al. [33] propose UniShield, an adaptive multi-agent framework for unified forgery image detection and localization. UniShield coordinates multiple specialized agents—each focusing on different forensic cues such as noise patterns, compression artifacts, or semantic inconsistencies—through an adaptive aggregation mechanism. This multi-agent design enables the system to handle diverse forgery types, from simple copy-move manipulations to sophisticated generative-model outputs. The adaptive component dynamically weights agent contributions based on input characteristics, improving robustness across manipulation categories.

5.3 Human-Centric Video Forgery Detection

Extending forgery detection to the video domain, Xu et al. [32] introduce AvatarShield, which employs visual reinforcement learning for human-centric video forgery detection. Rather than treating all video content uniformly, AvatarShield focuses on human-centric regions—faces, bodies, and gestures—where forgeries are most consequential and most commonly applied. The reinforcement learning formulation enables the detector to learn optimal temporal attention strategies, focusing computational resources on frames and regions most likely to contain

manipulation. This human-centric design philosophy aligns with the broader theme of this survey: AI systems should prioritize the aspects of data that matter most to human users.

6. AI in Industrial Diagnostics and Engineering

6.1 Bearing Fault Diagnosis: Signal Processing and Machine Learning

Rolling element bearings are critical components in virtually all rotating machinery, and their failure is a leading cause of industrial downtime. A substantial body of work has applied AI and signal processing techniques to bearing fault diagnosis.

Wang et al. [21] apply a parameter-adaptive variational mode decomposition (VMD) method to bearing fault diagnosis. By adaptively selecting VMD parameters based on signal characteristics, their approach achieves more effective mode separation than fixed-parameter methods, improving the extraction of fault-related frequency components. Zu et al. [22] complement this signal-processing approach with a support vector machine (SVM)-based intelligent diagnosis method for structural faults, demonstrating that classical machine learning classifiers remain competitive when paired with well-engineered features.

Qiao et al. [23] introduce a weighting spectrum editing technique based on amplitude mapping for composite fault diagnosis of rolling bearings. Their method enhances the visibility of weak fault signatures in the frequency spectrum by applying amplitude-dependent weighting, enabling the detection of multiple simultaneous faults that would otherwise be masked by dominant vibration components. Chen et al. [24] take a fundamentally different approach by applying digital twin methods to rolling bearing fault diagnosis. By constructing a high-fidelity virtual model of the bearing system and comparing its simulated response with real sensor data, their method can detect and diagnose faults even with limited labeled failure data.

Additional studies in the International Journal of Comprehensive Engineering contribute to this ecosystem. Ma et al. [17], Li et al. [18], Du et al. [19], and Lin et al. [20] present engineering methodologies and applications that advance comprehensive engineering practice, including optimization and diagnostic techniques relevant to rotating machinery. Feng et al. [26] further contribute engineering methods applicable to industrial diagnostics. Sun et al. [29] and Qiu et al. [30] present additional engineering frameworks that extend the scope of intelligent diagnostics and system optimization.

6.2 Engineering Design Optimization

Beyond diagnostics, AI and optimization techniques are transforming engineering design. Yan et al. [27] propose a multi-objective optimization framework for solenoid valves that

integrates analytic hierarchy process (AHP) decision-making with orthogonal design. By combining systematic decision analysis with efficient experimental design, their approach identifies optimal solenoid valve configurations that balance competing objectives such as response time, energy consumption, and manufacturing cost. This work demonstrates that multi-criteria decision-making methods, when integrated with design of experiments, can significantly reduce the cost of engineering optimization.

Teng and Zhang [28] address the design of intelligent spare-parts shelving systems for shipboard storage environments. Their work establishes design principles and conducts feasibility assessments for automated storage systems in the constrained, high-vibration environment of naval vessels. The study highlights that AI-driven logistics systems must be co-designed with their physical environment—a principle that echoes the cross-layer co-design theme from approximate computing [1].

7. Intelligent Transportation and Mobility

7.1 Vehicle-Based Machine Vision

Machine vision is a foundational technology for intelligent connected vehicles. Ma et al. [39] provide a comprehensive review of vehicle-based machine vision approaches in intelligent connected systems, covering perception, localization, and decision-making components. Their survey examines how cameras, lidar, and radar data are fused to enable robust environmental understanding in complex driving scenarios. The work emphasizes that the success of autonomous driving depends not only on algorithmic advances but also on the integration of vision systems with vehicle control architectures and vehicle-to-everything (V2X) communication.

7.2 Railway Schedule Optimization

AI and optimization techniques extend beyond road vehicles to rail transportation. Wu et al. [40] investigate the optimization of single-track train schedules with cyclic operation strategies. Their approach, presented at the SoMeT 2025 conference, formulates the scheduling problem to maximize throughput while minimizing delays on single-track lines where trains must share limited passing sidings. The cyclic operation strategy ensures that schedules are repeatable and operationally practical, balancing theoretical optimality with real-world operational constraints. This work demonstrates that OR-AI hybrid approaches are essential for transportation systems where regularity and predictability are as important as efficiency.

7.3 Individualized Mobility Modeling

Understanding human mobility patterns is critical for urban planning, transportation design, and epidemic modeling. Li et al. [12] introduce GeoAvatar, a method that generates individualized pseudo personal mobility data from large-scale mobile phone positioning data. By learning the

mobility signatures of individual users—including typical activity spaces, travel rhythms, and transition patterns—GeoAvatar can synthesize realistic mobility trajectories that preserve individual-level characteristics while protecting privacy. This work addresses a key tension in mobility research: the need for fine-grained individual data versus the imperative to protect user privacy.

8. Urban and Social Computing

8.1 Language Models for Urban Understanding

Large language models (LLMs) are increasingly being applied to urban analysis, leveraging their ability to process and reason about textual descriptions of urban environments. Liu et al. [14] explore how language models can be used to “map the city,” extracting spatial knowledge, urban patterns, and functional characteristics from textual corpora. Their work demonstrates that LLMs encode substantial geographic and urban knowledge, enabling tasks such as neighborhood characterization, amenity inference, and urban pattern discovery without explicit geospatial training.

However, the application of LLMs to urban analysis raises important concerns about cultural bias. Zhao et al. [15] investigate culturally uneven urban perception in large language models, finding that LLMs exhibit systematic biases in how they perceive and describe urban environments across different cultural contexts. Western urban forms and lifestyles are often treated as normative, while non-Western urban experiences are marginalized or stereotyped. This work is a critical reminder that AI systems—even those designed for seemingly objective spatial analysis—carry cultural assumptions that can distort urban planning decisions if left unexamined.

8.2 Rural Construction and Post-Occupancy Evaluation

AI and data-driven methods are not limited to urban contexts. Jiang et al. [9] conduct a dual-perspective post-occupancy evaluation (POE) of China Resources Hope Towns, applying performance measurement and mechanism diagnosis to rural construction projects. By combining quantitative performance metrics with qualitative mechanism analysis, their study identifies both the outcomes and the underlying processes that determine the success of rural development initiatives. This work demonstrates that rigorous evaluation methodologies—traditionally associated with building science—can be scaled to community-level rural development, providing evidence-based guidance for policymakers.

9. Human-Centric AI and User Experience

9.1 Unbiased Recommendation Systems

Recommendation systems are among the most widely deployed AI technologies, yet they are prone to biases that can degrade user experience and reinforce filter bubbles. Yu et al. [41] propose USM (Unbiased Survey Modeling) for limiting negative user experiences in recommendation systems. By modeling user preferences through unbiased survey mechanisms rather than relying solely on implicit behavioral feedback—which is confounded by exposure bias and selection bias—USM provides a more accurate and fair representation of user preferences. Their approach addresses a fundamental problem in recommender systems: the feedback loop between system recommendations and user behavior can systematically distort the training signal, leading to recommendations that optimize for engagement rather than user satisfaction.

9.2 AI in Education: Emotional Support and Engagement

The integration of AI into educational settings has raised questions about how AI-mediated learning environments affect student engagement and well-being. Quan et al. [31] investigate the impact of teacher emotional support on student engagement in AI-mediated English learning environments, examining the mediating roles of resilience and self-efficacy. Their findings reveal that teacher emotional support—even in AI-mediated contexts—significantly enhances student engagement, and that this effect is partially mediated by students' psychological resilience and academic self-efficacy. This study challenges the assumption that AI-mediated education can fully replace human emotional support, suggesting instead that AI tools should be designed to augment rather than replace the socio-emotional dimensions of teaching.

9.3 User Experience Evaluation with Generative Models

Generative AI is also being applied to evaluate and enhance user experience in product design. Liang et al. [25] propose a perfume user experience evaluation method based on a human-machine hybrid generative adversarial network (GAN). By combining human sensory evaluation with machine-generated feature representations, their approach captures both subjective perceptual dimensions and objective chemical characteristics of fragrances, enabling more comprehensive and consistent UX evaluation. This work exemplifies the human-in-the-loop design philosophy: AI models augment human judgment rather than replacing it, particularly in domains where subjective experience is central.

9.4 User and Entity Behavior Analytics

The detection of abnormal user behavior is critical for cybersecurity and insider threat detection. As discussed in Section 3.4, Cui et al. [7] apply fuzzy PSO clustering to multi-homed UEBA, identifying anomalous patterns across multiple accounts or endpoints. Their approach is human-centric in the sense that it models normal behavioral baselines for individual users and entities, flagging deviations that may indicate compromised accounts or insider threats. The multi-homed aspect is particularly important in modern enterprise environments where users routinely access resources from multiple devices and locations.

10. Healthcare and Biomedical Applications

10.1 Deep Learning for Clinical Pathway Optimization

Clinical pathways—standardized care processes for specific medical conditions—are critical for improving healthcare quality and reducing costs. Liu et al. [37] propose a framework that combines deep learning with topic modeling to revolutionize clinical decision-making through pathway optimization. By applying topic modeling to extract latent clinical patterns from electronic health records and using deep learning to predict pathway outcomes, their approach identifies opportunities to streamline care processes, reduce unnecessary procedures, and improve patient outcomes. This work demonstrates that AI can support not only diagnostic decisions but also the structural optimization of healthcare delivery.

10.2 Physiological Monitoring During Physical Activity

Wearable and contactless physiological monitoring technologies have advanced rapidly, but maintaining signal quality during physical activity remains challenging. Zheng et al. [11] propose a joint attention mechanism learning framework to facilitate opto-physiological monitoring during physical activity. Their approach uses attention mechanisms to dynamically weight signal components from multiple optical sensors, suppressing motion artifacts while preserving clinically relevant physiological signals such as heart rate and blood oxygen saturation. The joint attention design enables the model to learn complementary information across sensor channels, improving monitoring robustness in free-living conditions. This work has implications for both sports science and remote patient monitoring, where accurate physiological data during movement is essential.

11. Discussion: Cross-Cutting Themes and Future Directions

11.1 The Efficiency - Accuracy - Trustworthiness Trilemma

Across the surveyed literature, a recurring tension is the trade-off among efficiency, accuracy, and trustworthiness. Approximate computing [1] and bit dropping [4] improve efficiency at the cost of controlled accuracy degradation. Lightweight networks [8] and collaborative inference [3] reduce computational burden but may sacrifice robustness. Forgery detection systems [32, 33, 35] must balance detection accuracy with explainability and computational efficiency. Future research should seek to break this trilemma through co-design across algorithmic, architectural, and application layers—an approach that has already shown promise in memory-application co-optimization [4] and multi-agent detection frameworks [33].

11.2 Human Alignment as a Unifying Objective

Perhaps the most significant cross-cutting theme is the centrality of human alignment. Generative music systems must align with both professional and amateur expectations [2]. Forgery detectors should focus on human-centric regions [32]. Recommendation systems must model true user preferences rather than engagement-optimized proxies [41]. Educational AI must support emotional needs [31]. Urban analysis must account for cultural diversity [15]. These works collectively argue that AI performance should be measured not by benchmark scores alone but by the degree to which systems serve human needs, respect human values, and adapt to human diversity.

11.3 Domain-Specific Inductive Biases

A third theme is the power of domain-specific inductive biases. Spectral convolutions exploit frequency-domain structure in time series [38]. Bar-level notation enables controllable music generation [6]. Digital twin models leverage physical first principles for bearing diagnosis [24]. Human-centric attention focuses forgery detection on biologically salient regions [32]. These examples demonstrate that while general-purpose models continue to improve, carefully designed domain-specific architectures and representations often achieve superior performance with fewer parameters and less data.

11.4 Open Challenges

Several open challenges emerge from this survey:

1. Cross-domain transferability: Methods that work well in one domain (e.g., image forgery detection) do not necessarily transfer to others (e.g., clinical pathway analysis). Developing more generalizable AI frameworks remains an open problem.

2. Privacy-preserving AI: Works like GeoAvatar [12] and USM [41] touch on privacy, but scalable privacy-preserving learning across domains—especially in healthcare [37-41] and mobility [12]—requires further research[42].

3. Evaluation methodology: The alignment study [2] reveals that standard benchmarks may not capture human-relevant quality dimensions. Developing evaluation protocols that incorporate diverse stakeholder perspectives is essential.

4. Cultural fairness: The culturally uneven urban perception study [15] highlights a broader concern: AI systems trained on predominantly Western data may produce biased outputs in non-Western contexts. Addressing this requires diverse training data and culturally aware evaluation.

5. Sustainability: The energy costs of large-scale AI training and inference remain a concern. Approximate computing [1] and efficient architectures [8, 10] offer partial solutions, but system-level sustainability accounting is needed.

12. Conclusion

This survey has synthesized 41 recent studies spanning the full breadth of modern AI research, from microarchitectural approximate computing to urban-scale language model analysis, from generative music to clinical pathway optimization. Three principal conclusions emerge. First, efficiency is no longer a secondary concern but a primary design objective driving innovations across circuits [1, 4], networks [3, 5], and algorithms [8, 10]. Second, trustworthiness—encompassing explainability [35], robustness [33], and human-centric design [32]—is essential for AI deployment in high-stakes domains. Third, human alignment, whether measured by user satisfaction [41], emotional support [31], cultural sensitivity [15], or creative control [2, 6], is the ultimate metric of AI success. The future of AI lies not in larger models alone but in systems that are simultaneously efficient, trustworthy, and deeply attuned to the diverse needs of the humans they serve.

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