Integrations in Engineering and Technology

Online ISSN: XXXX-XXXX

An Online, Peer-Reviewed, Refereed, Open Access Journal

Review Article

COGNITIVE-INSPIRED EXPLAINABLE MACHINE LEARNING: ADVANCING HUMAN-CENTRIC, TRUSTWORTHY, AND PREDICTIVE ARTIFICIAL INTELLIGENCE-A COMPREHENSIVE REVIEW

***M RAMA KRISHNA**

Assistant Professor, Department of CSE, Adikavi Nannaya University, Rajahmanudry, India

***CORRESPONDING AUTHOR**

M Rama Krishna

ARTICLE HISTORY: 14.03.2026 RECEIVED: 27.03.2026 REVISED: ACCEPTED: 19.04.2026

ABSTRACT

Artificial intelligence (AI) and machine learning (ML) have transformed decision-making, automation, and predictive analytics across domains such as healthcare, finance, cybersecurity, education, and industrial systems. However, conventional ML and deep learning models are often criticized for their "black-box" nature, lacking transparency, interpretability, and alignment with human reasoning. These limitations reduce trust, accountability, and adoption in high-stakes applications. To address these challenges, cognitive-inspired explainable machine learning has emerged as an interdisciplinary paradigm integrating principles of human cognition, reasoning, memory, perception, and adaptive learning into intelligent systems. Unlike traditional ML approaches focused primarily on predictive accuracy, cognitive-inspired explainable ML emphasizes human-aligned reasoning, contextual understanding, transparent inference, and ethical responsibility. This review critically examines the theoretical foundations, historical evolution, methodologies, and architectural frameworks of cognitive-inspired explainable machine learning. It discusses cognitive computing principles, explainability techniques, neuro-symbolic intelligence, fairness, bias mitigation, robustness, and privacy-preserving models. The review also explores applications in healthcare diagnostics, precision medicine, pharmaceutical drug discovery, psychiatric disorder prediction, financial forecasting, cybersecurity, intelligent transportation, and smart governance. Comparative analyses of explainability methods and cognitive architectures are presented to identify strengths, limitations, and implementation challenges. Furthermore, the review highlights barriers to adoption, including computational complexity, interpretability-performance trade-offs, legal constraints, model uncertainty, data heterogeneity, and ethical concerns in autonomous decision-making. Future directions involving adaptive cognition, emotionally intelligent AI, continual learning, personalized intelligence, and collaborative human-machine ecosystems are also discussed, positioning cognitive-inspired explainable ML as a key pathway toward transparent, trustworthy, and socially responsible AI systems.

Keywords: *Cognitive-Inspired Machine Learning; Explainable Artificial Intelligence (XAI); Human-Centric AI; Trustworthy Artificial Intelligence; Predictive Intelligence; Cognitive Computing.*

INTRODUCTION

Artificial intelligence has witnessed extraordinary progress over the past several decades, fundamentally altering how computational systems perceive, interpret, and respond to complex real-world information. Machine learning, a major subdomain of artificial intelligence, enables computational systems to identify patterns, learn from data, and make predictions without explicit programming instructions [1]. These capabilities have significantly improved automation, decision support, image recognition, language processing, medical diagnosis, and personalized recommendations across multiple industries [2]. However, despite exceptional predictive achievements, machine learning models continue to face substantial criticism because many advanced systems, particularly deep neural networks, function as opaque "black-box" mechanisms whose internal reasoning

processes remain largely incomprehensible to human users [3].
The inability to interpret machine-generated decisions presents serious challenges, particularly in sensitive domains such as healthcare, pharmaceutical sciences, criminal justice, financial services, autonomous vehicles, and cybersecurity, where transparency and accountability are essential requirements [4]. In medical diagnosis, for example, clinicians may hesitate to rely on a machine learning model if it cannot adequately explain why a particular disease prediction was generated. Likewise, pharmaceutical researchers increasingly require interpretable computational systems capable of justifying drug candidate prioritization to ensure scientific validity and patient safety [5]. Consequently, interpretability and explainability have become central concerns in artificial intelligence research.
Traditional machine learning systems prioritize predictive performance while often neglecting interpretability and human understanding. High-performance algorithms such as deep neural networks, ensemble learning methods, and reinforcement learning architectures frequently exhibit superior accuracy but offer limited transparency regarding how decisions are produced [6]. This limitation has motivated the emergence of explainable artificial intelligence (XAI), an interdisciplinary research area dedicated to designing computational methods capable of providing understandable explanations for algorithmic predictions [7]. Explainable artificial intelligence aims to improve trust, accountability, fairness, and transparency while reducing risks associated with biased or unreliable automated decisions.
The increasing demand for explainability has simultaneously encouraged researchers to revisit insights from cognitive science and neuroscience to create more human-compatible artificial intelligence systems [8]. Human cognition involves reasoning, contextual adaptation, memory retention, perception, problem-solving, emotional intelligence, and explainable decision-making processes [9]. Unlike conventional machine learning algorithms that often depend solely on statistical optimization, humans generally justify their decisions through logical explanations, contextual evidence, and experiential reasoning. This distinction has led to the development of **cognitive-inspired machine learning**, an emerging paradigm designed to emulate selected mechanisms of human intelligence to improve machine reasoning and interpretability [10].
Cognitive-inspired machine learning integrates cognitive principles such as attention, memory, hierarchical reasoning, symbolic inference, and adaptive learning into artificial intelligence architectures [11]. By incorporating cognitive mechanisms, machine learning systems can potentially achieve improved transparency, enhanced contextual awareness, and greater trustworthiness. Importantly, cognitive-inspired frameworks seek to bridge the gap between purely statistical learning and human-like reasoning, thereby facilitating meaningful collaboration between humans and intelligent systems [12].
The convergence of cognitive-inspired computing and explainable artificial intelligence has subsequently given rise to a novel research direction known as **cognitive-inspired explainable machine learning**. This interdisciplinary paradigm aims to produce machine intelligence systems that not only demonstrate high predictive accuracy but also generate understandable, trustworthy, and contextually meaningful explanations [13]. Such systems are increasingly considered essential for achieving human-centric artificial intelligence, where technological innovations prioritize human welfare, fairness, and ethical accountability [14].
Human-centric artificial intelligence emphasizes collaboration between humans and machines rather than full automation or replacement of human expertise [15]. Instead of treating humans as passive recipients of algorithmic outputs, human-centric AI encourages transparent interactions in which intelligent systems explain reasoning processes, acknowledge uncertainty, and support informed decision-making [16]. This paradigm is particularly valuable in healthcare and pharmaceutical sciences, where physicians and pharmacists require interpretable decision-support tools capable of enhancing diagnostic precision while preserving professional autonomy [17].
The significance of cognitive-inspired explainable machine learning is further amplified by growing concerns regarding fairness, algorithmic bias, and ethical accountability. Numerous machine learning systems have demonstrated unintended discriminatory outcomes due to biased datasets, poor feature selection, or hidden algorithmic assumptions [18]. Trustworthy AI frameworks increasingly emphasize fairness, transparency, accountability, robustness, privacy preservation, and human oversight as essential principles governing responsible technological development [19]. Therefore, integrating cognitive intelligence with explainability mechanisms offers promising opportunities for addressing many of these concerns.
Recent advances in neuro-symbolic intelligence, causal inference, interpretable neural networks, attention mechanisms, and hybrid reasoning systems have substantially contributed to the development of explainable cognitive architectures [20]. These technologies combine symbolic reasoning with statistical learning to improve interpretability while maintaining predictive performance. Such approaches enable machine learning systems to provide rational justifications for decisions, thereby supporting trust and facilitating human validation [21].

The rapid evolution of cognitive-inspired explainable machine learning has generated increasing academic interest, yet comprehensive reviews integrating cognitive computing, explainable AI, trustworthy intelligence, predictive systems, and human-centric computational design remain limited [22]. Existing literature frequently addresses these components independently, resulting in fragmented understanding and limited interdisciplinary integration [23]. Therefore, a comprehensive synthesis examining theoretical foundations, practical applications, methodological innovations, ethical implications, and future research directions is urgently required.

The present review aims to comprehensively evaluate the conceptual foundations, methodological frameworks, and practical implications of cognitive-inspired explainable machine learning in advancing trustworthy and predictive artificial intelligence systems. The article critically analyzes explainability mechanisms, cognitive architectures, predictive intelligence frameworks, ethical considerations, fairness strategies, and domain-specific applications while identifying unresolved challenges and emerging opportunities [24]. A comparative overview of key methodologies employed in cognitive-inspired explainable machine learning is presented in Table 01.

Table 01: Comparative Overview of Cognitive-Inspired Explainable Machine Learning Approaches

Approach	**Core Principle**	**Explainability Level**	**Human-Centric Capability**	**Major Applications**
Symbolic AI	Rule-based reasoning	High	High	Clinical decision support
Deep Learning	Statistical pattern recognition	Low	Moderate	Image recognition
Explainable AI	Transparent prediction mechanisms	High	High	Healthcare analytics
Neuro-Symbolic AI	Combined symbolic and neural intelligence	High	Very High	Drug discovery
Reinforcement Learning	Adaptive behavioral optimization	Moderate	Moderate	Robotics

As shown in Table 01, explainability and human-centric adaptability differ substantially across computational paradigms. Neuro-symbolic intelligence and explainable AI demonstrate considerable promise for achieving balanced predictive performance and interpretability [25]. The conceptual relationship between cognition, explainability, trustworthiness, and predictive intelligence in cognitive-inspired machine learning systems is illustrated in Figure 01.

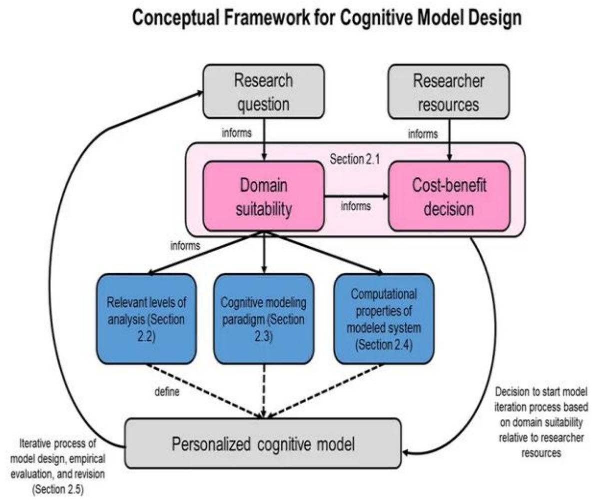

Figure 01: Conceptual Framework of Cognitive-Inspired Explainable Machine Learning [26]

The remainder of this review systematically explores the evolution, theoretical foundations, methodologies, applications, ethical considerations, challenges, and future perspectives of cognitive-inspired explainable machine learning. By synthesizing interdisciplinary evidence, this review seeks to establish a comprehensive scholarly foundation for future research and practical implementation of transparent, trustworthy, and human-centric artificial intelligence systems [27–29].

EVOLUTION OF MACHINE LEARNING AND COGNITIVE INTELLIGENCE

The evolution of machine learning and cognitive intelligence represents one of the most transformative scientific developments in modern computational science. Artificial intelligence has progressed from rule-based symbolic systems to highly sophisticated predictive architectures capable of recognizing patterns, generating language, and supporting complex decision-making processes. Despite remarkable advances in computational capabilities, researchers increasingly recognize that predictive accuracy alone is insufficient for achieving truly intelligent systems. Instead, future artificial intelligence requires human-like reasoning, contextual awareness, explainability, trustworthiness, and adaptability. The convergence of machine learning with cognitive science has consequently emerged as a critical pathway toward achieving human-centric artificial intelligence systems capable of transparent and interpretable decision-making [31].

The earliest foundations of artificial intelligence can be traced to philosophical and mathematical inquiries regarding automated reasoning and symbolic representation. During the mid-twentieth century, pioneering researchers envisioned computational systems capable of mimicking human intelligence through symbolic manipulation and logical inference. Early artificial intelligence models emphasized explicit rule-based reasoning systems in which expert knowledge was manually encoded into computational frameworks. These systems, commonly known as symbolic AI or expert systems, demonstrated promising results in structured environments where logical relationships could be formally represented.

One of the earliest milestones in machine intelligence was the conceptualization of the Turing Test by Alan Turing, which proposed evaluating machine intelligence based on a machine's ability to imitate human conversational behavior [32]. This conceptual framework stimulated research into computational reasoning and machine cognition. However, early symbolic systems suffered from substantial limitations because manually encoded rules could not efficiently adapt to uncertainty, ambiguity, or rapidly changing environments.

During the 1950s and 1960s, perceptron models introduced the concept of computational learning inspired by biological neural networks. These systems attempted to replicate basic aspects of neuronal processing through weighted mathematical functions capable of learning simple patterns from data [32]. Although early neural systems demonstrated limited performance, they established the conceptual basis for contemporary machine learning and deep learning architectures.

The historical progression of machine learning paradigms is summarized in Table 02.

Table 02: Historical Evolution of Machine Learning and Cognitive Intelligence

Period	**Major Development**	**Characteristics**	**Key Limitation**
1950–1970	Symbolic AI	Rule-based reasoning	Poor adaptability
1970–1990	Expert Systems	Knowledge-based automation	Limited scalability
1990–2010	Statistical Machine Learning	Data-driven prediction	Low interpretability
2010–2020	Deep Learning Revolution	High predictive accuracy	Black-box nature
2020–Present	Cognitive-Inspired Explainable AI	Human-centric intelligence	Computational complexity

As illustrated in Table 02, artificial intelligence development has evolved from symbolic reasoning toward cognitive-inspired explainable systems emphasizing trust, interpretability, and collaboration between humans and machines.

The 1970s and 1980s witnessed substantial growth in expert systems, which attempted to replicate specialist-level reasoning in fields such as medicine, engineering, and industrial automation. Expert systems employed large repositories of manually constructed decision rules to simulate human expertise. One notable example was medical diagnostic software capable of supporting clinicians in identifying infectious diseases based on symptoms and laboratory findings [33]. While these systems demonstrated practical value, their inability to generalize beyond predefined knowledge constraints significantly restricted their adaptability.

A major paradigm shift occurred during the 1990s with the emergence of statistical machine learning approaches. Unlike symbolic systems dependent upon manually encoded rules, statistical learning methods enabled computational models to identify hidden relationships directly from observational data. Algorithms such as decision trees, support vector machines, Bayesian classifiers, and artificial neural networks gained popularity due to their ability to learn predictive patterns without explicit programming.

Machine learning introduced several transformative advantages, including improved scalability, data-driven adaptability, and enhanced predictive performance across diverse application domains. Medical diagnosis, speech recognition, natural language processing, recommendation systems, and financial forecasting increasingly benefited from machine learning techniques capable of extracting meaningful information from large datasets. Nevertheless, many statistical learning systems remained difficult to interpret because prediction mechanisms frequently lacked transparent reasoning pathways [34].

The rise of big data, cloud computing, and advanced computational hardware subsequently accelerated the emergence of deep learning during the early twenty-first century. Deep learning architectures utilize multiple computational layers to automatically learn hierarchical feature representations from raw input data. Convolutional neural networks revolutionized image analysis, while recurrent neural networks and transformer architectures dramatically advanced natural language processing capabilities.

Deep learning systems achieved unprecedented predictive accuracy in areas including medical image analysis, autonomous vehicles, molecular modeling, language translation, and intelligent automation. However, despite exceptional performance, deep learning introduced a major challenge known as the black-box problem, wherein complex neural computations become nearly impossible for humans to interpret [35]. In high-risk environments, the absence of explainability generated significant ethical and practical concerns.

For example, if an artificial intelligence system predicts the presence of schizophrenia, cardiovascular disease, or adverse drug reactions without explaining contributing variables, healthcare professionals may struggle to trust or validate the recommendation. Similarly, in pharmaceutical drug discovery, researchers require transparent evidence supporting molecular predictions to ensure reproducibility and scientific accountability. Consequently, concerns regarding transparency stimulated growing interest in explainable artificial intelligence.

The emergence of explainable artificial intelligence (XAI) marked an important transition in machine learning research. Explainable AI seeks to make algorithmic outputs understandable through interpretable models, feature importance estimation, causal reasoning, visual explanations, and human-readable decision pathways [36]. Instead of prioritizing predictive performance alone, explainable artificial intelligence emphasizes transparency, accountability, and trust.

Several explainability techniques emerged to address interpretability limitations. These include local interpretable model-agnostic explanations (LIME), Shapley additive explanations (SHAP), saliency mapping, counterfactual reasoning, attention visualization, and surrogate models. Such techniques enable researchers to identify which variables contribute to predictions and explain why decisions are generated.

However, explainability alone does not fully address the challenge of human-compatible intelligence. Human cognition involves reasoning, perception, memory, contextual adaptation, intuition, and emotional understanding-capabilities that traditional machine learning frameworks only partially emulate. Therefore, researchers increasingly turned toward cognitive science for inspiration.

Cognitive intelligence refers to computational systems capable of mimicking selected characteristics of human thinking and reasoning processes. Cognitive architectures seek to model mechanisms such as learning, memory, problem-solving, contextual interpretation, and adaptive decision-making [37]. Unlike traditional statistical learning, cognitive-inspired systems attempt to integrate symbolic reasoning with probabilistic inference to create more interpretable and human-like intelligence.

The transition from conventional machine learning toward cognitive-inspired computational systems is illustrated conceptually in Figure 02.

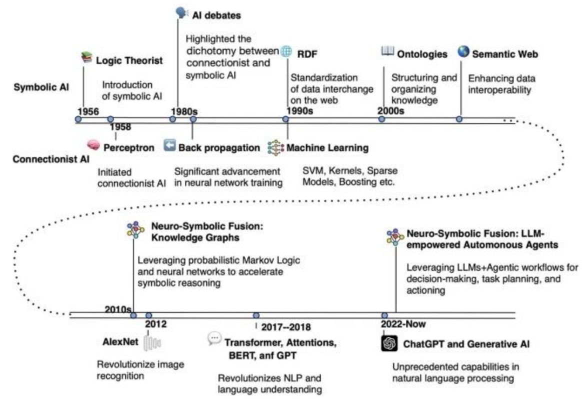

Figure 02: Evolution of Artificial Intelligence from Symbolic Systems to Cognitive-Inspired Explainable Machine Learning

As depicted in Figure 02, the evolution of artificial intelligence reflects a progressive movement from rigid rule-based computation toward adaptive, explainable, and human-aligned intelligence systems. Modern computational frameworks increasingly emphasize trust, interpretability, fairness, and collaboration rather than purely automated prediction.

An important advancement in cognitive-inspired intelligence is the emergence of neuro-symbolic artificial intelligence, which integrates symbolic reasoning with neural computation [56]. Symbolic systems contribute logical transparency, while neural networks contribute adaptive learning and predictive power. Together, these methods provide a balanced framework capable of generating interpretable and scalable intelligence systems.

Attention mechanisms constitute another cognitive-inspired innovation significantly improving machine intelligence. Human cognition selectively prioritizes relevant information while ignoring irrelevant stimuli. Attention-based machine learning models emulate this capability by selectively weighting important features during decision-making processes [38]. Transformer architectures, widely employed in language processing and predictive analytics, exemplify successful implementation of cognitive attention principles.

Memory-inspired learning also represents an important aspect of cognitive machine intelligence. Humans continuously integrate prior experiences into future decision-making processes. Cognitive-inspired machine learning increasingly incorporates long-term memory architectures capable of retaining historical contextual information for adaptive predictions. Such systems demonstrate significant value in healthcare monitoring, personalized medicine, and longitudinal behavioral prediction.

Human-centric artificial intelligence further accelerated the evolution of cognitive-inspired systems by emphasizing meaningful collaboration between humans and computational agents [60]. Human-centric intelligence prioritizes transparency, interpretability, fairness, and ethical responsibility. Instead of replacing human expertise, these systems function as intelligent collaborators supporting informed decision-making.

The increasing importance of trustworthy artificial intelligence has additionally influenced cognitive-inspired machine learning development. Trustworthy AI frameworks emphasize fairness, robustness, transparency, privacy, safety, and accountability [39]. Cognitive-inspired explainable systems are increasingly viewed as essential mechanisms for achieving these goals because they facilitate understandable and ethically responsible decision-making processes.

The rapid convergence of cognitive science, machine learning, explainability, and ethical artificial intelligence has consequently established cognitive-inspired explainable machine learning as a promising frontier in intelligent system development. These systems seek not only to predict outcomes accurately but also to explain reasoning, justify uncertainty, and align technological behavior with human values [40-41].

The subsequent section critically explores the theoretical foundations and architectural principles of cognitive-inspired machine learning, emphasizing human cognition, reasoning mechanisms, memory systems, and explainability strategies contributing to trustworthy artificial intelligence.

CONCLUSION

Cognitive-inspired explainable machine learning represents an emerging paradigm that combines human cognitive principles with explainable artificial intelligence to develop transparent, trustworthy, and predictive intelligent systems. While conventional machine learning models offer high predictive accuracy, their black-box nature limits interpretability and trust, particularly in critical domains such as healthcare and pharmaceutical sciences. The evolution from symbolic AI to deep learning and cognitive-inspired frameworks highlights the growing need for human-centric, ethical, and explainable computational systems. By integrating cognitive reasoning, explainability, and trustworthy AI principles, future intelligent systems can improve decision-making, transparency, fairness, and user confidence. Despite challenges related to complexity, bias, and scalability, cognitive-inspired explainable machine learning is expected to play a vital role in advancing responsible and human-aligned artificial intelligence.

REFERENCES

1. Russell SJ, Norvig P. Artificial intelligence: a modern approach. 4th ed. Harlow: Pearson; 2021.
2. Goodfellow I, Bengio Y, Courville A. Deep learning. Cambridge (MA): MIT Press; 2016.
3. Molnar C. Interpretable machine learning. 2nd ed. 2022.
4. Samek W, Müller KR. Towards explainable artificial intelligence. Proc IEEE. 2019;107(12):2475-9.
5. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. Nat Med. 2019;25(1):44-56.
6. LeCun Y, Bengio Y, Hinton G. Deep learning. Nature. 2015;521:436-44.
7. Adadi A, Berrada M. Peeking inside the black-box: a survey on explainable AI. IEEE Access. 2018;6:52138-60.
8. Lake BM, Ullman TD, Tenenbaum JB. Building machines that learn and think like people. Behav Brain Sci. 2017;40:e253.
9. Sun R. Cognitive architectures and artificial intelligence. AI Mag. 2007;28(2):25-39.
10. Langley P, Laird JE, Rogers S. Cognitive architectures: research issues and challenges. Cogn Syst Res. 2009;10(2):141-60.
11. Sun R. The importance of cognitive architectures: an analysis based on CLARION. J Exp Theor Artif Intell. 2007;19(2):159-93.
12. Laird JE. Introduction to soar. arXiv preprint arXiv:2205.03854. 2022 May 8.
13. Gunning D, Aha DW. DARPA's explainable artificial intelligence (XAI) program. AI Mag. 2019;40(2):44-58.
14. Floridi L, Cowls J. A unified framework of five principles for AI in society. Harv Data Sci Rev. 2019;1(1):1-15.
15. Shneiderman B. Human-centered artificial intelligence: reliable, safe & trustworthy. Int J Hum Comput Interact. 2020;36(6):495-504.
16. Amershi S, Weld D, Vorvoreanu M, Fourney A, Nushi B, Collisson P, et al. Guidelines for human-AI interaction. In: Proceedings of the CHI Conference on Human Factors in Computing Systems; 2019. p. 1-13.
17. Topol EJ. Deep medicine: how artificial intelligence can make healthcare human again. New York (NY): Basic Books; 2019.
18. Barocas S, Selbst AD. Big data's disparate impact. Calif Law Rev. 2016;104(3):671-732.
19. Jobin A, Ienca M, Vayena E. The global landscape of AI ethics guidelines. Nat Mach Intell. 2019;1(9):389-99.
20. Garcez AD, Lamb LC, Gabbay DM. Neural-symbolic cognitive reasoning. Berlin: Springer; 2009.
21. Besold TR, d'Avila Garcez AS, Bader S, Bowman H, Domingos P, Hitzler P, et al. Neural-symbolic learning and reasoning: a survey and interpretation. arXiv [Internet]. 2017 [cited 2026 May 24];1705.08412. Available from: https://arxiv.org/abs/1705.08412

22. Holzinger A, Langs G, Denk H, Zatloukal K, Müller H. Causability and explainability of artificial intelligence in medicine. Wiley Interdiscip Rev Data Min Knowl Discov. 2019;9(4):e1312.
23. Doshi-Velez F, Kim B. Towards a rigorous science of interpretable machine learning. arXiv [Internet]. 2017 [cited 2026 May 24];1702.08608. Available from: https://arxiv.org/abs/1702.08608
24. Rudin C. Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. Nat Mach Intell. 2019;1(5):206-15.
25. Guidotti R, Monreale A, Ruggieri S, Turini F, Giannotti F, Pedreschi D. A survey of methods for explaining black box models. ACM Comput Surv. 2018;51(5):1-42.
26. Schürmann T, Beckerle P. Personalizing human-agent interaction through cognitive models. Front Psychol. 2020;11:561510.
27. Lipton ZC. The mythos of model interpretability. Commun ACM. 2018;61(10):36-43.
28. Miller T. Explanation in artificial intelligence: insights from the social sciences. Artif Intell. 2019;267:1-38.
29. Arrieta AB, Díaz-Rodríguez N, Del Ser J, Bennetot A, Tabik S, Barbado A, et al. Explainable artificial intelligence (XAI): concepts, taxonomies, opportunities and challenges toward responsible AI. Inf Fusion. 2020;58:82-115.
30. Siau K, Wang W. Building trust in artificial intelligence, machine learning, and robotics. Cutting Edge Bus Technol. 2018;2(2):1-5.
31. Dwivedi YK, Hughes L, Ismagilova E, Aarts G, Coombs C, Crick T, et al. Artificial intelligence (AI): multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. Int J Inf Manage. 2021;57:101994.
32. Mitchell TM. Machine learning. New York (NY): McGraw-Hill; 1997.
33. Jordan MI, Mitchell TM. Machine learning: trends, perspectives, and prospects. Science. 2015;349(6245):255-60.
34. McCarthy J. Programs with common sense. Stanford AI Lab Memo. 1959.
35. Nilsson NJ. Artificial intelligence: a new synthesis. San Francisco (CA): Morgan Kaufmann; 1998.
36. Turing AM. Computing machinery and intelligence. Mind. 1950;59:433-60.
37. Haugeland J. Artificial intelligence: the very idea. Cambridge (MA): MIT Press; 1985.
38. Rosenblatt F. The perceptron: a probabilistic model for information storage. Psychol Rev. 1958;65:386-408.
39. Russell SJ, Norvig P. Artificial intelligence: a modern approach. 4th ed. Harlow: Pearson; 2021.
40. Jackson P. Introduction to expert systems. Harlow: Addison-Wesley; 1998.
41. Buchanan BG, Shortliffe EH. Rule-based expert systems. Reading (MA): Addison-Wesley; 1984.