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Research on the Innovation Path of Cross-Domain Knowledge Fusion Driven by Artificial Intelligence

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Abstract: *Artificial intelligence technology reconstructs the logic of knowledge production and application. Cross-domain knowledge fusion has become the core support for solving complex system problems and breaking through cutting-edge innovations. The knowledge boundary of a single domain restricts innovation efficiency. With the capabilities of data processing, semantic understanding and pattern mining, artificial intelligence weakens domain segmentation and promotes the cross-scenario circulation of knowledge elements. Current fusion practices suffer from problems such as isolated knowledge graphs, rigid mechanisms and lagging updates. Facing technological evolution and industrial demands, it is necessary to take the construction of interactive knowledge graphs, the design of human-machine collaboration mechanisms and the construction of dynamic update closed loops as paths to form a stable and efficient cross-domain knowledge allocation system. This study provides theoretical references and practical frameworks for the interdisciplinary field of artificial intelligence and knowledge management.*

Keywords: *Artificial Intelligence; Cross-Domain Knowledge; Knowledge Fusion; Innovation Path; Knowledge Graph*

1. Introduction

Knowledge production presents the characteristics of specialization and fragmentation. Disciplinary division and industrial barriers reduce the efficiency of knowledge collaboration. Real-world problems are multi-attribute, multi-dimensional and multi-agent. Traditional knowledge organization methods are difficult to match the needs of solving complex scenarios. Artificial intelligence technology covers the whole chain of data perception, feature extraction, logical reasoning and decision optimization[1]. Technological penetration drives the transformation of knowledge forms from static storage to dynamic interaction, and from single attribution to cross-border sharing. Driven by artificial intelligence, cross-domain knowledge fusion realizes the effective docking of concepts, rules, models and data in different fields. The fusion process improves the density of knowledge utilization and expands the boundary of innovation possibilities[2].With the parallel development of digital economy and intelligent technology, the construction of national innovation system emphasizes cross-disciplinary, cross-industry and cross-regional collaboration. Academic research, industrial R&D and social governance all put forward higher requirements for cross-border knowledge integration. Existing studies mostly focus on technological application or single-domain fusion, lacking systematic path design. Some results have problems such as loose logic, redundant expression and similar models. Based on the characteristics of artificial intelligence technology, this paper analyzes the practical necessity of cross-domain knowledge fusion, sorts out the current situation and bottlenecks of practice, and constructs a implementable, iterative and expandable innovation path. The research follows strict academic norms, promotes discussion with clear judgments and logical reasoning, and provides support for the theoretical improvement and practical promotion of related fields.

2. The Necessity of Cross-Domain Knowledge Fusion Driven by Artificial Intelligence

2.1 Single-Domain Knowledge Can Hardly Solve Complex Problems

Real-world problems break through domain boundaries. Scenarios such as urban governance, disease prevention and control, intelligent manufacturing and climate simulation involve multiple variables. Single-domain knowledge only covers partial dimensions of problems, and fragmented knowledge leads to incomplete problem analysis and limited solutions. The complexity of engineering

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systems is increasing. Technological products integrate multi-disciplinary principles and various types of technologies, and it is difficult to complete the whole process of design, R&D and operation and maintenance relying on single-disciplinary knowledge. Social demands are upgraded to compound types[3]. User demands cover dimensions such as function, experience, safety and ethics, and single-domain knowledge cannot form a full-dimensional response. Knowledge islands reduce the efficiency of resource allocation. Different subjects hold heterogeneous knowledge, and the lack of docking channels leads to repeated investment and waste of resources. Solving complex problems requires multi-dimensional knowledge support, and single-domain knowledge systems have natural shortcomings. Cross-domain fusion has become a prerequisite for problem solving.

2.2 The Unique Advantages of AI in Breaking Domain Barriers

At the data level, multi-source heterogeneous data is cleaned, annotated and aligned to form a unified expression, creating conditions for knowledge fusion. Using natural language processing, entity linking, relation extraction and other technologies, we can complete cross-domain semantic alignment, standardize and transform professional terms, and weaken semantic barriers. Through deep learning and graph calculation method, it can dig the correlation and internal law of tacit knowledge between different fields. The model can also dynamically adjust the weight of knowledge elements and the combination method according to the changes of the scene, so as to improve the flexibility and timeliness of knowledge application. Technology will help decrease the cost of interdisciplinary collaboration, broke industry, promote the efficient flow of knowledge.

2.3 Innovation Competition Forces Cross-Border Knowledge Integration

Global competition for innovation is becoming increasingly fierce, and countries generally give priority to breakthroughs in cutting-edge technologies. The development of core technologies requires more and more interdisciplinary knowledge, and the long-term accumulation of a single field can not form a prominent competitive advantage. Industrial upgrading has promoted the deepening of cross-border integration, and many new business models and formats are the result of the cross-integration of knowledge in multiple fields. Under this background, the boundaries of traditional industries are accelerating their dissolution, and the core focus of enterprise competition gradually shifts to the ability to integrate knowledge. Enterprises that can achieve efficient and high-quality knowledge integration can effectively transform this ability into their core market competitiveness[4]. As innovation competition becomes increasingly fierce, the existence form of knowledge is being reshaped, and cross-border integration has shifted from a selectable development strategy to an inevitable requirement of the times.

3. Current Situation of Cross-Domain Knowledge Fusion Driven by Artificial Intelligence

3.1 Typical Application Fields and Initial Results

The medical and health field has realized multi-disciplinary data integration. Medical images, inspection indicators, genetic data and clinical guidelines are processed by artificial intelligence to assist disease diagnosis and treatment plan optimization, improving the implementation efficiency of precision medicine. The intelligent manufacturing field integrates knowledge of design, process, supply chain and operation and maintenance. Digital twin combined with knowledge graph improves production flexibility and equipment reliability. The smart city field integrates knowledge of transportation, energy, security and government affairs. Artificial intelligence schedules public resources in real time to improve operation efficiency and emergency response capacity. The financial service field integrates rules of credit, risk control, marketing and supervision. Intelligent models reduce risk levels and improve service reach efficiency. The education and scientific research field realizes the interconnection of documents, experiments, data and models. Artificial intelligence accelerates knowledge dissemination and scientific research output[5]. Practices in various fields prove that cross-domain fusion has clear application value.

3.2 Main Limitations of Existing Fusion Modes

Fusion is mainly local docking. Most projects focus on the linkage of two or a few domains of knowledge, lacking global coverage design, and the knowledge network is fragmented. Knowledge

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graphs are constructed independently. Graphs in different fields adopt heterogeneous standards, with inconsistent entity definitions, relation descriptions and hierarchical structures, making cross-graph invocation difficult. The mechanism is mainly technology-driven, with insufficient human-machine collaboration design. The experience and domain intuition of human experts are not fully embedded, limiting the reliability of model output. The fusion process lacks standardized processes. There are no unified specifications for data access, semantic conversion, knowledge verification and update maintenance, resulting in weak system compatibility and scalability. Application scenarios are bound to specific tasks, with low knowledge reuse rate. Cross-border fusion stays at shallow combination, lacking in-depth integration of logic and principles.

3.3 Challenges Remain in Data and Semantic Gaps

Data quality restricts fusion effects. Multi-domain data have format differences, sampling deviations, missing values and noise information, leading to high data preprocessing costs. Data ownership and security restrict circulation, and privacy protection requirements increase the difficulty of data sharing. Semantic understanding has domain differences. The same term has multiple meanings in different scenarios, and manual rules are difficult to cover all ambiguous situations[6]. Domain knowledge has implicit characteristics. Experience, skills and intuition are difficult to encode, and there are obstacles in transforming implicit knowledge into structured knowledge. The generalization ability of models is limited. Cross-domain knowledge migration is prone to deviation, and model stability decreases in small-sample scenarios. Knowledge update lags behind real-world changes, and static fusion systems cannot adapt to dynamic environments. Data and semantic gaps exist for a long time, and cross-domain knowledge fusion still needs dual breakthroughs in technology and mechanism.

3.4 Shortages in Professional Talent Supply and Cross-boundary Competencies

The effective integration of interdisciplinary knowledge cannot be achieved without highly skilled professionals who possess both solid technical capabilities and in-depth knowledge in specific fields. However, people in the field of artificial intelligence generally have the problem of insufficient industry cognition, and professionals in various industries lack the practical application ability of intelligent tools, which makes it difficult for the two groups to carry out collaborative work smoothly[7]. At present, the talent training still follows the traditional mode of a single discipline, and the curriculum system and capacity construction are mostly limited to the independent discipline category, and the attention to the cultivation of cross-border integration thinking is still insufficient. In the process of knowledge integration, practitioners need to undertake multiple and complex tasks such as terminology conversion, logical alignment and achievement verification, but the current talent team generally does not have the corresponding comprehensive literacy. As the flow of talents has been limited for a long time, the talent exchange mechanism between scientific research institutions and enterprises is still not perfect, which seriously restricts the implementation of interdisciplinary knowledge integration mode.

4. Innovation Path of Cross-Domain Knowledge Fusion Driven by Artificial Intelligence

4.1 Constructing Interactive Knowledge Graphs Across Domains

It wants to break the existing barriers against cross-domain knowledge integration and consolidate the development foundation of knowledge integration. It is necessary to establish a unified underlying standard system, clarify the entity naming and relationship type, as well as the attribute format and hierarchy structure, so as to meet the access requirements of different fields. We need to construct a centralized knowledge graph hub that supports registration, filing, indexing, retrieval, scheduling, management, and query invocation. While preserving the relative independence of domain-specific sub-graphs, the hub shall use standardization mechanisms to facilitate cross-domain interconnection. Meanwhile, cross-domain mapping tools can be developed to support tasks such as entity alignment, relationship matching, and rule transformation. We can improve data processing accuracy through automated mapping, augmented by manual verification. In addition, a knowledge quality assessment module can be embedded to dynamically monitor the completeness, consistency and timeliness of knowledge, and to identify and correct low-quality content in real time. On this basis, we can configure the visual interactive interface, so that users can conduct retrieval, editing and debugging of interdisciplinary knowledge, thus lowering the application threshold and improving the efficiency of

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problem feedback[8]. An interactive map will provide interdisciplinary knowledge fusion, provide solid foundation support. However, in order to build such a map, in addition to the above architecture and technical conditions, it is also necessary to carry out governance and collaborative work from the ecological level. Using a decentralized and interoperable architecture helps to avoid over-reliance on a central hub, which can become a performance bottleneck in large-scale deployment scenarios. The introduction of block chain and distributed ledger technology can realize the full traceability of data without compromising the independent rights of the subjects in various fields, and build a foundation of trust between the subjects of cross-field cooperation. Meanwhile, in the knowledge graph, a semantic reasoning layer driven by large language models or symbolic artificial intelligence can be embedded to achieve dynamic semantic reasoning between originally unrelated entities.

4.2 Designing a Human-Machine Collaborative Mechanism for Cross-Border Problem Solving

To enhance the quality of solving complex problems, one effective approach is to establish a clear authority and responsibility boundary-based human-machine collaboration mechanism. Under this mechanism, artificial intelligence is responsible for data processing, association mining, model reasoning and solution generation. Human experts undertake core tasks such as goal setting, ethical assessment, critical decision-making and result verification. To achieve this goal, a two-way interaction channel needs to be established. Through this channel, human experts can implant constraints and prior knowledge into the model, and the model can also provide intermediate results and explainability information to the users. Additionally, a multi-expert collaboration module can be set up to gather professionals from various fields, forming a distributed decision-making team, and integrating the opinions of multiple experts through algorithms to output stable and unified decision conclusions. At the same time, an iterative optimization process can be introduced[9]. After the initial solution is verified, the results will be returned to the system, which will dynamically adjust the knowledge weights and model parameters. Through multiple rounds of iterative cycles, the reliability of the problem solution will be gradually improved. Meanwhile, a risk control mechanism can be embedded, conducting safety, ethical and compliance reviews for cross-domain decisions, thereby ensuring the overall operation mechanism, maintaining a reasonable balance between operational efficiency and stability.

4.3 Establishing a Dynamic Feedback Closed Loop for Knowledge Update

It can be composed of three main modules. The first is to deploy real-time sensing terminals to collect business data, user behaviors, environmental changes, and expert annotation information, ensuring the update of the system and obtaining continuous and stable data supply. The second is to build an incremental update engine, which is used to identify new knowledge, relationships and rule entries, and complete local updates at the lowest operating cost, avoiding the overall reconstruction of the system. The third is to establish an effectiveness verification mechanism, conducting sampling tests and cross-validation on the new knowledge[10]. Qualified content is included in the formal database, while unqualified content is returned for revision. Before the new knowledge is officially launched into the business system, it is necessary to simulate its interaction with the existing knowledge to detect potential side effects and sudden abnormal behaviors. At the same time, rules for cleaning outdated knowledge can be formulated, based on indicators such as timeliness, usage frequency, and impact scope, and setting a determination threshold. For knowledge that exceeds the standard, it will be archived or cleared. We enable external access interfaces to display relevant research results, industry standards, and policy documents. This closed-loop operation mode can effectively ensure the timeliness of the knowledge system. Relying on dynamic iterative updates, it can continuously maintain the long-term stable operation of cross-domain integration[11].

4.4 Establish a Compound Talent Cultivation and Competency Support System

It is suggested that universities add interdisciplinary majors and cross-disciplinary courses, integrating artificial intelligence tools with professional knowledge in various fields into a unified talent cultivation system. To strengthen students' ability to solve complex interdisciplinary problems, instructional approaches such as case-based teaching and project-based training should be enhanced, and cross-disciplinary competency certification standards should be established. Assessment indicators are set up for key capabilities such as knowledge transformation, model application, integration design and effectiveness verification, and the certification results are used as the reference basis for talent evaluation and project access. Build a platform for collaborative education and research and teaching. Enterprises and scientific research institutions can open real application scenarios and jointly build

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talent training and practical training bases. We will promote two-way flow of talents, and encourage professionals to participate in cross-disciplinary work through part-time work, employment and project cooperation[12]. To guide scientific research teams toward cross-disciplinary exploration, relevant departments should optimize the incentive mechanism by incorporating interdisciplinary integration achievements into the professional title evaluation system. Additionally, they may establish special incentives in project applications and performance assessment indicators. We will build a shared learning platform and carry out systematic training centering on the integration of domain knowledge and intelligent technology. We aim to improve the talent development system and enhance the professional competencies of all participants in knowledge integration, and to facilitate the effective implementation of relevant development pathways, thereby providing sustained talent support and human resource guarantees for the industry's advancement.

5. Conclusion

Artificial intelligence promotes the transformation of knowledge production methods and organizational forms. Cross-domain knowledge fusion has irreplaceable value in responding to complex problems and innovation competition. Single-domain knowledge systems have boundary constraints. Artificial intelligence weakens domain segmentation with data, semantic and reasoning capabilities. Current fusion practices have achieved partial results, but also face problems such as structural isolation, single mechanism and lagging updates. Constructing interactive knowledge graphs across domains, designing human-machine collaborative problem-solving mechanisms and establishing dynamic feedback update closed loops can form a systematic innovation path. Future research can focus on standard systems, security mechanisms, ethical norms, quantitative evaluation and other directions. The in-depth integration of artificial intelligence and cross-domain knowledge fusion will push knowledge innovation into a new stage.

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