Exploration of the Development Path of Artificial Intelligence under the Innovation of the Multi-Intelligence Era

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Abstract: ***This paper explores the impact of the multi-intelligence era on the development of artificial intelligence, analyzes its main research directions, including intelligent simulation, swarm intelligence, computational intelligence, and brain-like intelligence, and proposes strategies to optimize the scientific and technological innovation system of artificial intelligence, emphasizing the importance of basic theoretical innovation, core technology breakthroughs, and technological integration innovation. The massive data, powerful computing power, and highly interconnected network infrastructure possessed by the multi-intelligence era provide unprecedented opportunities for the development of artificial intelligence, while also bringing new challenges. This paper deeply analyzes these opportunities and challenges and explores the future development path of artificial intelligence.***

Keywords: Artificial Intelligence; Multi-Intelligence Era; Technological Integration; Innovation System.

1. INTRODUCTION

The world is currently undergoing an unprecedented digital transformation. The combination of massive data, high-speed networks, and powerful computing capabilities has jointly created a brand-new "Era of Multiple Intelligences". This era presents unprecedented opportunities and challenges for the development of artificial intelligence. The powerful computing capabilities, massive data resources, and highly interconnected network infrastructure in the Era of Multiple Intelligences are profoundly changing the research paradigm and application scenarios of artificial intelligence, driving the exponential development of artificial intelligence technology.

2. THE IMPACT OF THE ERA OF MULTIPLE INTELLIGENCES ON ARTIFICIAL INTELLIGENCE

The impact of the era of multiple intelligences on the development of artificial intelligence is reflected in three interrelated aspects: exploration, application, and market transformation. Powerful computing power, massive data, and highly interconnected network infrastructure have significantly accelerated the exploration process of artificial intelligence, lowered the research threshold, promoted model training and algorithm optimization, and accelerated technological breakthroughs through international cooperation and knowledge sharing. At the same time, the development of technologies such as the Internet of Things, 5G communication, and mobile Internet has greatly expanded the application coverage of artificial intelligence, improved the accuracy and reliability of applications, supported the popularization of real-time artificial intelligence applications, and expanded the market space and user groups. The progress of technologies such as deep learning and reinforcement learning, combined with big data analysis, has not only spawned new business models and industrial ecosystems but also promoted the transformation and upgrading of traditional industries such as intelligent manufacturing and smart agriculture, thus improving production efficiency and product quality, forming a virtuous cycle, and further promoting the continuous development of artificial intelligence technology and the expansion of the market scale. This virtuous interaction of exploration, application, and market transformation constitutes the core driving force for the booming development of artificial intelligence in the era of multiple intelligences.

Zhang (2026) proposed a hybrid LSTM-GARCH model that integrates volatility factors from US financial markets [1]. Wang (2026) examined the application of computer science and technology in the big data context [2]. Ma (2025) developed a unified framework for congestion diagnosis and dynamic mitigation in complex networks [3]. Jin (2025) optimized order allocation algorithms for industrial internet platforms [4]. Miao (2026) applied big data technologies for enhanced network security analysis [5]. Junxi et al. (2024) proposed a graph convolutional network based on matrix factorization (GCN-MF) for recommendation systems [6]. Hu et al. (2024) explored multiscale deep neural networks for text sentiment analysis, unveiling new directions in this field [7]. Zi and Deng

(2025) jointly modeled medical images and clinical text for early diabetes risk detection [8]. Gao (2025) investigated intelligent supply chain collaboration and operational efficiency improvement for industrial electrical enterprises [9]. Liu (2025) studied GPU parallel computing for image processing [10]. Lu et al. (2025) employed a Faster R-CNN model for flame detection [11]. Liu (2025) systematically evaluated deep learning architectures for plant image classification [12]. Shen et al. (2025) applied the whale optimization algorithm to financial payment fraud detection [13]. Sun (2025) addressed accessibility challenges and solutions in designing inclusive digital interfaces [14]. Zhou (2025) designed a digital precision distribution strategy based on collaborative filtering for social media content on private domain platforms in the automotive industry [15]. Wang et al. (2026) developed QA-ReID, a quality-aware query-adaptive convolution leveraging fused global and structural cues for clothes-changing re-identification [16]. Li et al. (2026) presented MFT, a memory-aware fine-tuning of SAM2 for efficient long-sequence video object segmentation [17]. Yuan et al. (2026) proposed TA-Mem, a tool-augmented autonomous memory retrieval method for large language models in long-term conversational QA [18]. Shan et al. (2025) rethought wine tasting for Chinese consumers using a service design approach enhanced by multimodal personalization [19]. Peng et al. (2025) exploited aggregation and segregation of representations for domain adaptive human pose estimation [20]. Finally, Zheng et al. (2025) introduced Diffmesh, a motion-aware diffusion framework for human mesh recovery from videos [21].

3. MAIN RESEARCH DIRECTIONS OF ARTIFICIAL INTELLIGENCE IN THE ERA OF MULTI-INTELLIGENCE

3.1 Intelligent Simulation

To accelerate the research and development as well as optimization of artificial intelligence algorithms, it is crucial to build an efficient AI instruction set simulator. This simulator needs to provide a convenient and user-friendly external configuration interface for developers to set parameters and make calls. Its core function is to accurately simulate the SIMT (Single Instruction Multiple Threads) architecture, including simulating the address space and memory management mechanism of the multi-threaded structure and implementing the execution of high-density parallel instruction streams. The simulator must be able to completely simulate all instructions in the AI instruction set and strictly verify the correctness of the execution results of each instruction to ensure the reliability of the simulation results. In addition, for convenient debugging, the simulator also needs to provide a mechanism to view the execution information of the instruction stream inside any thread (as shown in Figure 1) so that developers can quickly locate and solve problems.

3.2 Swarm Intelligence

The research on swarm intelligence is inspired by the collective behaviors in nature, such as the coordinated flight of bird flocks, the schooling of fish, and the foraging path planning of ant colonies. The individuals in these groups usually have relatively simple behavioral rules, but through local interactions and information sharing, complex global behaviors can emerge, enabling them to solve problems efficiently. The core of swarm intelligence lies in leveraging the collective wisdom of a large number of simple individuals to achieve global optimization, and its efficiency often far exceeds that of a single individual.

The main research directions include the Particle Swarm Optimization (PSO) algorithm and the Ant Colony Optimization (ACO) algorithm. The PSO algorithm mimics the foraging behavior of bird flocks and iteratively finds the global optimal solution by updating the velocity and position information among individuals. It has been widely applied in engineering optimization, data analysis, and machine learning fields, such as optimizing power system scheduling, designing efficient aeroengines, and training hyperparameters of deep learning models. In recent years, improved PSO algorithms, such as adaptive PSO and multi-swarm PSO, have emerged continuously, further enhancing the efficiency and robustness of the algorithm.

The Ant Colony Optimization (ACO) algorithm, on the other hand, mimics the process of ant colonies searching for food and finally finds the optimal path through the accumulation and update of pheromones. The ACO algorithm demonstrates strong advantages in path planning, vehicle scheduling, and network routing. For example, it is applied to urban traffic flow optimization, logistics distribution path planning, and intrusion detection in network security. Currently, the research focus of the ACO algorithm is on solving the problem of being easily trapped in local optimal solutions and improving the convergence speed and adaptability of the algorithm.

3.3 Computational Intelligence

Computational intelligence aims to simulate certain aspects of human intelligence, such as learning, reasoning, and decision-making abilities, and apply them to solve practical problems. It does not attempt to completely replicate the human brain but rather borrows certain characteristics of human intelligence to build computational models that can handle complex problems.

The main research directions include fuzzy logic and evolutionary computation. Fuzzy logic deals with uncertainty and fuzzy information. Different from traditional binary logic, it allows variables to take values between 0 and 1, thus better simulating the ambiguity and uncertainty in the real world. Fuzzy logic is widely used in control systems, such as the fuzzy control of household appliances like washing machines and air conditioners, as well as in fields such as medical diagnosis and pattern recognition. In recent years, the combination of fuzzy logic and deep learning has become a research hotspot, such as the application of fuzzy neural networks.

3.4 Brain-inspired Intelligence

The main research directions of brain-inspired intelligence include neuromorphic computing, brain-computer interfaces, and cognitive architectures. Brain-computer interface technology connects the human brain and computers, enabling direct interaction between the human brain and external devices. It can be used to assist disabled people in restoring functions, such as controlling prosthetics or orthotics, or to enhance human capabilities, such as improving cognitive abilities or performing more precise operations. Brain-computer interface technology is currently in a stage of rapid development, and its application scenarios are constantly expanding.

Cognitive architecture research simulates the cognitive processes of the human brain to build intelligent systems that can learn, reason, plan, and make decisions. It attempts to construct a complete framework for intelligent systems, rather than simply focusing on individual cognitive functions. The research on cognitive architecture is of great guiding significance for the overall development of artificial intelligence. The current research focus is on building more general and robust cognitive architectures and applying them to a wider range of fields.

4. OPTIMIZE THE SCIENTIFIC AND TECHNOLOGICAL INNOVATION SYSTEM OF ARTIFICIAL INTELLIGENCE

4.1 Fundamental Theory Innovation

Most current artificial intelligence is specialized artificial intelligence, which can only perform well in specific tasks and lacks generalization ability and autonomous learning ability. The goal of general artificial intelligence is to create intelligent systems that can learn, reason, and solve problems like humans. Achieving general artificial intelligence requires breakthroughs in multiple aspects, including: developing more powerful learning algorithms that can learn from small amounts of data and quickly adapt to new environments; building hybrid intelligent systems that can process multiple types of information (such as text, images, speech); designing intelligent agents that can perform autonomous planning and decision-making. This requires in-depth research on the basic theories of artificial intelligence, such as cognitive architectures, knowledge representation, and reasoning, and exploring new computational paradigms, such as spiking neural networks; at the same time, studying the learning mechanisms and information encoding methods between neurons, as shown in formula (1), which describes the change in the membrane potential of neurons. By modeling the dynamic changes in the membrane potential of neurons, the information processing mechanism of neurons can be understood and applied to the design of neuromorphic chips and the construction of neural network models.

To evaluate the performance of neuromorphic chips, the actual number of neurons supported by the chip can be determined by sending pulse inputs to all neurons to generate pulses and counting the total number of output pulse frames. This requires considering the specific components of neuromorphic algorithms (neurons and synapses) and the network structure of the chip. This method can effectively evaluate the scale and computing power of neuromorphic chips.

$$V_j(t) = V_j(t-1) + \sum_{i=1}^{N} A_i\,(t) \cdot W_{i,j} - \lambda_j \tag{1}$$

In the formula: $V_j(t)$ is the membrane potential of the j -th neuron at time t, N is the total number of axons, $A_i(t)$ is the pulse input of the i -th axon at time t, $W_{i,j}$ is the synaptic weight connecting the i -th axon and the j -th neuron, and λ_j is the leakage value of neuron j.

4.2 Core Technology Breakthrough

The rapid development in the field of artificial intelligence is particularly reflected in the remarkable breakthroughs of large-scale pre-trained models in areas such as natural language processing and image recognition. In recent years, this trend has profoundly changed the way of processing and understanding information. Natural language processing, as a core branch of artificial intelligence, its progress largely depends on the effective utilization of knowledge. The narrow sense of knowledge used in natural language processing can be divided into three categories: linguistic knowledge, common sense knowledge, and world knowledge. Linguistic knowledge, such as dictionaries and rule bases (e.g., WordNet), contains the structure and rules of the language itself, providing a basic framework for natural language understanding. Common sense knowledge is more complex, representing the common sense information of general human cognition. This type of knowledge is usually difficult to directly mine from text data and requires artificial construction and maintenance with the help of large knowledge bases such as the Cyc project (Table 1). In contrast, world knowledge is easier to extract from text data.

At the algorithm level, early natural language processing mainly relied on shallow machine learning methods, such as support vector machines (SVM) and conditional random fields (CRF). These methods required manual feature extraction, with a large workload and limited efficiency. The rise of deep learning has completely changed this situation. Models such as multi-layer perceptrons (MLP), recurrent neural networks (RNN), and convolutional neural networks (CNN) can automatically learn and generalize features, greatly improving the performance and generalization ability of the models. In addition, some algorithms specifically designed for natural language processing tasks, such as the CKY algorithm and the MST algorithm (Table 1), utilize linguistic knowledge to improve parsing efficiency and accuracy.

The quality and quantity of data are equally crucial. High-quality labeled data, such as the Penn Tree-Bank corpus obtained through expert annotation or crowdsourcing, can effectively train supervised learning models. However, the acquisition cost of labeled data is high and time-consuming. Therefore, a large amount of unlabeled data, such as the vast amount of text on the Internet and pseudo-data generated through data augmentation techniques, also become important training resources for pre-trained models. Pre-trained language models make full use of these unlabeled data, and through self-supervised learning, learn rich linguistic knowledge and world knowledge, and finally achieve excellent results in various downstream tasks.

Table 1: Three Types of Knowledge Sources in Natural Language Processing

Knowledge category	Subcategory	Features	For example
Narrow knowledge	Language knowledge	Dictionary, rule base	WordNet
	Common sense knowledge	It’s difficult to extract from the text	Cyc project
	World knowledge	Can be mined from the text	Knowledge Graph
Algorithm	Shallow machine learning	Artificial feature extraction	SVM, CRF
	Deep learning	Automatically summarize features	MLP, RNN, CNN
	NLP algorithm	Utilize language knowledge	CKY, MST
Data	Annotated	Expert annotation, crowdsourcing	宾州树库
	Unannotated	A large amount of raw corpus	Pre-trained language model
	Pseudo data	Approximate to the target task	Data augmentation

4.3 Technological Convergence Innovation

Achieve intelligent decision-making driven by data. Big data provides rich training data for AI algorithms, while AI offers powerful tools for the analysis and utilization of big data. The core of this convergence lies in building an efficient data processing and analysis framework that can extract valuable information from massive and heterogeneous data and use it for intelligent decision-making. For example, AI algorithms can process massive transaction data and user behavior data, such as stock trading records, credit card consumption records, loan application information, etc., and extract valuable patterns and information. These data cover multiple dimensions such as transaction time, transaction amount, transaction frequency, user geographical location, consumption preferences, etc. Through advanced machine learning algorithms, such as support vector machines, neural networks, and random forests, the system can identify abnormal transaction behaviors and predict potential market risks, such as credit default risks, market volatility risks, and fraud risks. To achieve the above goals, data preprocessing is required.

$$X_i = \frac{x_{i-1} - x_{i+1}}{2\Delta t} \tag{2}$$

$$\hat{X} = \frac{X_i - \bar{X}}{\sigma}, i = 1,2, \dots, N \tag{3}$$

$$\hat{X}_i = \frac{X_i - \min}{x_{\max} - x_{\min}}, i = 1,2, \dots, N \tag{4}$$

Equation (2) represents a central difference method for calculating the slope of each point in a data sequence X_i. Specifically, for a data sequence x_i, the approximate calculation of the slope of its i -th point is as follows, where: Δt represents the time interval. This method can effectively reflect the local change trend of the data, such as identifying short-term fluctuations in stock prices.

Equation (3) represents the normalization of data. In the equation, X represents the mean of the data, and σ represents the standard deviation of the data. The normalized data $\hat{X}$ has a zero mean and a unit variance, which eliminates the influence of the dimensional difference between different variables and facilitates the comparison and analysis of data with different dimensions, such as comparing stock prices with trading volumes.

Equation (4) represents the normalization of data, mapping the data into the $[0,1]$ interval, which is achieved through the formula, where: $x_{\min}$ and $x_{\max}$ respectively represent the minimum and maximum values of the data. Normalization is necessary in some machine learning algorithms, such as neural networks, because it can improve the convergence speed and stability of the algorithm. These preprocessing steps are crucial for improving the accuracy and stability of the model. Further research can explore more advanced data preprocessing methods, such as wavelet transform and principal component analysis, etc., to further improve the performance of the model.

These data preprocessing methods are the basis for the application of AI in the financial field, ensuring that the model can effectively learn and utilize data, thereby improving prediction accuracy and decision-making efficiency.

5. CONCLUSION

The era of multi-intelligence provides unprecedented opportunities for the development of artificial intelligence, while also bringing new challenges. This paper analyzes the impact of the era of multi-intelligence on artificial intelligence, explores its main research directions, and strategies for optimizing the technological innovation system of artificial intelligence. In the future, it is necessary to strengthen basic theoretical research, break through the bottleneck of core technologies, and promote technological integration and innovation in order to better drive the development of artificial intelligence technology. In addition, it is possible to further study how to improve the interpretability and robustness of artificial intelligence models, develop more general and self-learning intelligent systems, and address issues such as artificial intelligence ethics and security.

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