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Data and knowledge-driven intelligent investment cognitive reasoning model

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Short Paper

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Abstract

The modeling and analysis of information flow from various sources (e.g., analyst reports, news, and social media), and their impact on assets and investment decision-making, have drawn lots of attention. In this paper, we propose a new knowledge inference design framework that provides concrete prescriptions for developing systems capable of supporting knowledge-based investment decision-making. Our framework design incorporates the advantages of both knowledge graphs and symbolic reasoning engines through the concept of a dual system. On the other hand, it overcomes the weaknesses of traditional expert systems, saving time in the knowledge input process, reducing the introduction of errors, and achieving more comprehensive knowledge coverage to obtain better predictive performance. Moreover, our proposed design artifacts are of significant importance in addressing the issues of causality and interpretability in the literature.

Keywords: Design Science Research, Knowledge Graph, Expert System, Dual-system theory, Knowledge Inference

Introduction

As the financial markets evolve and information technology becomes increasingly pervasive, the complexity of investment decisions escalates. Given that companies are embedded within industry chains and economies at large, factors such as national economic policies, industry market environments, and corporate internal performance, now form the bedrock of investment decisions. Traditionally, investment decisions have hinged primarily on technical analysis and fundamental analysis. While fundamental analysis appraises the intrinsic value of listed companies by evaluating macroeconomic, industry, and company factors, technical analysis scrutinizes market behavior, largely predicated on stock market prices and trading volumes.

The incorporation of intelligent models in the decision-making process has been necessitated by the escalating complexity of investment decisions and the impact of factors such as individual knowledge limitations, cognitive biases, and information scarcity. These models not only assist investors in navigating the convoluted investment landscape but also contribute to an improvement in the success rate of investments. However, extant research has been primarily confined to the application of machine learning (Paiva et al., 2019), deep learning (Tellez Gaytan et al., 2022), and news text sentiment analysis (Li et al., 2020) to predict stock price trends and guide investment decisions. These methods, despite their efficiency in data processing, largely fall under Kahneman's *System 1* thinking, characterized by swift, automatic, perceptual intelligent processes. Moreover, these models typically fail to grasp deep semantic relations and can lack global thematic consistency, struggling with tasks requiring long-term planning or complex reasoning (Conway-Smith & West, 2022). Such methods, albeit their proven utility in certain contexts, are inherently flawed due to their inability to provide nuanced reasoning which is paramount in complex investment decisions.

A distinct lack of attention has been given to the potential of fundamental analysis, particularly in the context of employing intelligent models, like *symbolic reasoning engines*. These systems leverage expert knowledge for reasoning and decision-making (Chen et al., 2020), embodying the *System 2* thinking Kahneman characterized by explicit propositional knowledge and adherence to logical standards, enabling higher level rationality that allows for complex thinking, hypothetical reasoning, and long-range planning. Such systems can offer investors an explainable line of reasoning, enhancing their comprehension and evaluation of the stock's fundamental state and the company's overall situation.

Moreover, the significant yet often overlooked drawback to existing methods, such as deep learning, lies in their "black box" nature. The intricate network of interconnections and weighted computations within a deep neural network lends itself to a lack of interpretability and explanation. This becomes a formidable challenge in sectors where transparency and interpretability are essential, such as the financial sector where regulatory agencies demand explainable prediction models to ensure reliability. Hence, the opacity of these deep learning models obstructs effective regulatory scrutiny and control. Explainable AI (XAI) is crucial for fostering transparency and trust in AI systems by enabling humans to understand the underlying reasoning behind AI decisions. As Franklin (2022) rigorously elucidates, XAI holds significant promise for t errors caused by spurious correlations, promoting users' best interests and performance enhancements for specific tasks. Thus, the incorporation of XAI in the decision-making process may provide a viable solution to the transparency issues plaguing current intelligent models.

In recognizing these challenges, this paper aims to make substantive theoretical contributions by addressing the limitations of current models predominantly based on System 1 thinking. This paper proposes to incorporate a cognitive reasoning model into the intelligent decision-making process, which holds significant potential to mitigate existing deficiencies. To further elucidate this proposition, we draw on *Dual System Theory*, which posits the coexistence of intuitive (System 1) and analytical (System 2) thinking processes. This theory assists in bridging the gap between complex AI algorithms and human cognitive capabilities, hence promoting better understanding and acceptance of AI outcomes. It essentially represents a form of XAI, enhancing the transparency and interpretability of AI decision-making systems. By introducing an intelligent reasoning system design that utilized the idea of dual system theory to, integrates knowledge acquisition with expert rule-based reasoning, this research endeavors to empower decision-makers in enterprises with more precise and effective decision-making strategies, enhancing their practical applications.

Literature Review

Knowledge Graphs

Knowledge graph is a type of structured knowledge database that can represent entities, relationships, and properties in a computationally accessible format. It is a multi-dimensional graph that consists of nodes and edges, where each node represents an entity or a concept, and each edge represents a relationship between two entities. A knowledge graph can be used to integrate data from multiple sources and domain-specific knowledge to build up a comprehensive presentation of the hidden knowledge behind the data. By using knowledge graphs (KGs), we can gain an in-depth understanding of the underlying relationships and patterns in the data, which can lead to better decision-making and more effective solutions.

In recent years, there have been advancements in using deep learning techniques for knowledge representation, such as Knowledge Graph Embedding (KGE) (Wang et al., 2017). KGE is a way to encode the entities and relationships in a knowledge graph into low-dimensional vectors, which can be used for various tasks such as link prediction, entity classification, and relation extraction. KGE is a promising approach that has been shown to achieve state-of-the-art performance on various benchmarks, and it has the potential to improve the efficiency and effectiveness of knowledge graph-based applications.

The information in the financial market has strong real-time characteristics, and KGs can assist in dynamic predictions of the financial market, which is the reason why KGs are increasingly showing their value in the financial field. Currently, research on stock price prediction models in the financial field mainly uses the node2vec algorithm, which is based on knowledge graph embedding, to transform the graphical knowledge graph into a low-dimensional vector representation. The information in the knowledge graph is then imported into deep learning models in the form of feature vectors, helping to improve prediction accuracy. For example, Long et al. (2020) used a knowledge graph to mine stock correlations and employed a bidirectional long short-term memory network (BiLSTM) with attention and a convolutional neural network (CNN) for predicting future price trends based on market information and trading behavior features. Besides, Tao et al. (2022) converted the knowledge graph into market information of weighted stock correlation and used it as input data for a convolutional long short-term memory (ConvLSTM) network to deeply extract market features. Then, the stock price variation feature is obtained through a graph convolutional neural network (GCN) and integrated with the market information feature of the knowledge graph to predict the closing price of the stock.

Cognitive Reasoning System

To simulate the decision-making process of experts to solve complex problems in a certain field, Stanford University invented the first expert system Dendral in 1965. The main components of an expert system can be divided into a *knowledge base* and *inference engine*, and to achieve a better expert reasoning system, disciplines such as *knowledge representation, knowledge acquisition, data mining, fuzzy reasoning, artificial intelligence,* and others have been extended (Zhang, 2010).

To alleviate the problems of investment risk and lack of interpretability, Chen et al. (2020) proposed a stock selection framework based on ontological reasoning. This framework uses the Web Ontology Language (OWL) to represent the knowledge in fundamental analysis, and the domain knowledge it covers combines quantitative financial ratio analysis, qualitative news, and supply chain analysis, which can cover most of the information required for stock selection. In a case study, the results of this model were generally consistent with the research reports of major investment institutions, and the corresponding reasoning basis can be listed for the output results, verifying the effectiveness and practicality of the proposed method. In addition, Chen et al. (2020) also proposed a method for detecting financial statement fraud using ontology reasoning. The system uses an ontology model represented by OWL and Semantic Web Rule Language (SWRL) for reasoning, and the reasoning engine of the system generates detection results of accounting standard violations based on 35 rules provided by experts. Through the interpretable detection results of the system, external auditors and regulatory agencies can easily identify potential financial statement fraud behaviors of a company and understand the reasons behind them.

The field of artificial intelligence has, in recent times, experienced a growing interest in *symbolic reasoning engines*—an evolution of the expert system—as they demonstrate superior performance in areas demanding explicit knowledge representation, logical inference, and explainability. Meseguer (2018) introduces various symbolic methods that address important reasoning needs within rewriting logic, highlighting how they are supported by symbolic engines like Maude. The integration of symbolic reasoning with other AI techniques, such as probabilistic reasoning and deep learning, is further enhancing its capabilities and applicability. A symbolic reasoning engine has been applied in tasks such as Task-Oriented Dialogue Generation (Yang et al., 2022) and Chess Commentaries Generation (Lee et al., 2022), enabling the incorporation of logical and rule-based reasoning to enhance the quality and coherence of generated dialogues and commentaries.

Zhou (2017) has proposed an *Assertional Logic Theory*, which avoids semantics from being redundantly defined. Instead, the proposed theory allows the definition of special forms of assertions and the creation of additional objects. This extension of assertional logic supports the inclusion of multiple and nested assertions, simplifying the integration of new building blocks by formalizing them as syntax objects and specifying their interaction with the basic form of assertions. Ding et al. (2019) used this knowledge representation and reasoning theory to win the SAT math problem-solving competition.

Dual System Theory

In recent years, the development of artificial intelligence has gradually shifted its focus from perception to cognition. In the field of artificial intelligence, cognitive reasoning refers to applying human cognitive abilities and methods to computers, enabling them to reason and judge complex problems like humans. Traditional logical reasoning methods include rule-based reasoning, case-based reasoning, and model-based reasoning (Zhang, 2010), while the dual-system model has recently become a popular research topic in cognitive reasoning.

The dual-system model is a cognitive model proposed by Daniel Kahneman. This model divides the human brain's information processing pattern into two systems: the fast and intuitive System 1 and the slow and rational System 2 (Kannengiesser & Gero, 2019). System 1 is a fast and automatic thinking mode that does not require deliberate thinking or time and attention to make decisions but rather relies on existing experience and intuition for quick inference and judgment. In contrast, System 2 is a slow and conscious thinking mode that requires conscious analysis and comparison of information, deep thinking, and reasoning to make more complex decisions.

The utilization of the dual-system model in constructing cognitive graphs through multi-hop reasoning has garnered significant attention in the field of Artificial Intelligence. CogKR emulates the cognitive processes of the human brain, with System 1 expanding the subgraph by retrieving information from neighboring entities and edges, and System 2 conducting relationship reasoning on the expanded cognitive graph generated by System 1 (Du et al., 2023). CogQA comprises two modules: System 1, responsible for entity extraction and semantic encoding, and System 2, which performs reasoning on a cognitive graph constructed from extracted entities. These modules iteratively interact to identify answers, with System 2 guiding System 1 in selecting the next entity to consider. By incorporating human-like reasoning processes, CogQA aims to enhance the interpretability of entities and the completeness of the knowledge graph, thereby improving the quality of question-answering outcomes (Ding et al., 2019).

Research Gap

In the existing literature, the application of knowledge graphs (KGs) for stock market prediction has predominantly been situated within the framework of System 1 thinking. However, this approach has limitations as it often involves transforming the KGs into knowledge graph embeddings, which are low-dimensional vectors used as input features for deep learning models. Although this enables the utilization of neural networks for prediction tasks, it fails to fully leverage the rich information encoded within the knowledge graph itself. The knowledge base is reduced to a mere feature vector, neglecting its potential to provide explicit and interpretable reasoning for the predictions.

Another research gap lies in the limitations of traditional expert systems, where the knowledge repository is manually curated by human experts. This approach proves to be time-consuming, labor-intensive, and prone to limited scalability and adaptability. To address this gap, our proposed model takes advantage of KGs and assertional logic theory to design a method for building a knowledge repository for the expert system in a dynamic manner. By integrating a knowledge graph framework, we can capture and represent knowledge in a structured and interconnected manner, allowing for a more efficient and scalable expansion of the knowledge base.

Furthermore, a significant research gap exists in the lack of studies that explore the integration of KGs as System 1 and the symbolic reasoning engine as System 2. By combining the advantages of both systems, we aim to develop an AI system that is not only capable of processing and analyzing large amounts of data (System 1), but also exhibits reasoning capabilities, explanation generation, and adaptability to new knowledge (System 2). This integration will provide a holistic approach to AI systems, enabling a more comprehensive understanding of the underlying data and fostering explainability and transparency in decision-making processes.

By addressing these research gaps, our study contributes to the advancement of AI systems by proposing a novel approach that aligns knowledge graphs - a fundamental representation of knowledge - with a symbolic reasoning engine as a supplement to cognitive intelligence. This alignment ultimately leads to the development of a more robust and interpretable AI system.

System Design

Design Science Research Framework

In essence, design science research can be viewed as a process that involves three interconnected cycles of activities (Figure 1), namely the *Relevance Cycle*, *Rigor Cycle*, and *Central Design Cycle* (Hevner, 2007). Overall, design science research involves a continuous and cyclical process that draws upon existing knowledge, generates new knowledge, and applies it in a practical context. By integrating the Relevance, Rigor, and Design Cycles, researchers can develop innovative and effective solutions to real-world problems.

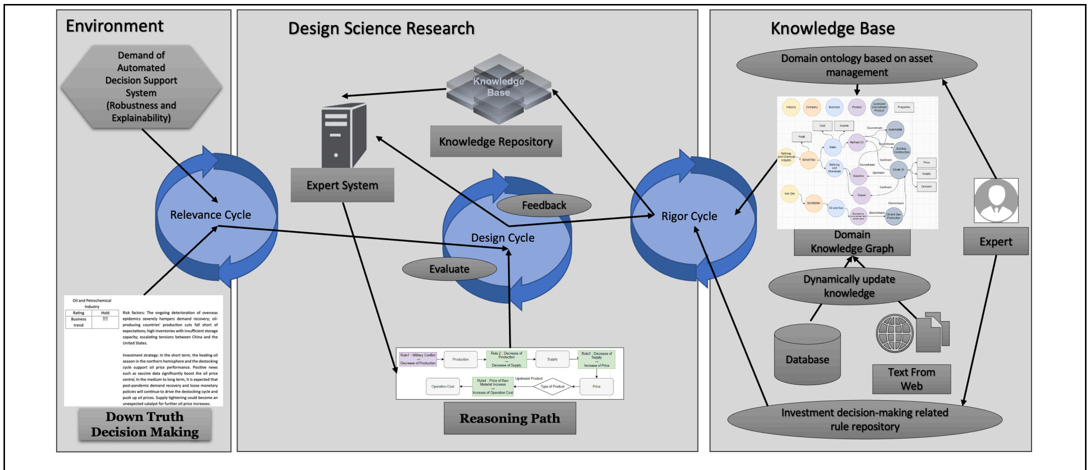

Figure 1. Proposed Model Illustration based on Hevner's Three Cycle View of Design Science Research

Relevance Cycle

The relevance Cycle takes into account the requirements and needs of the environment in which the research is conducted. This cycle ensures that the research is aligned with the practical needs of the real-world context and that any artifacts developed are tested in that context.

In the current era of big data and complex information, enterprise decision-makers need to make quick and accurate decisions. However, due to the large volume of data and high complexity, it is often difficult to respond quickly to market changes. Therefore, the business problem that our proposed framework aims to solve is to automatically acquire knowledge and use expert rules to construct an investment decision support system that can generate clear reasoning similar to industry research reports.

Articles of industry research reports are collected during the relevance cycle to act as down truth data for evaluation in the design cycle. The outputs of the proposed artifact are compared with the investment advice provided by the experts in these articles.

Rigor Cycle

The rigor Cycle involves the use of established theories, methods, and domain knowledge to ensure that the research is conducted rigorously and systematically. This cycle builds upon the existing knowledge base, incorporating new knowledge generated by the research to enhance it further.

As a project in collaboration with the financial institution, we obtain accurate domain knowledge by communicating with industry researchers from the institution, which lays the knowledge base for the proposed investment reasoning model. The domain knowledge studied in this project is the mining industry, where a company's business performance is influenced by various factors, including macroeconomic factors, supply and demand in the upstream and downstream industry chains, and the company's internal financial status. The industry researchers provided causal rules for the interrelationships among these factors and used them to construct an expert system to achieve automated reasoning and decision-making. These rules are the main components of the inference engine of a symbolic reasoning engine.

Secondly, the proposed model leverages the knowledge acquisition strength of the knowledge graph to overcome the weakness of the expert system. In traditional expert systems, domain experts are required to manually input all domain knowledge, which can be time-consuming and prone to errors. A knowledge graph provides a structured and comprehensive representation of industry knowledge, and our model transforms this knowledge into a format that is suitable for reasoning. This not only saves time and reduces errors in the knowledge input process but also allows for more comprehensive knowledge coverage, which can improve the accuracy and robustness of the model. Additionally, the knowledge graph can be updated and expanded over time, which enables the model to adapt to changes in the industry and remain relevant and effective in the long run. All the above-mentioned knowledge will be stored in the knowledge repository of the proposed artifact in the central design cycle. The rigor cycle will receive feedback from the evaluation module of the design cycle and modify the structure or content of the knowledge base to meet the expected output.

In our proposed framework, we apply Assertional Logic Theory (Zhou, 2017) to the financial asset management field, to establish a knowledge equation model for complex knowledge and implement the "model-acquisition-application" methodology.

Central Design Cycle

The Central Design Cycle, as the center of the whole system design, takes account of the element from the relevance cycle and rigor cycle to design a system with a purpose to fulfill relevant demand. It is where the research activity takes place in a more focused and iterative manner. This cycle involves the design, construction, and evaluation of artifacts and processes, which are then refined based on feedback received from testing in the relevant environment.

The proposed system framework design adopted the theory of dual-system concept, which integrates the strengths of knowledge graph and symbolic reasoning engine to provide users with more comprehensive and interpretable reasoning results. The knowledge base obtained from the rigor cycle is separated into two systems, namely System 1 (Knowledge Graph) and System 2 (Causal Rules), acting as the knowledge repository for the expert system to provide decision support outcomes.

Knowledge graph working as System 1 (Figure 2), a fast and intuitive system, can quickly obtain and mine various knowledge and information related to various entities and the relationships involved in the mining industry. By organizing this information into a graph structure, with entities as nodes and relationships as edges, it becomes easier to visualize and understand the complex interconnections between different parts of the industry. Then, the use of assertional logic provides a way to define the semantics of the information contained in the knowledge graph. Instead of defining the semantics of each piece of information separately, the semantics can be defined in terms of assertions, which are statements about the relationships between entities in the graph. By defining the semantics in this way, the system becomes more extensible, allowing new relationships to be defined as needed.

System 2 is a slow and conscious thinking mode that requires reasoning to make more complex decisions, the knowledge base obtained from System 1 can be further expanded to do a more complex causal inference. System 2 is mainly derived from the causal rules provided by the domain experts, who have a deep understanding of interrelationships among the properties of each entity in the domain area. Figure 3 has shown examples of causal rules given by domain experts and how these rules can be formed into a complete reasoning path. System 2 relied on the knowledge information obtained in System 1 to activate the rules node, while System 1 required System 2 to make cognitive reasoning which is reliable for decision-making.

The output of the symbolic reasoning engine is compared with the down-truth decision-making from real-world practitioners, to evaluate the performance of the expert system. To optimize the performance of the symbolic reasoning engine, the evaluation result in the central design cycle is feedbacked to the rigor cycle to finetune the structure of knowledge base.

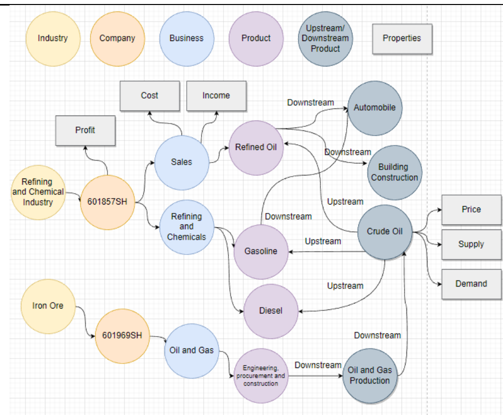

Figure 2. Illustration of Simplified Knowledge Graph in System 1

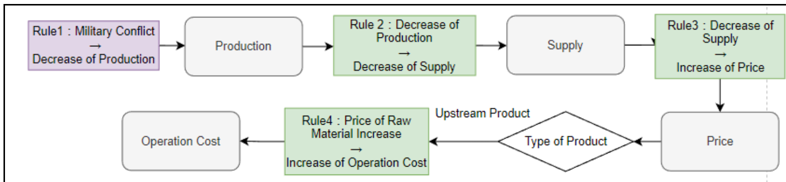

Figure 3. Illustration of Simplified Reasoning Path in System 2

Investment context

The proposed artifact aims to assist industry researchers in automatically generating industry research reports. The primary goal of this research is to develop a system that leverages text extraction from online sources and uses it as a trigger for an expert system to generate industry reports, with a specific focus on the mining industry. The innovative aspect of this model lies in its ability to rapidly and dynamically generate industry research reports, reducing the time and effort required by expert human researchers.

Procedure of result-generating process

Text Analysis and Pre-processing

The initial step involves web scraping of news articles related to the mining industry. The collected text is then subjected to natural language processing techniques, including GPT-3 and other similar tools. These techniques encompass tasks such as part-of-speech tagging, named entity recognition, and keyword extraction. By applying these techniques, the text data is transformed into a structured format that facilitates further analysis.

Event Extraction and Relation Building

The structured text data is then subjected to event extraction processes. Techniques like semantic role labeling are utilized to extract and summarize relevant information such as entities, events, and temporal aspects. This information is organized and used to construct an event relation graph, which represents the interconnections between different events and entities in the text.

Symbolic Reasoning Engine and Decision-making

The event relation graph serves as a trigger for the symbolic reasoning engine. This symbolic reasoning engine incorporates domain knowledge repositories and rules repositories to perform reasoning and decision-making processes. The main focus is to predict how specific events will impact macro factors of the industry as a whole, such as revenue, production, and profitability. By utilizing the event relation graph, the symbolic reasoning engine generates the framework structure and content points for the industry research reports.

Text Generation using GPT-3

Based on the generated framework structure and content points, GPT-3 is employed to generate the actual text of the industry research report. The results generated are based on the symbolic reasoning engine which can output a clear and transparent reasoning path, ensuring that the generated text adheres to industry standards and regulations, enabling accurate and real-time report generation.

Scenario Demonstration

A company, XYZ Mining Corp, wants to analyze the impact of recent events in the mining industry and generate a research report based on the findings. A large amount of text data from various news articles related to the mining industry are collected and it is concluded that a major conflict happened in region A. From the knowledge base provided by System 1, it is known that Region A is the major supply location of the raw material of product B. In the meantime, product B contributed to the major income of XYZ Mining Corp.

System 2 which consists of various rules will decide which rule node satisfied the above criteria. For example, in Figure 3, the symbolic reasoning engine will alert decision-makers about the potential risk of a drastic decrease in the supply of the raw material of product B, which may cause the increased operational cost of XYZ Mining Corp. The output result in Figure 3 will be utilized and fed into GPT-3 to produce the industry research report's actual text. The generated text complies with industry standards and regulations, ensuring the provision of precise and up-to-date information. The system upholds transparency by presenting a transparent reasoning pathway underlying the generated outcomes.

By following this procedure, the system automates the analysis of news articles related to the mining industry, extracts relevant events and information, applies reasoning and decision-making processes, and generates industry research reports using GPT-3. This enables XYZ Mining Corp to stay informed about the industry's developments and make data-driven decisions based on accurate and up-to-date information.

Conclusion

This paper proposes a framework for automatically acquiring knowledge and data to construct an investment decision support system that generates explainable results of reasoning paths similar to industry research reports. The proposed framework leverages the strengths of the knowledge graph and symbolic reasoning engine to overcome the limitations of traditional expert systems, where domain experts manually input all domain knowledge. The framework utilizes accurate domain knowledge obtained through collaboration with industry researchers in the mining industry, where a company's business performance is influenced by various factors such as macroeconomic factors, supply and demand in the upstream and downstream industry chains, and the company's internal financial status. The industry researchers provided causal rules for the interrelationships among these factors and used them to construct a symbolic reasoning engine for automated reasoning and decision-making. These rules are the main components of the inference engine of the symbolic reasoning engine.

The proposed framework also transforms the knowledge graph into a format that is suitable for reasoning. This approach saves time and reduces errors in the knowledge input process and allows for more comprehensive knowledge coverage, improving the accuracy and robustness of the model. Moreover, the knowledge graph can be updated and expanded over time, enabling the model to adapt to changes in the industry and remain relevant and effective in the long run.

This paper proposes incorporating a cognitive reasoning model based on Dual System Theory to address the limitations of current System 1-based models and enhance transparency, interpretability, and decision-making strategies in AI systems. The research aims to empower decision-makers with more effective strategies for practical applications.

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