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Introducing Neuro-Symbolic Artificial Intelligence to Humanities and Social Sciences: Why Is It Possible and What Can Be Done?

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***Abstract* – With the support of artificial intelligence (AI), the smart applications in all walks of life have brought great changes to human society. Not only being concerned, analysed and criticized by scholars from Humanities and social sciences, AI also plays an important role in empirical research methods, thus facilitating the transformation of research paradigms in these fields. At present, neuro-symbolic AI, as a new product of the integration of two major factions in the field of artificial intelligence - connectionism and symbolism, has high application value in studying and solving the humanistic and social problems involving massive data due to its learning capability of perceiving the environment as well as reasoning capability of manipulating symbols. The introduction of neuro-symbolic AI is also of great significance for the development of emerging interdisciplinary fields such as digital humanities and computational social sciences. This paper aims to clarify the connections between neuro-symbolic AI and Humanities and social sciences, summarize the latest developing trends and representative applications, and explore a feasible path for the expansion of pluralistic methodologies in Humanities and social sciences to adapt to the age of big data.**

***Keywords* – Neuro-symbolic AI, digital humanities, computational social sciences, pluralistic methodology, research paradigm.**

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1. Introduction

To date, artificial intelligence (AI) has long been concerned by researchers from humanities and social sciences as a study subject. The societal issues of consciousness, ethics, privacy and law relating to AI applications have been widely discussed based on the fact that AI technology is constantly infiltrating into various fields. On the other hand, the studies in Humanities and social sciences are also greatly influenced by AI-related tools which contributes to the transformation of their research paradigms. Currently, a new AI method called neuro-symbolic AI has begun to appear in the empirical studies in the fields such as pedagogy, management, art and psychology, showing high applicability and performance. However, a systematic review of such method applied in humanities and social sciences is insufficient to demonstrate its value and potential especially for those researchers not from areas of computer science. Gefen et al. [1] had made a good beginning recently, but this study along with other previous published reviews provide little discussions on introducing the neuro-symbolic AI into humanities and social sciences regarding two questions: why is it possible and what can be done? Based on these considerations, this paper attempts to answer these questions based on a thorough literature review. The structure of this paper includes the following three aspects: 1) a brief introduction of the history, current situation and prospect of neuro-symbolic AI; 2) an in-depth analysis on the contributing factors and conditions for neuro-symbolic AI to be needed and 3) a detailed summary of the state-of-art of neuro-symbolic AI applications in academic community. The findings and conclusions can be helpful for the researchers to embrace pluralistic research methodologies in humanities and social sciences in the era of big data.

2. What is Neuro-Symbolic AI?

Strictly speaking, neuro-symbolic AI is not a brand-new AI. It is the product of two divergent technical camps, symbolism and connectionism, developing towards unity. Literally, "neuro" refers to artificial neural networks (ANNs) while "symbolic" refers to the concepts, knowledge and logic rules constructed by human beings. Since computer scientists began to create thinking machines in the early 1950s, the development of AI can be summarized into two paths: symbolism and connectionism. Symbolists advocate that the machine can manipulate, understand and reason symbols by constructing a set of internal logical rules and background knowledge, so as to understand the objective world and solve problems. This kind of AI imitates the process of abstract thinking in the human brain, and uses symbols and corresponding manipulation rules to represent and apply knowledge. Expert system, which is based on past knowledge and experience to assist human beings to solve new problems, is a typical symbolic AI. As for connectionists, they insisted on direct training of a neural network based on a large number of labelled data, so that the machine can learn unknown patterns from the data or perceive specific objects from the environment. The learning and perception function of such machine comes from the signal transmissions in the parallel interconnected network composed of a series of adaptive units. The network will adjust the strength of the connection between units according to input data to achieve machine learning, which roughly simulates the interaction between biological nervous system and the real world. Deep learning, a neural network model having multiple layers and multiple parameters, is a representative application of connectionism AI [2].

In the past decade, deep learning has made breakthroughs in many areas such as natural language processing, image recognition and social networks, while the development of symbolic AI is hindered by poor performance of dealing with abnormal, unstructured data or noisy scenes. Many connectionists thus believe that symbolic AI will be eventually replaced. However, the current deep learning technology is not as perfect as people expect. As the problems and data encountered in practice become more and more complex, ANNs has gradually presented several disadvantages, i.e., poor interpretability (results are difficult to be clearly explained and are prone to overfitting problems), weak expandability (lack of generalization capability in the face of exceeding the distribution scope of machine training) and insufficient simplicity (requiring a large number of training samples and model parameters). In contrast, symbolic AI, although lacking the general learning ability of the former, can perfectly define and introduce existing empirical rules and structured knowledge with transparent computing process and explainable results. As Gary Marcus summed up, the current bumping wall of connectionism AI has once again attracted the attention of academic and industrial circles to symbolic AI, which was originally ignored; this time, however, it is no longer a dispute of substitution. Instead, they learn from each other and complement each other's advantages. Hence, machine will have both capabilities of knowledge-driven understanding and data-driven learning [3]. As a result, neuro-symbolic AI came into being, and more and more appeared in the branches of computer science and other fields of science and engineering.

The birth of neuro-symbolic AI, which integrates neural network and symbolic reasoning system, is not a coincidence. Its inevitability stems from a development path of imitating human beings of AI technologies. On one hand, human thinking is the synthesis of deductive thinking and inductive thinking, and the reasoning process is usually compatible with these two modes of thinking. The mechanism of symbolic AI is similar to the deductive reasoning mode, that is, the mode that the conclusion is obtained from the premise and inference rules. The mechanism of neural AI is similar to the inductive reasoning mode, which induces or analogizes from the data that already has a certain law. Neuro-symbolic AI is the result of imitating the process of human thinking, which integrates the basic mechanisms of two modes of thinking [4]. On the other hand, current biological evidence shows that the cognitive intelligence of higher animals has an integrated architecture. The most typical example is the intellectual continuum of human being that is based on a mixture of low-level and high-level mechanisms [5]. The low-level mechanism refers to the reflex nervous system, which is a simple neural network with predefined conditioned reflex mechanism. It provides a basic operation pattern for humans in terms of built-in goals and behavioural response, so as to ensure that people can respond immediately to emergencies. At the high end of the intelligent continuum is the prefrontal lobe of the human brain, which can not only deal with simple associations, but also have the functionality to deal with complex symbolic relationships, such as understanding and using language [6]. Generally speaking, it is the existence of the integrated architecture of human cognitive intelligence that makes neuro-symbolic AI possible to appear. The neural part and the symbolic part of the AI system correspond to the low-level and high-level of the human intelligence, respectively.

At present, various neuro-symbolic AI systems with diverse features and terminologies have been applied. Henry Kautz [7] introduced a taxonomy for current neuro-symbolic AI applications in his AAAI 2020 report. He made a systematic summary of the neuro-symbolic AI from the perspective of computer science, and believed that in the AI systems with integrated architecture can be categorized into five types, as shown in Table 1. Type 1 can be treated as standard neural AI, only its input and output data are composed of interpretable symbols (such as text in

Table 1. Kautz's taxonomy of neuro-symbolic AI

No.	Type	Basic feature
1	symbolic Neuro symbolic	The input and output of neural network are symbolic knowledge
2	Symbolic[Neuro]	Symbolic reasoning system with built-in neural network
3	Neuro → Symbolic	The output of neural network is used as the input of symbolic reasoning system
4	Neuro∪compile[Symbolic]	Symbolic knowledge is compiled into the training process of neural network
5	Neuro[Symbolic]	Neural network computing engine with built-in symbolic reasoning

language translation or question answering programs), which is essentially an extension of standard deep learning. Type 2 is a hybrid system with a core neural network coupled by a symbolic problem solver. Neural network is integrated within the symbolic problem solver as a pattern recognition subroutine. In type 3 system, the neural network forms a cascade relationship with a symbolic system through its input and output, and solves the sub-problems in complex tasks in turn. Type 4 system displays a deeper coupling relation between neural and symbolic approaches, including three cases: 1) symbolic knowledge is compiled into the training set (vectorized data) of neural network for training operations; 2) symbolic knowledge is transformed into initial architecture and weight set of neural network, or logical neural networks are constructed to make the network units correspond to the elements of logical formulas one by one; 3) the symbolic knowledge is mapped to an embedding vector, which acts as the constraint of the neural network loss function [8]. Finally, type 5 refers to a fully-integrated system that can carry out true symbolic reasoning within a deep neural network engine. In practice, type 5 neuro-symbolic AI should possess five merits: it can easily handle the pattern recognition problems that the mainstream connectionist AI is good at; it is able to flexibly adapt to noisy data; the calculation process and results are easy to understand, explain and evaluate; it can easily manipulate symbols for reasoning tasks, and can seamlessly access knowledge systems and empirical rules [9].

In Kautz's taxonomy, type 1-4 categories are a summary of the existing neuro-symbolic AI systems, while type 5 is a practical prediction based on the state-of-art of AI. Kautz's taxonomy could be helpful for beginners to distinguish the basic characteristics and capabilities of neuro-symbolic AI systems, and then facilitates the application of neuro-symbolic AI in other emerging fields, especially those in humanities and social science.

3. Why is it Possible for Neuro-Symbolic AI to be Applied in Humanities and Social Sciences?

The central themes of humanities and social science is human and human society, which cover the pattern, origin and evolution of human behavior, spiritual and cultural activities and social phenomena from ancient times to the present. Due to close relations between human and society, anthropological phenomena such as the creation of art and the formation of belief are impossible to avoid the influence of the social environment in which they exist. Meanwhile, social phenomena such as the immigrations and religions can't be separated from the subjective choice of social individuals. Such interconnections of research objects of humanities and social science showed that these two fields are internally bonded, of which the knowledge and methods are also closely linked. For this reason, humanities and social science are often put together, to be discussed. This paper focuses on the intersection of connotation and extension of humanities and social science and the commonness of research topics, that is, the human and social problems that reflect human's subjectivity and interactive activities. For convenience, the two disciplines are regarded as a whole field, in which the reasons and contributing conditions of application of neuro-symbolic AI are discussed.

Nowadays, the rapid innovation of information technology is strongly changing the social environment and historical process of human beings, and the scopes of humanities and social science are constantly expanding. Massive digital texts, audio and images from the Internet, social media and electronic literature have greatly enriched the research materials of humanities and social science, so that they are no longer limited to the materials with physical media. Technologies such as blockchain, cloud computing and virtual reality have further expanded the research horizon and scene of humanities and social science, transcended the field of real existence and showed a new information world [10]. The popularization and application of big data and its related information technology have made the boundaries of humanities, social sciences and natural sciences more blurred, and the corresponding research has become more and more specific, refined and comprehensive. Therefore, with the help of information technology, the scientific empirical methods have widely infiltrated into the fields of humanities and social sciences and developed into a research paradigm called digital empirical approach, shifting the way these fields process, analyze and display data. As pointed out by Mi and Zhang [11], such paradigm that conforms to the current digitalization trend is the fourth research paradigm after qualitative research, quantitative research and simulation research, its typical feature is that research model and analysis are data-driven. Digital modeling is one of the most typical digital empirical methods, which is more in line with human's cognitive activities, compared to the traditional scientific modeling. It can directly establish the perceptual connection to the phenomenal world through the digital depiction of sensory information and language symbols. Throughout the development history of scientific modeling, from empirical model, conceptual model, logical model, mathematical model to data-driven model, this actually reflects the evolution and improvement of human's understanding of the real world. In a sense, the data-driven model (algorithm) has laid the cognitive foundation of today's AI technologies [12].

The performance of AI applications in specific fields or tasks has been far better than that of human beings. However, it can only follow instructions of human beings and is limited to a narrow area. In essence, it is a non-autonomous machine, which is also called weak AI [13]. In contrast, strong AI can truly independently act, make judgement and solve problems, which has not yet been achieved but has been taken as a goal and has been discussed for a long time in the academic community. Despite this, current AI is still regarded as a general-purpose technology. In other words, AI has developed into a revolutionary technology that has a far-reaching impact on human society. For researchers, AI is a powerful tool on which empirical research relies, especially in dealing with prediction or recognition tasks involving a large amount of data. Particularly, driven by the popularization of scientific positivism, numerous researchers in humanities and social sciences carried out empirical researches on humanistic and social phenomena and started to pay great attention on the data-driven quantitative research method associated with AI.

At present, emerging disciplines such as digital humanities and computational social sciences are the typical subdisciplines of humanities and social sciences, which result from integration of information technology and main disciplines. The role of "computing" has been emphasized in the process of knowledge discovery and representation through computing methods, and attributes of objectivity, accuracy and verifiability can be added to anthropological and sociological studies to cope with the shortcomings of traditional qualitative studies such as lack of quantitative basis and difficult to verify. In these emerging cross-disciplines, a large number of data-centric social problems have increased the researchers' demand for AI approaches. For example, using machine learning to achieve association semantic analysis and text mining to help researchers find new knowledge and new evidence of literature apart from those discovered by human [14]. However, human and social studies focus on human behavior, culture and societal activities, which involve a mixture of different and unique individual experiences and subjective factors and thus are more complex than the natural phenomena with only objectivity. In the face of such researches, relying merely on neural AI based on mathematics and statistics, the results may be accurate, but could be far from the actual situation, or even meaningless to the research object. Therefore, the research and practice of humanities and social sciences put forward higher requirements for AI tools: in addition to realizing efficient data mining and pattern learning, it can also accept human built professional knowledge and common sense, and achieve symbol manipulation and knowledge reasoning.

Symbolic AI represented by machine learning skips the step of establishing a special mathematical or physical model, and directly obtains the approximate solution or prediction of the problem by training a neural network composed of a large number of irregular parameters. Such method still has limitations in the transparency of the computing process and the interpretability of the results. Therefore, for researchers who attach importance to interpretation, reasoning and criticism, such a tool of "knowing but not knowing why" is obviously unacceptable. Fortunately, neuro-symbolic AI excel in symbolic reasoning, text understanding and image information, compared to neural AI. In a word, the reason why neuro-symbolic AI is possible to be introduced into the field of humanities and social sciences can be summarized in two aspects, 1) the urgent need for proper methodologies to cope with human and social issues in the era of big data; 2) the development of AI technology with integrated architectures and 3) the growing popularization and influence of positivism.

4. What can be Done With Neuro-Symbolic AI?

Neuro-symbolic AI can provide innovative tools for researchers in the field of humanities and social sciences, making quantitative and verifiable human and social research possible, which has been seen in the publication and exchange of international academic literature in many fields. According to the statistics of foreign literature published in the past ten years (Figure 1), there were only 3 studies focus on neuro-symbolic AI regarding science and engineering from 2012 to 2016, but they have increased rapidly since 2017, reaching 77 by 2021. In the field of humanities and social sciences, the annual average number of literatures not exceed one in 2012-2018, then increased significantly after 2019, reaching 6 in 2021. This shows that neuro-symbolic AI are popular in the field of AI, and has the universality across multiple fields. Especially in the field of humanities and social sciences, the published literature covers many disciplines, including management, journalism and communication, psychology, art and education. The number of literatures of management is the largest, accounting for nearly a half. Meanwhile, according to the publication time of the literature, the neuro-symbolic AI was first introduced in the field of management. As early as 2004, Corchado et al. [16] proposed a neuro-symbolic AI method for optimizing the internal organization management of enterprises. In the last decade, when neuro-symbolic AI has not yet become a popular method, Hatzilygeroudis and Prentzas [17,18] in the field of risk management took the lead in introducing such methods to improve the efficiency of risk assessment in the banking and insurance industries.

According to Kautz's taxonomy, type 2 neuro-symbolic AI applied in the field of humanities and social sciences has the largest number, 5, as listed in Table 2. Among them, four relevant literatures involved the field of management [17], [18], [19], [20], and one involved the field of Journalism and communication [21]. The method used in the literature adopted a symbolic reasoning system along with a neural network to improve the efficiency and accuracy of enterprise risk management and false news identification. Besides, there is a literature on the application of type 1 neuro-symbolic AI method in the fields of journalism and communication [22] and education [23]. Researchers mainly rely on deep neural networks to carry out pattern recognition, but the input calculation data is replaced by symbolic knowledge or knowledge map. Two literatures involving type 3 neuro-symbolic AI method have management research background [24], [25].

In addition, there are three literatures associated with type 4 AI, which involve the field of art [26] and pedagogy [27], [28]. It is worth noting that at present, only one literature from the field of psychology, and the applied methodology conform to the features of type 5 neuro-symbolic AI. In this study, Franklin et al. [29] proposed a comprehensive neural network model with symbolic reasoning elements, which can be used to quantitatively explain the occurrence mechanism of human cognitive process. According to the statistical results in Table 2, neuro-symbolic AI emerged early in management studies, which may be relevant to the essential features such disciplines and the prevalence of positivism [30]. Management research is usually very comprehensive and interdisciplinary, and researchers are keen on an objective and accurate theoretical framework. Therefore, these fields are often sensitive to the latest development of AI methods and are willing to try to apply them. Neuro-symbolic AI received much attention in the fields of psychology, pedagogy and Journalism and communication, which may be attributed to the major research paradigm in which the modelling and verification process require a large number of data (or samples). Obviously, the integrated architecture of neuro-symbolic AI is suitable for researchers in these disciplines to quantitatively explain and predict psychological, education or information propagation. As for the art, it has also begun to welcome neuro-symbolic AI, as exemplified by digital art. Artistic expression and creation are no longer human privileges. The potential of AI art creation is also being developed by scientists and artists in various countries.

The existing practice has proved that the advantages of AI methods are particularly prominent in text mining, image analysis and network analysis [1]. The answer to how neuro-symbolic AI can be used in the field of humanities and social sciences can be found from these three applications.

Compared with the statistical methods, AI text mining has greatly freed human's labor force from the burden of text retrieval, work classification, semantic annotation, information extraction, etc., and its quantitative results can not only give a new perspective for the interpretation of classics, but also provide new evidence for the identification of anonymous works [31]. Due to transparent analysis mechanism and powerful symbol manipulation, neuro-symbolic AI do well in mining of a tremendous number of text messages; thus, ensure the accuracy of text analysis with complex or missing semantics. Its computing process and results are easier to be verified and explained by scholars.

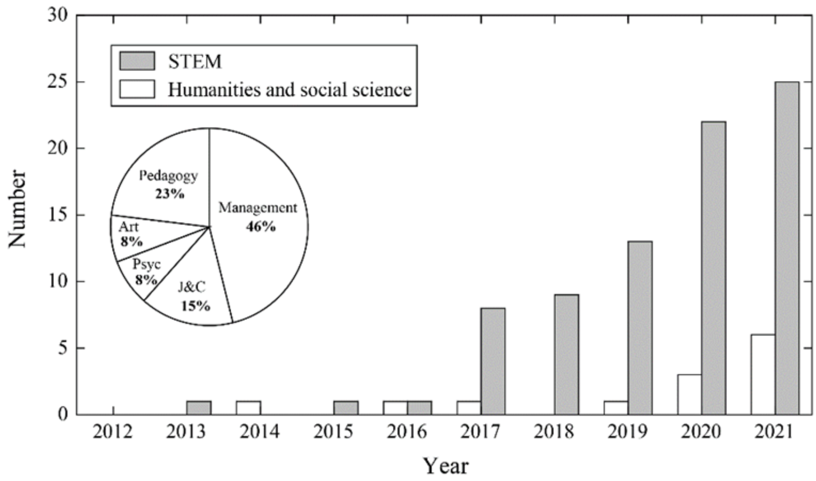

Figure 1. Literature publication of neuro symbolic AI (2012-2021). STEM refers to a wide range of fields relating to science, technology, engineering and mathematics; PSY refers to psychology and J&C refers to journalism & communication (Note that the science and engineering literature mainly refers to the published statistical data from Sarker et al. [15], and the data scope is limited to two parts, one part is from the papers published several top conferences regarding AI research from 2011 to 2020; another part was collected by author using Google Scholar)

Table 2. Statistics on 5 types of neuro symbolic AI in humanities and social sciences (2012-2021)

Subject	Type 1	Type 2	Type 3	Type 4	Type 5	Total
Management	0	4	2	0	0	6
Journalism & communication	1	1	0	0	0	2
Psychology	0	0	0	0	1	1
Art	0	0	0	1	0	1
Pedagogy	1	0	0	2	0	3
Total	2	5	2	3	1	13

AI also plays a great role in image analysis. For example, scholars of art history can determine the similarity between art works and identify the hidden patterns by virtue of image analysis methods, so as to trace the evolution of art style [32]. With the help of neuro-symbolic AI, the established empirical rules and symbol system can be used for the training of neural networks to significantly improve the performance of computer in image understanding and identification. Therefore, the image analysis method based on neuro-symbolic AI will provide more reliable technical support for the research fields of archaeology, art or history that pay attention to human creative art works.

In addition to analysis text, language and images, network analysis that is closely related to AI methods has made great progress in studying human and social problems in the form of network. Originated from graph theory, network analysis is particularly used to study complex and interrelated phenomena [33]. Currently, Internet, social networks, Internet of things and other network-style applications developed based on specific network protocols, which makes data with network format occupy an important position in the research materials of humanities and social sciences. In this context, as a supplement to the classical descriptive and inferential statistical methods, network analysis can play an important role in the study of social phenomena involving massive data with network structures. Generally, neuro-symbolic AI itself is a combination of a symbolic system in the form of network and an artificial neural network. Hence, neuro-symbolic AI is inherently applicable to network analysis of human and social phenomena. For example, in the field regarding library and information, knowledge graph (KG) has been applied to network analysis, knowledge management and visualization to reveal the inner relationship among data. In essence, KG is a semantic network, which typically results from combination of symbolic AI and neural AI. Owing to its excellent performance in semantic expression, data storage and reasoning, KG can provide practical solutions for the organization, analysis and expression of research data and materials in humanities and social sciences [9].

5. Conclusions

In terms of practical value, neuro-symbolic AI has been proved to be a successful tool for empirical research regarding humanities and social sciences within the era of big data. Despite this, the relationship between such smart tools and classic qualitative methods that attaches importance to text interpretation is not antagonistic or substitutive, but should be complementary and mutually supportive. Many anthropological and sociological problems are heterogeneous and involve subjective factors like human value, which are difficult to be observed and quantified in controllable and accurate experiments. The pursuit of accurate results by means of empirical methodologies alone may fail to truly understand human and social issues as a whole. In contrast, qualitative methods could capture the full picture of the problem and emphasize the comprehensive interactions between researchers and study materials without excluding different views. However, qualitative methods are not good at dealing with problems involving large and heterogeneous datasets. As human and social problems become more and more complex and variable, methodologies from humanities and social sciences have experienced diversified evolution to adapt the situation, as represented by development of post-positivism. The core spirit of post-positivism is that it is not wise to rely solely on scientific empirical methodology [34]. The latest neuro-symbolic AI deserves to be considered and utilized because it can provide an alternative to the traditional methods for interpretation and solving of new problems. Moreover, in terms of instrumental properties, tools based on neuro-symbolic AI can't replace human cognition and researchers in humanities and social sciences have the responsibility to achieve the final interpretation and verification and establish the technical path of study. In the foreseeable future, neuro-symbolic AI will be a smart tool only to help human beings to overcome difficulties in research and practice.

References

[1]. Gefen, A., Saint-Raymond, L., & Venturini, T. (2021). AI for Digital Humanities and Computational Social Sciences. In *Reflections on Artificial Intelligence for Humanity* (pp. 191-202). Springer, Cham.

[2]. Zhou, Z. (2016). *Machine learning*. Tsinghua University Press. (In Chinese).

[3]. Marcus, G. (2020). The next decade in ai: four steps towards robust artificial intelligence. *arXiv preprint arXiv:2002.06177*.

[4]. Wei, B. (2022). Analysis on the fusion path of semiotic and connectionist artificial intelligence. Research on Dialectics of nature, 38(2), 23-29. (In Chinese).

[5]. Kelley, T. D. (2003). Symbolic and sub-symbolic representations in computational models of human cognition: what can be learned from biology?. *Theory & Psychology*, *13*(6), 847-860.

[6]. Velik, R., Zucker, G., & Dietrich, D. (2011). Towards automation 2.0: a neurocognitive model for environment recognition, decision-making, and action execution. *EURASIP Journal on Embedded Systems*, *2011*, 1-11.

[7]. Kautz, H. (2022). The third AI summer: AAAI Robert S. Engelmore Memorial Lecture. *AI Magazine*, *43*(1), 93-104

[8]. Garcez, A. D. A., & Lamb, L. C. (2020). Neurosymbolic AI: the 3rd wave. *arXiv preprint arXiv:2012.05876*.

[9]. Wang, M., Wang, H., & Li, B. (2022). Overview of key technologies of the new generation knowledge map. *Computer research and development, 2022*, 1-18. (In Chinese).

[10]. Ma, F. (2018). Promote the deep integration of big data, artificial intelligence and other information technologies with Humanities and social science Research. *Evaluation and management, 2018*(2), 5. (In Chinese).

[11]. Mi, J., & Zhang, C. (2018). The fourth research paradigm: social science research transformation driven by big data. *Academia Bimestris, 2,* 11-27. (In Chinese).

[12]. Wang, G. (2020). Research on Humanities and social science in the digital world. *Tianjin Social Sciences, 5,* 4-12. (In Chinese).

[13]. Huang, X. (2018). Philosophical reflection on the upsurge of artificial intelligence. *Journal of Shanghai Normal University (PHILOSOPHY AND SOCIAL SCIENCES), 47*(4), 34-42. (In Chinese).

[14]. Huang, S. (2019). Humanistic computing and digital Humanism: concepts, problems, paradigms and key links. *Library construction, 5,* 68-78. (In Chinese).

[15]. Sarker, M. K., Zhou, L., Eberhart, A., & Hitzler, P. (2021). Neuro-symbolic artificial intelligence: Current trends. *arXiv preprint arXiv:2105.05330*.

[16]. Corchado, J. M., Borrajo, M. L., Pellicer, M. A., & Yáñez, J. C. (2004, July). Neuro-symbolic system for business internal control. In *Industrial conference on data mining* (pp. 1-10). Springer, Berlin, Heidelberg.

[17]. Hatzilygeroudis, I., & Prentzas, J. (2014). Fuzzy and neuro-symbolic approaches in personal credit scoring: Assessment of bank loan applicants. In *Innovations in Intelligent Machines-4* (pp. 319-339). Springer, Cham.

[18]. Prentzas, J., & Hatzilygeroudis, I. (2016). Assessment of life insurance applications: an approach integrating neuro-symbolic rule-based with case-based reasoning. *Expert Systems*, *33*(2), 145-160.

[19]. Sohrabi, S., Katz, M., Hassanzadeh, O., Udrea, O., Feblowitz, M. D., & Riabov, A. (2019). IBM scenario planning advisor: Plan recognition as AI planning in practice. *Ai Communications*, *32*(1), 1-13.

[20]. Golovko, V., Kroshchanka, A., Kovalev, M., Taberko, V., & Ivaniuk, D. (2020, February). Neuro-Symbolic Artificial Intelligence: Application for Control the Quality of Product Labeling. In *International Conference on Open Semantic Technologies for Intelligent Systems* (pp. 81-101). Springer, Cham.

[21]. Fitzpatrick, B., Liang, X., & Straub, J. (2021). Fake news and phishing detection using a machine learning trained expert system. *arXiv preprint arXiv:2108.08264*.

[22]. Koloski, B., Perdih, T. S., Robnik-Šikonja, M., Pollak, S., & Škrlj, B. (2022). Knowledge graph informed fake news classification via heterogeneous representation ensembles. *Neurocomputing*.

[23]. Grivokostopoulou, F., Perikos, I., & Hatzilygeroudis, I. (2017). Difficulty estimation of exercises on tree-based search algorithms using neuro-fuzzy and neuro-symbolic approaches. In *Advances in combining intelligent methods* (pp. 75-91). Springer, Cham.

[24]. Katz, M., Srinivas, K., Sohrabi, S., Feblowitz, M., Udrea, O., & Hassanzadeh, O. (2021). Scenario planning in the wild: A neuro-symbolic approach. *FinPlan 2021*, 15.

[25]. Preece, A. D., Braines, D., Cerutti, F., Furby, J., Hiley, L., Kaplan, L., ... & Xing, T. (2021, April). Coalition situational understanding via explainable neuro-symbolic reasoning and learning. In *Artificial Intelligence and Machine Learning for Multi-Domain Operations Applications III* (Vol. 11746, pp. 453-464). SPIE.

[26]. Aggarwal, G., & Parikh, D. (2020). Neuro-symbolic generative art: a preliminary study. *arXiv preprint arXiv:2007.02171*.

[27]. Shakya, A., Rus, V., & Venugopal, D. (2021). Student Strategy Prediction Using a Neuro-Symbolic Approach. *International Educational Data Mining Society*, 118-129.

[28]. Venugopal, D., Rus, V., & Shakya, A. (2021, June). Neuro-Symbolic Models: A Scalable, Explainable Framework for Strategy Discovery from Big Edu-Data. In *Proceedings of the 2nd Learner Data Institute Workshop in Conjunction with The 14th International Educational Data Mining Conference*.

[29]. Franklin, N. T., Norman, K. A., Ranganath, C., Zacks, J. M., & Gershman, S. J. (2020). Structured Event Memory: A neuro-symbolic model of event cognition. *Psychological Review*, *127*(3), 327-361.

[30]. Lv, L. (2015). Management theory, practice and concept from the perspective of post positivism. *Journal of management, 12*(4), 469-476. (In Chinese).

[31]. Michel, J. B., Shen, Y. K., Aiden, A. P., Veres, A., Gray, M. K., Google Books Team, ... & Aiden, E. L. (2011). Quantitative analysis of culture using millions of digitized books. *science*, *331*(6014), 176-182.

[32]. Joyeux-Prunel, B. (2019). Visual Contagions, the Art Historian, and the Digital Strategies to Work on Them. *Artl@ s Bulletin*, *8*(3), 8.

[33]. Borgatti, S. P., Mehra, A., Brass, D. J., & Labianca, G. (2009). Network analysis in the social sciences. *science*, *323*(5916), 892-895.

[34]. Wo, Y. (2005). Three related issues on quantitative and qualitative research of social sciences. *Academic research, 2005*(4), 41-47.