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THINKING-LOOP: The Semantic Vector Driven Closed-Loop Model for Brain Computing

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ABSTRACT High complexity, meaning a model in which components interact in multiple ways and follow certain local rules, is a huge challenge for brain research. This paper presents a semantic vector-driven closed-loop model, namely THINKING-LOOP, for brain computing to improve the understanding and development of complex cognition. The proposed model is a three-layer fusion of data, information and knowledge with human intelligence, which exploits ontological knowledge modeling, rule-based reasoning and a human-computer interaction mechanism. The interaction and collaboration within the model depend on a pair of complementary schemes in a loop: the top-down scheme from the knowledge layer to the data layer that is used to search for stable cognitive patterns; and the bottom-up scheme from the data layer to the knowledge layer that is used to deeply analyze cognitive functions. As a key factor, human beings participate in the whole learning process of the model, which in turn assists human beings to make decisions. To verify the applicability of the present model in cognitive research, a series of fMRI experiments and analytic methods (e.g. statistical tests and network topology analysis) were conducted. The results show that the proposed model is able to take into account the characteristics of different types of brain patterns and cognitive functions, thereby achieving reasonable decision-making level.

INDEX TERMS Expert systems, human computer interaction, brain informatics, fMRI, data mining.

I. INTRODUCTION

Cognition is the most basic but complex process of human beings, which is an important topic of academic study in fields including psychology, neuroscience and artificial intelligence. In understanding cognitive aspects, we usually focus on their definitions and purposes from the perspective of theories and concepts, as well as their information processing and transformation mechanisms from the perspective of informatics. Obviously, this is one of the greatest research challenges today, and the challenge mainly comes from two aspects. From the perspective of brain informatics, the information processing and change mechanisms of human cognition are extremely complicated. For example, human cognitive activities are accompanied by complex physiological and chemical

changes, which implies many unique informatics paradigms and functional mechanisms. From the perspective of social psychology, the complex environment may cause a great disruption for the study of cognitive mechanisms induced by a single factor. For example, in the process of interaction between individuals and environments, they are often affected by multiple factors in the environment, thereby can be induced to a variety of cognitive processes. At present, the understanding and development of cognition are still in its infancy. But even facing such a big challenge, the pace of scientists and researchers in different fields to explore brain cognition has not been stopped.

Many technologies and methodologies have been used to study human cognition from behavioral experiments, brain imaging, computational modeling, and their combination, etc. [1] In particular, with the development of magnetic resonance imaging (MRI) technology, neuroimaging research

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has received widespread attention. For example, the Human Connectome Project [2] has recently completed imaging of over 1000 young adults and the OpenfMRI database [3] also contains large-scale images from over 3000 subjects across all datasets. As time goes by, the category and scale of neuroimaging data will only increase and not decrease. Meanwhile, a large number of electronic literature resources related to neuroimaging techniques and methods are also increasing. Obviously, neuroimaging research has entered the era of big data [4]. Especially in the field of cognitive neuroimaging, specificity and complexity are its prominent features. On the one hand, traditional cognitive experiments require limiting the number of stimulus conditions and tasks, whose purpose is to reduce interference between multiple cognitive processes. This design approach is suitable for studying a single cognitive process. However, it is a big challenge for us to combine these datasets to realize the comparative analysis of multiple cognitive processes. Therefore, how to organize the diversity of data with different cognitive specificity based on contextual information and knowledge for further analysis from the perspective of big data will be an important research tendency. On the other hand, the complexity are reflected in the indicator calculation and pattern analysis methods. Up to now, a variety of computational analysis methods have been proposed to gain insight into the information-processing patterns and mechanisms of cognitive processes. However, their effectiveness still needs to be verified. Therefore, how to mine the stable indicators and analysis methods is another important direction.

Starting from the above consideration, this paper presents a semantic vector driven closed-loop model, namely THINKING-LOOP, for brain computing to systematically analyze the brain patterns and its cognitive characteristics by combining ontological modeling, statistical tests, rule-based inference, and a human-computer interaction mechanism. In particular, an ontology in the knowledge layer with different conceptual entities and entity hierarchical relations is used to uniquely describe the context, which gives a common semantic understanding for different brain data. The information layer, as a bridge between knowledge and data, provides a priori conditions for human-computer interaction. The statistical principles of the data are explored in the data layer for verifying and mining new information and knowledge. The complementary closed-loop scheme with the three-layer fusion of data, information and knowledge is described to understand the THINKING-LOOP, as shown in Figure 1.

To explain information processing in the THINKING-LOOP, two types of learning and inference schemes are distinguished: top-down ($K \mapsto I \mapsto D$) and bottom-up ($D \mapsto I \mapsto K$) processing. In the top-down procedure, high-level semantic knowledge or contextual information guide information processing. The bottom-up process, in contrast, is carried out in the opposite direction; from the stimulus to high-level conceptual understanding, with each successive stage performing an ever more complex analysis of the input. In the current scenario, the

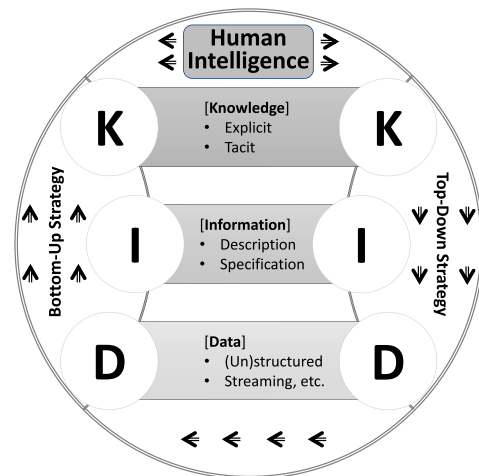


FIGURE 1. Closed-loop learning and thinking in the THINKING-LOOP with the top-down and bottom-up schemes.

top-down scheme is designed to select significant brain patterns and explore effective computational methods. And the bottom-up scheme is designed to understand cognitive characteristics and its information-processing mechanisms. In this closed-loop model, human as a key factor participate in the process of human-computer interaction (HCI) and contribute to their wisdom [5]. Conversely, the output of the model provides valuable decision-making support for people. In conclusion, this paper considers the systematic integration and analysis problems of the multiple source components in brain informatics [6]. The main contributions of this work may be summarized as below.

- It proposes a novel closed-loop model, namely THINKING-LOOP, which is capable of personally mining the prior knowledge and incorporating the mined knowledge to interact with data and/or information for systematic analysis more deeply. A complementary dual scheme (the top-down and bottom-up processing) is designed for a learning algorithm that embeds the THINKING-LOOP in an iterative way, to continuously improve the learning and inference results.
- It proposes a semantic vector to improve the expressiveness and quantification of complex brain functions using a simple representation. And that may make it easier for computers to integrate and process the three-layer fusion of data, information and knowledge using a systematic methodology.
- It performs an empirical evaluation of the presented model on real functional MRI (fMRI) data for emotion perception, human reasoning, and problem-solving processes. The structural and functional characteristics of complex brain cognition are explored and re-recognized from the network topology perspective.

The remainder of this paper is organized as follows. Section II reviews previous work related to the use of computational and analytical methods on cognitive assessment concerning fMRI scans and human-in-the-loop HCI

methodologies. Section III describes the theoretical framework and computational mechanism of the proposed THINKING-LOOP. Section IV sets out the experimentation with the results. Before concluding in Section VI, Section V discusses the current experimental results and presents some other application scenarios of the THINKING-LOOP.

II. RELATED WORK

The past decade has seen an explosion of research papers and newspaper articles involving the technique of functional neuroimaging, most notably fMRI. This technique can provide the measure of activity at/between different locations within the human brain while people are performing various cognitive tasks. Here, we briefly discuss existing computational and analytical methods in fMRI studies and review relevant research pertaining to the THINKING-LOOP.

The earliest methods compared the measurements at each location (volumetric pixels or “voxels”) [7] statistically using correlation coefficients and t-tests, etc. The first step in fMRI statistics is almost to construct a “map” of such statistics, and then estimate the change in each voxel’s activity in response to the experimental manipulation, showing the distribution of activity over the brain [8]. Moreover, some methods for looking further into particular regions (Regions of interest, ROIs) [9] have been proposed, such as voxel-wise analysis [10]. This, in a manner, makes up for the disadvantages of voxel-level analysis, such as to control for Type I error, explore one’s data simply, select functional areas and so on. Early work focused on examining individual voxels and regions from a univariate analysis perspective.

As opposed to univariate methods, the multivariate analysis considers the synergistic effect of two or more independent variables, such as multivoxel pattern analysis (MVPA) in the field of fMRI. The MVPA, which can proceed along two main branches of analysis, considers spatial patterns of activity over ensembles of voxels to recover what information they represent collectively: classifier-based MVPA and pattern-similarity MVPA [11]. The former uses classifiers from machine learning to learn a weight for each voxel, and these weights together determine the decision boundary between experimental conditions [12]. The latter, computing the matrix of pairwise distances between fMRI patterns and (optionally) comparing this matrix to other similar matrices, focuses on the similarity of voxel patterns [13]. Activity patterns are viewed as points in a high-dimensional voxel space, where the distance between points indicates their similarity [14]. Many or most of the above methods assume that cognitive functions are attributable to the isolated operations of single brain areas, which do not consider the connection characteristics between nodes or regions.

Our brain consists of spatially distributed, but functionally linked regions that continuously share information with each other. Brain connectivity analysis is another type of key technology and methodology to understand the neural underpinnings of cognition by revealing how cognitive functions arise from interactions within and between distributed

brain systems, such as static and dynamic connectivity analysis whether anatomical, functional, or effective. On the one hand, the brain’s structural and functional systems have features of complex networks (such as small-world topology, highly connected hubs, and modularity) at the whole-brain scale of human neuroimaging [15]. Details of some related technologies have been explored, such as brain templates and atlases [16], complex network construction [17] and graph indicators calculation [18]. Moreover, the dynamic aspect of brain connectivity also attracted a lot of attention in the fMRI community [19]. The above methods mainly focus on the indirect measurement of neural processes. On the other hand, two key approaches (including Dynamic Causal Modelling and Granger Causality Mapping) have been proposed to explore directed influences between neuronal populations (effective connectivity) in fMRI data [20]. Up until now, fMRI studies in functionally linked subnetworks have reported fruitful results to inspire our practice and re-cognition. There are two large opposing network systems in the brain, one including the brain’s default mode network [21] and the other composed of attentional or task-based systems, such as somatosensory, visual, or attention networks [22], [23].

There is no doubt that the above computational analysis methods have greatly promoted the development of cognitive neuroscience. However, the innovation in computing methods alone cannot meet the demand for neuroscience big data, and a new computing framework is urgently needed. The main reason is that the typical experimental paradigm limits the diverse expression of cognitive functions, so that most of the shared data can only be studied from a single cognitive perspective. If we want to take advantage of the comparative analysis by integrating multiple datasets and methods, several challenges will be encountered, such as the multi-centrality problem. The meta-analysis is an effective tool for multi-angle comparative research, and has been widely applied. However, it mainly focuses on the comparison of results and ignores the synchronous participation and integration of data, information and knowledge. In addition, human beings as the most advanced agent should actively participate in the interaction with the computational model.

Today, HCI methodologies have been widely applied to many fields including mechanical engineering and automation, biological health monitoring, assisted driving, robotic techniques, and so on. Working in this growing field requires a synergetic combination of research on human intelligence in cognitive space and machine intelligence in computational space. On the one hand, machine intelligence techniques, especially the automatic machine intelligence techniques whose aim is to free human practitioners and researchers from these menial tasks, is the fastest growing technical field for health informatics [24]. However, brain informatics-based big data is full of uncertainty and complexity, which makes the application of fully automated approaches difficult or even impossible, or at least the quality of results from automatic approaches might be questionable [25].

Moreover, the complexity of brain cognitive function has detained non-experts from the application of such solutions. Consequently, the integration of the knowledge from a domain expert with the information and data can sometimes be indispensable, and will greatly enhance the knowledge discovery process. Hence, interactive learning puts the “human-in-the-loop” to enable what neither a human nor a computer could do on their own [26]. This idea is supported by a synergistic combination of methodologies of two areas that offer ideal conditions toward unraveling such problems: HCI and knowledge discovery/data mining, with the goal of supporting human intelligence with machine intelligence to discover novel, previously unknown insights into data [27].

Inspired by these research achievements and their valuable results, this work proposes a semantic vector driven closed-loop model exploiting a combination of ontological knowledge representation, statistical tests, complex network analysis and HCI methodologies to enable effective computation for the model with the provision of wisdom services. In particular, the applications of the THINKING-LOOP model in the fields of brain and cognitive sciences with the computational theory are discussed in the paper. To understand our proposal, a description of the THINKING-LOOP (in Section III) and examples with the realistic experiments of task-related fMRI data (in Section IV) is given.

III. THINKING-LOOP: CONCEPTUAL AND COMPUTATIONAL FRAMEWORK

In this section, the proposal is described for the THINKING-LOOP. Some principal components of the closed-loop model include the human-machine interaction and semantic vector combined with the rule-inference mechanism. Here, all components will be individually described in the Section III-B, after a introduction about the architecture and information-processing pipeline of the THINKING-LOOP in Section III-A.

A. ARCHITECTURE OF THE THINKING-LOOP

The key mechanism of the THINKING-LOOP is to integrate the actions of human thinking and interaction into the data mining and knowledge discovery process. Support for decision-making is realized by combining the advantages of data- and knowledge-driven methods. Based on the constraints and definitions, the comprehensive information-processing architecture for the THINKING-LOOP is shown in Figure 2.

The input of the THINKING-LOOP is multiple Thinking-Entities ($TEs \geq 3$) composed of the three-layer fusion of formatted data, information and knowledge organized by ontology technology. Semantic vectors (SVs) serve as an important interface to connect computers and people to implement human-computer interactive operations. The output of the presented model is a list of the association pairs between concepts in the knowledge layer and patterns/indicators defined in the information layer whose feature properties are observed in the data layer, after rule-based inference. In this model,

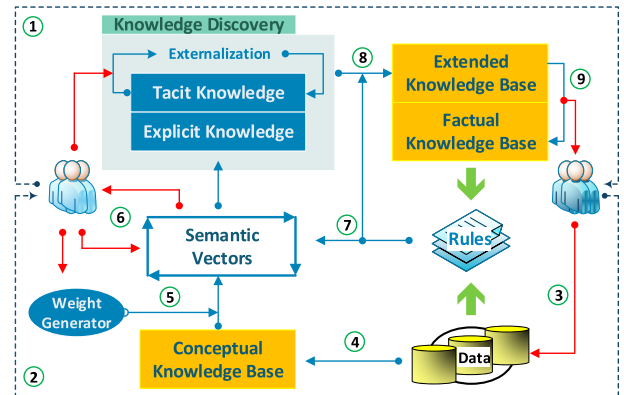


FIGURE 2. The architecture and information-processing pipeline of the THINKING-LOOP. The dotted arrows indicate two schemes from top-down and bottom-up perspectives respectively. The red arrows indicate multiple human-computer interaction processes between human and the model. The blue arrows indicate information flows that run within the model. Details of various processes are described as follow: ① Knowledge-driven process: In this process, the ability of participants is continuously improved by learning the existing theory and knowledge. ② Data-driven process: Participants obtain new information and knowledge by observing, summarizing and analyzing phenomena at different angles from data. ③ Practical process: In the course of the practice, participants will get new observation data based on experience and knowledge, which is a sub-process from ②. ④ Data mapping process: The knowledge representation of the data is implemented in this process. ⑤ Heuristic learning process: The computer will generate different symbols to control the initial conceptual weight change (excitement, suppression or constant) in this human-computer interaction process. ⑥ Active learning process: Participants can selectively forget some of the weight activation symbols generated in the previous step based on the contextual environment of Thinking-Entities. The action symbols obtained by the ⑤ and ⑥ processes are synthesized to control the next change in weight. Iterate between the processes ⑤ and ⑥ until the condition of convergence is reached. ⑦, ⑧ and ⑨ are the processes of rule inference. Through the above learning and inference processes within human-computer interaction, some explicit knowledge will be discovered to be integrated into the factual knowledge base for forming new knowledge and raising awareness. And some tacit knowledge will also be discovered to be integrated into the extended knowledge base for promoting and inspiring the participant’s rethinking, re-practice, and re-recognition.

the hybrid data-driven and knowledge-driven strategies in learning and inference stages are defined:

- **The top-down scheme:** In the learning stage, the SVs are obtained from prior knowledge with the conceptual description of the Thinking-Entity, and the metric and/or pattern characteristics of the data are measured concurrently; in the inference stage, some information is obtained from the knowledge layer to the data layer, in the purpose of verifying indicators with stability and measuring patterns with special significance.
- **The bottom-up scheme:** In the learning stage, the SVs are obtained by an iterative human-computer interaction process and the characteristics of original data are also evaluated concurrently; in the inference stage, some information is obtained from the data layer to the knowledge layer, in the purpose of exploring more meaningful semantic knowledge or contextual information related to patterns and/or indicators.

This current closed-loop model is not only one that generates evidential information to complement and correct

TABLE 1. List of essential symbols and abbreviations.

Symbol	Description
DSV	the SV from expert or personal inclination
LSV	the SV from human-computer interaction
$Dist(x, y)$	measure the distance between x and y
$Sdif$	the vector of semantic distance between Thinking-Entities
$Kdif$	the conceptual difference matrix between Thinking-Entities
$Ddif$	the data features of difference matrix between Thinking-Entities
C_n^m	combination, $\frac{n!}{m!(n-m)!}$ ($n \geq m$)
$ABS(X)$	takes absolute value for X
$zeros(m, n)$	generates a new matrix of the given shape and type, filled with zeros.
$rand(m, n)$	generates a matrix of the given shape with random floats in the interval [0.0, 1.0]

existing knowledge but also one that generates hypothetical information to inspire us for carrying out the next phase of experimental design and related work. Therefore, the ability of participants is continuously improved during the never-ending learning process of interacting synergistically with the model. This section explains the connectionist architecture of each element in THINKING-LOOP, and then its details are described as follows. For the convenience of readers, a list of essential symbols and abbreviations are shown in Table 1.

B. DETAILED DESIGN IN THE THINKING-LOOP

Figure 2 systematically describes the architecture of the THINKING-LOOP and its input, output, and information processing. Assuming those constraints, some important issues need to be identified: (1) How to construct a semantic vector with the integration and processing of multiple resources (from the data layer, the information layer, and the knowledge layer) for systematic brain research; (2) How to implement semantic vector-driven interactive learning in the current closed-loop model; and (3) How to make inference and judgment to generate new meaningful and valuable decision-making, and then guide further experiments for obtaining more evidence in the new loop.

1) CONSTRUCTION OF THE SEMANTIC VECTOR

Figure 3 illustrates the overall information flow of constructing semantic vectors, which considers the multi-dimensional integration of resources from the data layer (*DataL*), information layer (*InfoL*), and knowledge layer (*KnowL*), simultaneously.

In particular, the formalization and characteristics of semantic vectors are given below.

Definition 1. The semantic vector is the concept space with weight coefficient using ontological modeling, and these weights are obtained through the systematic analysis within a human-computer interaction, which is given by

$$SV = \{c_1 : v_1, c_2 : v_2, \dots, c_{n_1+n_2} : v_{n_1+n_2}\} \quad (1)$$

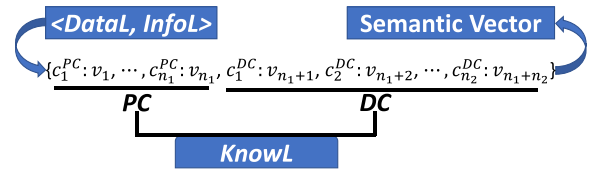


FIGURE 3. Construction of the semantic vector, in which n_1 to n_2 are numbers of different dimensions of concepts and instances.

where c_i refers to the i^{th} concept in semantic vectors, v_i refers to the value of the weight coefficient corresponding to the i^{th} concept.

The multiple brain data with different contexts, that are organized as different entities in the model, can be mapped to the same semantic vector space for further study using knowledge- and data-driven methods. Several important characteristics are included in the semantic vector.

- **Maneuverability.** The maneuverability of semantic vectors is reflected in the concept of expansion or reduction in the ontology of the *KnowL* and personalized data mapping. For example, the concept in the ontology can be adjusted by the expert during the analytical process. The adjusted ontology will affect the distribution of concepts in the semantic vector and may affect its dimensions. In addition, the concepts defined in the *KnowL* can be encoded as binary features (i.e., c_1, \dots, c_n in Equation 1) as follows: the concept was 1, if the corresponding context and meaning is related to the generation process of brain data; otherwise the concept was 0. At this point, the brain data is mapped to a semantic vector space with "0-1" properties, such as $DSV = \{c_1 : 0, c_2 : 1, \dots, c_n : 0\}$.
- **Computability.** The computability of semantic vectors means that the semantic distance between brain data with different contexts can be measured based on the respective semantic vectors. For example, the difference between $DSVs$ can be measured by the Hamming distance algorithm and used to determine the semantic similarity between brain data. Furthermore, each concept can also correspond to a weight from zero and one. Then we can measure the contribution of the cognitive process corresponding to the concept defined in semantic vectors for different experimental tasks. The new semantic vector, such as $LSV = \{c_1 : 0.3, c_2 : 0.24, \dots, c_n : 0.1\}$ whose weights are acquired through human-computer interaction, is constructed.
- **Comparability.** The comparability of semantic vectors means that the semantic similarity between multiple pairs of data defined in the Thinking-Entity is comparable. Since multiple sets of data are mapped into the same semantic space, this provides a prerequisite for comparing multiple datasets at the same latitude. Then, the semantic distance between different datasets is measured by the above distance calculation method. Finally, the relative approximation properties between the datasets are obtained by comparison. For example,

```

"Thinking-Entity": {
  "hasDATA": < "User1.nii", "User2.nii", ..., "UserN.nii" >,
  "hasINFO": < "Atlas", "ROIs", "Nets", ... >,
  "hasKNOW": < "Func1", "Func2", ... >
}

```

FIGURE 4. Example of Thinking-Entity in the THINKING-LOOP.

three sets of data are analyzed, representing D_a , D_b and D_c , respectively. If $Dist(D_a, D_b) > Dist(D_a, D_c)$ is obtained after the above semantic mapping and similarity calculation procedure, it shows that there is a stronger semantic approximation between D_a and D_c compared with D_b .

Moreover, the Thinking-Entity, which is the basic operating unit involved in the whole life cycle of the THINKING-LOOP, is interpreted and defined for systematically constructing and computing semantic vectors. As an example, Figure 4 shows the core elements in a Thinking-Entity, which is organized by three-layer resources from the *DataL*, *InfoL*, and *KnowL*.

Next, we introduce the definition of each layer in the THINKING-LOOP.

Definition 2. The *DataL* is described as a four-ingredient tuple, which includes the following four types of data in the systematic analysis process:

$$DataL = (CD, OD, PD, RD) \quad (2)$$

where original data, denoted by *OD*, is the original signal obtained by sensors or devices. A contextual data (*CD*) is a description of the circumstance for the *OD*. Especially, the acquisition of original experimental data often corresponds to a certain experimental purpose for the study of brain cognition, that is, the *OD* has direct and indirect correlation with one or more functional concepts in the *KnowL*. At this time, the text description with the concept description corresponding to the current experimental task is stored in the *CD*, which becomes an important source and basis for understanding the meaning of the original data and clarifying the purpose of the experiment. Furthermore, it is necessary to record and store some procedural or result data for improving the efficiency of the model and realize multi-aspect analysis quickly. The procedural data (*PD*) can be intuitively understood as the data generated during preprocessing and feature extraction. The result data (*RD*) refers to a collection of features and/or indicators with special meaning, which may be some cognitive biomarkers for the brain research.

Definition 3. The *InfoL* is described as a three-ingredient tuple, which includes the description and definition of a piece of brain information:

$$InfoL = (PrI, FrI, ArI) \quad (3)$$

where the *PrI* (Pattern-related Information) is the pre-defined patterns or information-processing mechanisms in the brain, *FrI* (Function-related Information) indicates that some specific cognitive functions correspond

to a certain pattern, and *ArI* (Analytical Information) includes the mathematical models and qualitative methods used in the pattern analysis. The information may come from both current data analysis results and published literature sources, which is a message that contains relevant meaning, implication, or input for decision and/or action.

Definition 4. The *KnowL* is a hierarchical ontology organized by multiple concepts, and it can be expressed as:

$$KnowL = (PC, DC) \quad (4)$$

where primitive concepts ($PC = \{PC_1, \dots, PC_n\}$) are those that have only necessary conditions (in terms of their properties) for membership of the class; defined concepts ($DC = \{DC_1, \dots, DC_m\}$) are those whose description is both necessary and sufficient for a thing to be a member of the class.

A formal knowledge representation will serve as a benchmark for individualized operations and learning, enabling the integration and comparison of different Thinking-Entities. In particular, the concept refers to the name of the basic unit that can constitute an ontology-based empirical knowledge representation to express a visible or invisible entity. It is a high-value form of information that is ready to apply to decisions, actions, and interactions with the person in variable environments.

2) SEMANTIC VECTOR DRIVEN INTERACTIVE LEARNING

In the previous section, we mainly introduced the semantic vector and its several important definitions. In this section, we introduce the semantic vector-based learning and interaction methods in the THINKING-LOOP.

a: Top-down Learning Method

As mentioned earlier, obtaining effective patterns and indicator calculation methods in the study of cognitive and behavioral characteristics is one of the most important directions in the field of brain sciences. However, as we all know, there are thousands of definitions and calculation methods for existing patterns and indicators. How to choose quantitative indicators and evaluation methods has become a huge challenge in the process of cognitive research. The purpose of the top-down learning method in the THINKING-LOOP is to compare the effectiveness of different indicators and patterns by utilizing prior knowledge in the *KnowL*, which is similar to the feature or pattern selection process in machine learning.

In the top-down learning method, multiple datasets resulting from variable environments or experimental tasks are regarded as entities of learning, and the main processes include:

- 1) Based on the prior knowledge and information defined in the THINKING-LOOP, the semantic distance (SemanDist) among different Thinking-Entities is measured by the knowledge-driven method;
- 2) Data features within different indicators and patterns are measured by the data-driven method, and their

differences can be compared by statistical theory, as shown in Algorithm 1.

Algorithm 1 Top-down learning scheme

Input:

N Thinking-Entities TEs with different $DSVs$, $TEs = \{TE1, \dots, TEi, \dots, TEN | N > 2\}$;
the indicators and/or analysis methods from $InfoL$, $PASet = \{< PI_k, AI_k > | 1 < k < M\}$.

Initialize:

$Sdif = zeros(1, A_N^2)$
 $Ddif = zeros(M, A_N^2)$

Output:

$Sdif$ and $Ddif$

```

1: PROCEDURE in KnowL & InfoL
2: Setting  $m = 1$ 
3: for  $i=1, i<N, i++$  do
4:   for  $j=i+1, j<N+1, j++$  do
5:      $Sdif[m] = \text{SemDist}(DSVi, DSVj)$ 
6:      $m++$ 
7:   end for
8: end for
9: PROCEDURE in DataL
10: for  $k=1, k<M+1, k++$  do
11:   for  $i=1, i<N+1, i++$  do
12:     Calculating data features of  $TEi$  ( $FTEi$ ) based on  $PI_k$  and  $AI_k$ 
13:   end for
14:   Setting  $n = 1$ 
15:   for  $i=1, i<N, i++$  do
16:     for  $j=i+1, j<N+1, j++$  do
17:        $Ddif[k, n] = \text{Dist}(FTEi, FTEj)$ 
18:        $n++$ 
19:     end for
20:   end for
21: end for

```

The results obtained through the top-down learning method will be used as input to the rule engine, and then used to select relatively effective patterns and feature extraction methods.

b: Bottom-up Learning Method

The main purpose of the bottom-up learning method is to mine the different connotation-related concepts implied by patterns or data features. In this procedure, comprehensive learning in *KnowL* and *InfoL* is still an important part of the entire knowledge discovery process. Its computational procedure is described in Algorithm 2.

Obviously, the difference from the top-down learning procedure is the acquisition and calculation of the weight coefficient in the semantic vector. In the top-down learning procedure, the weights (only 0 or 1) in the semantic vector are set by experts or users. In the bottom-up learning method, however, the weights (from 0 to 1) are obtained through human-computer

Algorithm 2 Bottom-up learning scheme

Input:

N Thinking-Entities TEs with different $DataL.CD$, $TEs = \{TE1, \dots, TEi, \dots, TEN | N > 2\}$;
the metrics and analysis methods in $InfoL$, $PASet = \{< PI_k, AI_k > | 1 < k < M\}$;
the maximum number of iterations, max_{iter} , and the level of marginal significance, $P - Value$.

Initialize:

$Kdif = zeros(n_1 + n_2, A_N^2)$
 $Ddif = zeros(M, A_N^2)$
 $LSVs = rand(n_1 + n_2, N)$

Output:

$Kdif$ and $Ddif$

```

1: PROCEDURE in KnowL & InfoL
2: for  $i=1, i<N, i++$  do
3:   for  $j=i+1, j<N+1, j++$  do
4:     Randomly initialize  $LSVi$  and  $LSVj$  within 0 to 1;
5:     while  $max_{iter} \neq 0$  do
6:       Convergence conditions analysis with  $LSVi$  and  $LSVj$ ;
7:       if Satisfy convergence conditions then
8:         break;
9:       else
10:        Step 1: Generating random weight adjustment (enhancement and suppression) symbols by machine for each concept in  $SV$ ;
11:        Step 2: Changing the adjustment symbols generated in Step 1 by the user based on the information obtained;
12:        Step 3: Updating weights in  $LSVi$  and  $LSVj$  according to symbols from Step 1 and Step 2;
13:         $max_{iter} --$ ;
14:       end if
15:     end while
16:      $Kdif[:, m] = ABS(LSVi - LSVj)$ 
17:      $m++$ 
18:   end for
19: end for
20: PROCEDURE in DataL like Algorithm 1

```

interaction processes with multiple iterations. The following steps describe this procedure that differs from the top-down learning method in detail.

- **Convergence conditions.** Steps 1 to 3 in Algorithm 2 are iterated until the algorithm reaches a predefined stopping criterion; in particular, the procedure is stopped if the statistical significance is reached between $LSVi$ and $LSVj$ corresponding to different Thinking-Entities in an iteration or after a predetermined number of iterations. As mentioned above, a comparative analysis strategy is defined in the THINKING-LOOP, that is, comparing the semantic and data characteristics of two Thinking-Entities at each time. The basic consensus here is that when human performs multiple tasks

using a domain-specific knowledge framework, the execution strategies are more or less relevant among different tasks, but some take the same operation and some take the opposite operation on details [28]. In particular, when the behaviors are recorded from two kinds of different circumstances or experimental tasks, multiple identical or similar cognitive processes will be called simultaneously, which reflects the overlap and correlation [29]. However, due to differences of pre-set goals, the degree of participation of the cognitive process under each task is also different on details, which leads to the positive or negative correlation trend when evaluating the overall processes. Therefore, the convergence condition is to determine whether there is the statistical significance between the two $LSVs$ ($LSVi$ and $LSVj$), including positive correlation and negative correlation. Here, the semantic distance can be used as a priori condition to judge the positive or negative relationship between two Thinking-Entities. In particular, if there is a large semantic distance between two Thinking-Entities, then it is considered to be a negative correlation in the calculation process of the corresponding $LSVi$ and $LSVj$; otherwise, it is a positive correlation.

- **Weight computing.** In Step 1, a control vector (CV) consists of randomly generated three signs -1, 0, and 1, and is of the same size as LSV . In this vector, sign -1 means that the weight of the corresponding concept in LSV will decrease in the next weight updating process; sign 0 means that the weight will not be changed; and sign 1 means that the weight of the corresponding concept in LSV will increase in the next weight updating process. During the interaction process, the user can control the symbol change in CV by judging the contribution of the concept to each Thinking-Entity, thereby changing the next weight-updating action. In this paper, the user can set these symbols to zero according to personal understanding and observation in each iteration, that is, forgetting the weight-updating action in an interactive process. For example, if a concept c_i in SV is considered to be closely related to Thinking-Entity DOi , but sign -1 in CV is randomly generated by computer for this concept during the generation of control variables. Then the sign -1 can be set to sign 0 so that it does not participate in the next weight updating, and vice versa. In the initial phase of each iteration, the number and distribution of signs -1, 0, and 1 in the CV are random. We consider to obtain one CV for two Thinking-Entities during the processes of human-computer interaction in Step 1. Then, how to update the weights of both $LSVs$ for different Thinking-Entities at one time. At this time, the CV generated by the computer is set to control the weight-updating process of the $LSVi$. And, the CV of the $LSVj$ is generated by comparing the semantic distance between the two Thinking-Entities, which includes two cases in Step 2.

- When the semantic distance is small enough to be considered as positive correlation: If sign 1 appears in CV during an iteration and the current weight of the corresponding position in $LSVi$ is greater than $LSVj$, the corresponding position of CV for $LSVj$ is also set to sign 1. Conversely, the corresponding position is set to sign -1. If sign -1 appears in CV during an iteration and the weight of the corresponding position in $LSVi$ is greater than $LSVj$, the corresponding position of CV for $LSVj$ is also set to sign -1. Otherwise, the corresponding position is set to sign 1. In other cases, $LSVi$ and $LSVj$ have the same control symbol for CV .

- When the semantic distance is large enough to be considered as negative correlation: if sign 1 appears in CV during an iteration and the weight of the corresponding position in $LSVi$ is greater than $LSVj$, the corresponding position of CV for $LSVj$ is set to sign -1. Conversely, if the weight of the corresponding position in $LSVi$ is smaller than $LSVj$, the position is set to sign 1. If sign -1 appears in CV during an iteration and the weight of the corresponding position in $LSVi$ is smaller than $LSVj$, the corresponding position of CV of the $LSVj$ is also set to sign 1. Conversely, the corresponding position is set to sign -1. In other cases, the CVs of $LSVi$ and $LSVj$ have the same control signs.

The weight of concepts in the $LSVi$ and $LSVj$ is calculated based on these signs after obtaining the CV in Step 3. In combination with the above,

$$w(t+1) = \begin{cases} w(t) + \frac{1-w(t)}{RIN}, & \text{sign in } CV = 1 \\ w(t), & \text{sign in } CV = 0 \\ w(t) - \frac{w(t)}{RIN}, & \text{sign in } CV = -1 \end{cases}$$

where w represents the weight of the concept, t indicates the order of human-computer interaction, and RIN indicates the number of remaining iterations.

Finally, the weight of each concept, which is the real number of the closed interval $[0, 1]$, is obtained by the use of human-machine interaction design in the bottom-up learning procedure for each Thinking-Entity. Obviously, we will acquire more details of the knowledge layer for each Thinking-Entity in this procedure, such as the contribution of different concepts within one task or among multiple tasks.

3) KNOWLEDGE INFERENCE WITH RULES

Through the above learning process, we get $Sdif = zeros(1, A_N^2)$, $Kdif = zeros(n_1 + n_2, A_N^2)$ and $Ddif = zeros(M, A_N^2)$. Here, the $Sdif$ represents the semantic distance between multiple Thinking-Entities; the $Kdif$ represents the weight differences corresponding to all concepts between multiple Thinking-Entities; and the $Ddif$ represents the differences in patterns or indicators between multiple Thinking-Entities. The first two are the results obtained through the calculation in the $KnowL$ and the $InfoL$, and the last one is the result obtained through the calculation in the $DataL$. These results will serve as input to the inference engine and

then generate new information and knowledge based on rule constraints.

Considering different learning schemes, two types of inference mechanisms are used in the rule engineering:

- **Top-down inference rule.** The top-down inference rule is used to infer the learning results obtained by the Algorithm 1, $Sdif$ with $Ddif$. First, we sort the elements in the $Sdif$ and the $Ddif$ for each row from large to small and get their positional indexes. Then, the positional indexes of the $Ddif$ for each row are compared with that of the $Sdif$. When the positional indexes of $Ddif$ for a row are consistent with that of the $Sdif$, the $\langle PrI_k, ArI_k \rangle$ pair corresponding to the current row is output, which is defined in the $InfoL$.
- **Bottom-up inference rule.** The bottom-up inference rule is used to infer the learning results obtained by the Algorithm 2, $Kdif$ with $Ddif$. Here, the elements of $Kdif$ and $Ddif$ for each row are also sorted from large to small and get their positional indexes. Then, the positional indexes of the $Ddif$ for each row are compared with that of the $Kdif$ for each row. When positional indexes of two rows are consistent by the above comparison, the corresponding position of $\langle PrI_k, ArI_k \rangle$ pair with concept c is given and output by using a form of $\langle \langle PrI_k, ArI_k \rangle, c \rangle$ pair, where c is the concept from the SV.

Through this kind of inference mechanism based on comparative index-matching procedures, this model can select some candidate patterns/indicators and investigate their fruitful meaning in the knowledge layer for further study.

IV. EXPERIMENTS AND EVALUATION

From the above description, we can see that the current model can be quickly converted and personalized in different fields based on the customization of experts and users. In this paper, we focus on the application of the THINKING-LOOP in the field of brain cognition, especially the extensible mining and analysis of the hidden correlation between complex cognitive processes and brain function mechanisms. At this time, brain, cognition, patterns, and indicators become several important concepts involved in the current model.

Further, functional neuroimaging based network analysis and mining methods have become an important research direction in the field of cognitive science. Its main aim is to explore subnetwork structures with unique cognitive and functional characteristics from the whole complex network and provide more efficient and effective indicators to measure their information-processing mechanisms. Therefore, a realistic use case combining multiple fMRI datasets and network analysis methods is used to evaluate the effectiveness of this model. In order to realize the semantic vector driven complex cognitive understanding and analysis, acquisition processing and organization strategies of the resources are firstly defined in the $DataL$, the $InfoL$ and the $KnowL$ of the THINKING-LOOP.

A. DATA PROCESSING IN THE $DataL$

From the description in Section III, at least two Thinking-Entities are required to achieve effective learning and inference in the THINKING-LOOP with sorting and comparison strategies. In current work, three task-based fMRI datasets mapped to three abstract Thinking-Entities were acquired for emotional face recognition (EFR) task, number series completion (NSC) task, and number placement puzzles (NPP) task to verify the effectiveness of this model, which are primarily related to emotion, reasoning, and problem-solving processes, respectively.

The usage data from 58 in total (female/male: 19/39; ages 20-79 yr) Chinese healthy participants with a college (or higher) education were finally adopted for group-level analyses in the present study. Specifically, the number of participants recruited for the EFR, NSC, and NPP was 30, 13, and 15, respectively. All of the participants were right-handed, had normal or corrected-to-normal vision, and reported no history of neurological or psychiatric disorders. Prior to their participation in the study, written informed consent was obtained from each participant after the nature and possible consequences of these studies were explained. These experiments were approved by the Ethics Committee of Xuanwu Hospital, Capital Medical University, Beijing. The detailed context of the original data and the method of obtaining its procedural data are described below.

1) EXPERIMENTAL DESIGN

The experimental design in detail for these three datasets is defined by:

- **The EFR experiment.** The dataset was acquired by performing an fMRI experiment designed in accordance with the Hariri paradigm [30]. The participants were displayed with blocks of trials that required them to decide either of which two affective facial expressions presented on the bottom of the screen match another expression at the top of the screen. Four types of emotionally valenced faces were presented, showing sadness, anger, fear, and happiness expressions, respectively. Trials were presented in blocks of 6 trials of the same task, with the stimulus presented for 2 s and a 1 s interval.
- **The NSC experiment.** A number series completion task was performed for each of the participants, which were required to predict the next number in the visually displayed sequence (e.g., 2, 4, 6, 8, 10) [31]. On every trial, five numbers in a number series were shown one by one on the computer screen in white digits of 36 size font against the black background. Participants were required to make the choice between “A” and “B” by pressing the button as exactly as possible after an option of answers (e.g., “A. 16 B. 17”) was presented. All numbers including answers ranged from 0 to 99, and only addition and subtraction were needed. Additionally,

totally 72 tasks were evenly and pseudo-randomly distributed in six sessions for each participant.

- **The NPP experiment.** Event-related fMRI data were recorded while participants were solving simplified number placement puzzles (Sudoku; Nikoli Publishing, Tokyo, Japan) on a 4×4 grid [32]. The goal of this experiment is to fill a 4×4 grid so that each column, each row, and each of the four 2×2 boxes contains the digits from one to four only one time each. Each trial of the experiment started with a red star shown for 2 seconds as a warning (the stimulus was visually shown on a black screen), and then the participants were asked to give the answer for the cell marked with “?” in the grid by using digits from one to four. For each subject, there were two sessions each that contained repetition times of 360 or more.

2) DATA PROCESSING

All the original fMRI data were acquired from different experiments. The data preprocesses went through a unified protocol before being input into the THINKING-LOOP. The preprocesses of fMRI data were performed with SPM12 software (the Wellcome Centre for Human Neuroimaging, London, UK, <http://www.fil.ion.ucl.ac.uk>). Functional images were corrected for slice-timing differences and realigned to the median image to correct rigid body motion. Cases with head movement exceeding 2 mm or 2 degrees were excluded from further analysis. The high-resolution anatomical image was co-registered with the mean image of the EPI series and then spatially normalized to the Montreal Neurological Institute (MNI) template. After applying the spatial normalization parameters to the EPI images, all volumes were re-sampled into $3 \times 3 \times 3 \text{ mm}^3$ and smoothed with an 8-mm FWHM isotropic Gaussian kernel. As nuisances, the motion parameters and the global average of white matter (WM) and cerebrospinal fluid (CSF) signals were regressed out from the fMRI time series data. The WM and CSF masks were derived from the standard set of tissue probability maps provided in SPM and thresholded at 0.99 (for WM) and 0.90 (for CSF) to minimize confounding with GM signals. The resulting residual time series was temporarily filtered to remove the effects of low-frequency scanner drifts with 0.008 Hz high-pass. The procedural data, which are intermediate results produced by data preprocesses, are also stored in the THINKING-LOOP for possible pattern analysis and metric calculations in the future.

The fMRI time-series were extracted from spatially distributed brain regions based on pre-defined ROIs. For each ROI, the average of BOLD signal intensity was calculated among all the voxels within the region. For better understanding the nature of the complexity of brain networks related to the above experimental tasks, a hybrid brain atlas which embracing the structural atlas of AAL (Automated Anatomical Labeling) [33] and the functional atlas of Dosenbach [34] were proposed. The proposed brain atlas was extended on the basis of the 160 ROIs of the entire Dosenbach by

TABLE 2. Functional networks and their related pattern information.

Functional Networks ^a	Related ROIs ^b
DN_{CORE}	$PCC, amPFC, pIPL$
DN_{MTL}	$RSC, PHC, HF, vmPFC, pIPL$
DN_{SUB3}	$dmPFC, IFG, TPC, LTC, IPL$
DAN	$FEF, IPS \sim SPL, MT+$
VAN	$IFG, vTPJ, AI$
SN	ACC
$FPCN$	$dIPFC, preSMA, aIPL, ITG, rIPFC$
$COCN$	$dACC \sim msFC, rIPFC, dAI$
CAA	$BG, MI, Thalamus, Amygdala$

^a DN_{CORE} =the core default network (DN) subsystem, DN_{MTL} =the DN subsystem centred around the medial temporal lobe (MTL), DN_{SUB3} =the third DN subcomponent, DAN =the dorsal attention network, VAN =the ventral attention network, SN =salience network, $FPCN$ =the frontoparietal control network, $COCN$ =the cingulo-opercular control network, CAA =the core affect architecture.

^b PCC =the posterior cingulate cortex, $mPFC$ =the medial prefrontal cortex, $amPFC$ =the anterior mPFC, $pIPL$ =the posterior inferior parietal lobule, RSC =the retrosplenial cortex, PHC =the parahippocampal cortex, HF =the hippocampal formation, $vmPFC$ =the ventral mPFC, $dmPFC$ =the dorsomedial PFC, IFG =the inferior frontal gyrus, TPC =the temporopolar cortex, LTC =the lateral temporal cortex, FEF =the frontal eye field, $IPS \sim SPL$ =the intraparietal sulcus–superior parietal lobule, $MT+$ =the middle temporal motion complex, $vTPJ$ =the ventral temporoparietal junction, AI =the anterior insula, ACC =the anterior cingulate cortex, $dIPFC$ =the dorsolateral PFC, $preSMA$ =the supplementary motor area, aIP =the anterior IPL, ITG =the inferior temporal gyrus, $rIPFC$ =the rostrolateral PFC, $dACC \sim msFC$ =the dorsal ACC–medial superior frontal cortex, dAI =the dorsal AI, BG =the basal ganglia, MI =the mid insula.

incorporating 10 ROIs from AAL. Similar to the ROIs defined by Dosenbach atlas, the 10 ROIs from AAL in the extended atlas were also considered as the corresponding voxels with the center point MNI coordinates and the radius of the ROI. In this paper, the 170 ROIs of the proposed atlas were all represented as spheres with radius of 5 mm, i.e. each sphere consists of 19 voxels and the size of each one is $3 \times 3 \times 3 \text{ mm}^3$.

B. INFORMATION ORGANIZATION IN THE InfoL

The *InfoL* consists of three parts: the *PrI*, *FrI*, and *ArI*. In current work, multiple representative brain networks are discussed, such as the Default (Mode) Network (DN), the Attention Network (AN), the Salience Network (SN) and the Control Network (CN) [35]. In addition, we also define an emotionally related network, the core affect architecture (CAA) [36]. Here, various brain network structure information is represented in the *PI*, which is described in Table 2.

These networks corresponding to functional meanings or cognitive processes were stored in the *FrI* of the *InfoL*, which comes from existing research work. For example, existing research showed that the DN (including DN_{CORE} , DN_{MTL} and DN_{SUB3}) has a greater correlation with spontaneous cognition, mental and emotional processes; the AN (including DAN and VAN) is the network for redirecting attention from one entity to another; and the CN exhibits different information-processing mechanisms during short-term and long-term task execution. Obviously, these network characteristics, on the one hand, can be used as the reference

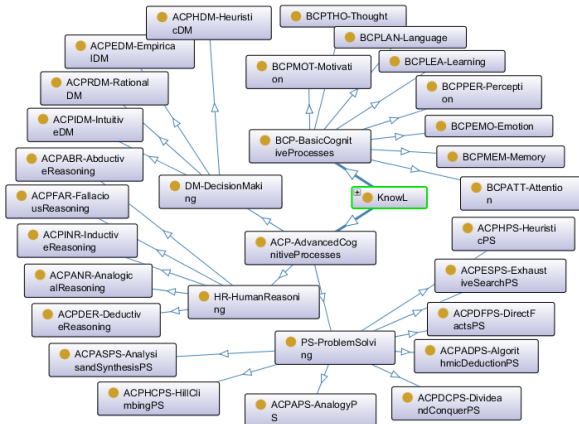


FIGURE 5. The definition of cognitive concepts in ontology of the knowledge layer.

to evaluate the rationality of decision making, and on the other hand, encourage us to discover new information and knowledge on the basis of these existing patterns.

Some methods such as statistics, machine learning, and network topology analysis are defined in the *ArI* of the *InfoL*. In particular, three commonly used index calculation methods, including the Clustering Coefficients Index (CCI), the Local Efficiency Coefficients (LEC), and the Global Efficiency Coefficients (GEC), are estimated in this paper. These indicators will be measured during the learning process of the *DataL* in the THINKING-LOOP.

C. CONCEPTUAL DEFINITION IN THE KnowL

Human cognition is usually summarized as some complex mental activities such as human reasoning [37], problem-solving [38] and decision-making [39] that typically rely on the combination and interaction of more elementary processes such as perception, learning, memory, emotion [40], [41], etc. In this paper, these cognitive functions or processes are represented as concepts, which are organized into hierarchical ontology structures. And the hierarchical relations in the ontology are constructed by reference to the Cognitive Atlas that aims to develop a knowledge base (or ontology) that characterizes the state of current thought in cognitive science [42]. The cognitive function-related ontology in the *KnowL* is shown in Figure 5.

D. COGNITIVE LEARNING AND INFERENCE IN THE THINKING-LOOP

1) THE RESULTS OF COGNITIVE LEARNING

The goal of learning is to measure the level of difference between Thinking-Entities. Through the interactive learning processes defined in Section III, we can easily get the results of the *Sdif* and *Kdif*.

a: Learning Results in Semantic Difference

First, we constructed *DSVs* of *ERF*, *NSC*, and *NPP* entities from the definition of the *KnowL*, as shown in Figure 6.

Thinking-Entities	ACPRDR	ACPNR	ACPAR	ACFAR	ACEDM	ACPHDM	ACPHDM	ACPHDS	ACPHDS	ACPHDS	ACPHDS	ACPHDS	ACPHDS	ACPHDS	BCPLEA	BCPLAN	BCPTHO	BCPMEM	BCPMOT	BCPEMO		
EFR	0	0	1	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	1	1
NSC	1	1	0	1	1	0	1	1	1	1	0	0	1	1	1	1	0	0	0	1	1	0
NPP	1	0	0	0	1	0	1	1	1	1	0	1	1	1	1	0	0	0	1	0	1	0

FIGURE 6. The results of data mapping for EFR, NSC, and NPP entities.

TABLE 3. Semantic differences between Thinking-Entities.

<i>Sdif</i>	EFR vs. NSC	EFR vs. NPP	NSC vs. NPP
	15	13	4

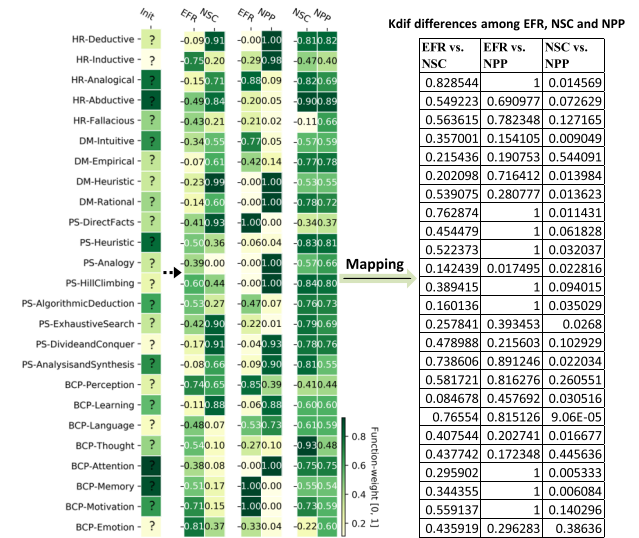


FIGURE 7. The results of interactive learning in the bottom-up processing.

Then, the semantic distance between Thinking-Entities, *Sdif*, was calculated by the hamming distance evaluation method, as shown in Table 3.

b: Learning Results in Knowledge Difference

In the process of calculating *Kdif*, two parameters need to be preset, namely *max_iter* and *P-Value*. Here, the *P-Value* was set to 0.01 in the convergence condition, and the maximum number of interactions *max_iter* was set to 30 times. After multiple interactions, the conceptual weights and their differences between Thinking-Entities were measured, as shown in Figure 7.

c: Learning Results in Data Difference

The *Ddif* is measured by combining with the graph and statistics related theory. First, the BOLD signal time series of the task states from the scans for each participant was extracted. Then, the Pearson correlation coefficient matrix was calculated by the 170×170 extended brain atlas. These matrices used the Fisher transformation to calculate the Z-score of each cell in the matrix. In addition, the adjacent matrices of different subnets were constructed based on the related ROIs defined by *InfoL*. Further, the indicators (including, CCI, LEC, and GEC) of the subnet at 1-100 sparsity were calculated separately. Finally, we used the analysis of

TABLE 4. The comparison of differences between Thinking-Entities in the DataL.

Subnetworks	CCI			LEC			GEC		
	EFR	EFR	NSC	EFR	EFR	NSC	EFR	EFR	NSC
	vs.	vs.	vs.	vs.	vs.	vs.	vs.	vs.	vs.
	NSC	NPP	NPP	NSC	NPP	NPP	NSC	NPP	NPP
<i>DN_{CORE}</i>	3	1	0	0	1	1	8	11	1
<i>DN_{SUB3}</i>	7	0	1	8	1	1	10	2	2
<i>DN_{MTL}</i>	1	4	5	2	4	5	4	8	4
<i>DAN</i>	15	29	3	8	22	1	7	7	8
<i>VAN</i>	8	0	0	11	1	0	11	14	4
<i>SN</i>	0	0	0	0	0	0	0	10	10
<i>FPCN</i>	1	10	0	1	11	3	0	5	6
<i>COCN</i>	0	0	2	0	0	2	2	2	6
<i>CAA</i>	61	23	12	39	14	9	11	1	6

variance (ANOVA) statistical method to determine whether there is a significant difference between Thinking-Entities with the same indicator for the subnet at all sparsity levels. Here, the P -Value was set to 0.05, and a variance homogeneity test was performed. In this paper, the number of sparsity that shows a significant difference is counted for each subnet and is used as a criterion for determining $Ddif$. Therefore, the magnitude of the difference in the $DataL$ is proportional to the number of sparsity obtained by the above counting method.

In practice, we randomly selected 13–14 participants from each dataset for maintaining an approximately consistent data size. The assessment results of the difference between the Thinking-Entities are finally obtained from the $DataL$, as shown in Table 4.

2) THE RESULTS OF COGNITIVE INFERENCE

According to the two types of knowledge inference rules defined in Section III, we have obtained some interesting results.

- From the top-down inference scheme, we can select some $\langle PrI_k, ArI_k \rangle$ pairs that reflect better consistency from knowledge to data. Here, some combinations of DN_{CORE} with CCI, VAN with LEC, CAA with CCI, and CAA with LEC were selected.
- From the perspective of the bottom-up inference scheme, we hope to verify the reliability of existing information and obtain some new knowledge through the constraints of the data layer. Here, the tacit knowledge of some network patterns was explored in this process, such as $\langle\langle CAA, CCI \rangle, Emotion \rangle$ and so on. The complete inference results from a one-time run of one expert are shown in Table 5.

V. DISCUSSIONS AND PROSPECTS

In this section, we discuss the usefulness, areas for improvement, and summarize other potential applications in the THINKING-LOOP.

A. DISCUSSIONS

In this paper, the THINKING-LOOP is presented to implement the top-down and bottom-up schemes for different goals. The former focuses on the advanced feature analysis of brain patterns, while the latter focuses on the cognitive

understanding of brain patterns. Therefore, we discuss current learning and reasoning results from the above two perspectives.

- **The top-down loop.** An experimental task is often designed to observe specific cognitive processes. For example, the EFR task is mainly to observe the process of emotional cognition, the NSC task is mainly to observe the cognitive process of reasoning, and the problem-solving process is uncovered by the NPP task. Considering the differences in experimental tasks and cognitive functions, we can obtain the semantic distance between different Thinking-Entities. From Table 3, we can see that there is a large semantic distance between EFR and NSC/NPP, but the semantic distance between NSC and NPP is relatively short. These results are consistent with current cognitive theory and previous fMRI studies, on the one hand, which emphasizes the correlation between reasoning and problem solving [43]. On the other hand, emotion is seen as an independent factor that is perceived and studied for its impact on advanced cognition [44], [45]. In addition, the quantitative semantic distance allows us to visually and objectively compare differences between Thinking-Entities in detail. For example, we can further see that the difference between EFR and NSC seems to be greater than that between EFR and NPP based on numerical comparisons in $Sdif$. These quantified results in the $KnowL$ are used to constrain the observation results of the $DataL$ from Table 4, which in turn verify the rationality of the hypothesis. For example, we find that the CAA network corresponding to the features more conforms to the cognitive rules of the $KnowL$, that is, the emotions show greater specificity and correlation for the CAA network. These findings are in line with analysis results of emotion [36]. Moreover, we also find that the emotional process has a correlation with DN_{CORE} and VAN from the inference results, which is similar to the previous study [46], [47]. Furthermore, the calculation methods for different types of indicators also serve as an important factor affecting the results of learning and inference. For example, the CCI and LEC that measure the local transmission capacity of the network are more conducive to express the network characteristics than the GEC that measures the global transmission capacity of the network from the distribution of inference results in Table 4, which complements the Pan's results in [48].
- **The bottom-up loop.** Table 5 shows the subnet-related cognitive processes, which are the inference results based on Figure 7 and Table 4. From these results, we find that DN_{CORE} , VAN , and CAA are all related to the emotional process obviously, and these results are also consistent with that in the top-down scheme. The SN has a large correlation with reasoning, which is similar to previous research studies [49]. The fMRI studies have previously implicated both the $FPCN$ and $COCN$, which play dissociable roles in control, but their

TABLE 5. The inference results obtained by the interactive processes of an expert from the bottom-up scheme.

Subnetworks	CCI	LEC	GEC
<i>DN_{CORE}</i>	HeuristicProblemSolving; Emotion	AnalysisandSynthesisProblemSolving; Motivation	DeductiveReasoning; InductiveReasoning; AnalogicalReasoning; IntuitiveDecisionMaking; EmpiricalDecisionMaking; HeuristicDecisionMaking; RationalDecisionMaking; HillClimbingProblemSolving; AlgorithmicDeductionProblemSolving; DivideandConquerProblemSolving; Learning; Language; Memory
<i>DN_{SUB3}</i>	HeuristicProblemSolving; Emotion	HeuristicProblemSolving; Emotion	HeuristicProblemSolving; Emotion
<i>DN_{MTL}</i>	AnalysisandSynthesisProblemSolving; Motivation	AnalysisandSynthesisProblemSolving; Motivation	DirectFactsProblemSolving; Perception; Attention
<i>DAN</i>	DirectFactsProblemSolving; Perception; Attention	DirectFactsProblemSolving; Perception; Attention	-
<i>VAN</i>	HeuristicProblemSolving; Emotion	HeuristicProblemSolving; Emotion	DeductiveReasoning; InductiveReasoning; AnalogicalReasoning; IntuitiveDecisionMaking; EmpiricalDecisionMaking; HeuristicDecisionMaking; RationalDecisionMaking; HillClimbingProblemSolving; AlgorithmicDeductionProblemSolving; DivideandConquerProblemSolving; Learning; Language; Memory
<i>SN</i>	AbductiveReasoning; ExhaustiveSearch-ProblemSolving	AbductiveReasoning; ExhaustiveSearch-ProblemSolving	AnalogyProblemSolving
<i>FPCN</i>	DirectFactsProblemSolving; Perception; Attention	DirectFactsProblemSolving; Perception; Attention	AnalogyProblemSolving
<i>COCN</i>	-	-	-
<i>CAA</i>	HeuristicProblemSolving; Emotion	HeuristicProblemSolving; Emotion	FallaciousReasoning; Thought

respective contributions are unclear [50], [51]. From the results in Table 5, we find that the reasoning results between *FPCN* and *COCN* are significantly different, which potentially supports the above conclusions. Further, the *FPCN* exhibits a richer functional meaning than the *COCN*, which may be closely related to the attributes of the network. For example, the *FPCN* not only reflect engagement of specific tasks, but also serve as a code that can be transferred to facilitate learning novel tasks. Especially, the *FPCN* is related to attention and perception [52], [53]. However, the *COCN* is more related to word and language tasks [54]. We also observed that the heuristic problem solving and emotion processes have a higher co-occurrence than others. Does this mean that they have a similar cognitive mechanism, which deserves further exploration by designing new experiment. The current results are drawn from an expert. Obviously, with the changes of people, the output of the model may be slightly different, which reflects the individualized interaction and inference ability of this dynamic model.

Based on the above discussion, we can find that the top-down and bottom-up schemes in the THINKING-LOOP constitute a supervisory loop, which can achieve mutual verification of decision rationality. And, towards never-ending learning workflow interacting within the THINKING-LOOP, more novel results will be discovered.

B. NEEDED IMPROVEMENTS

Some areas still need to be improved in the current study. First, three or more types of Thinking-Entities driven by

research purposes (three types in our study) can trigger the inference process of the model. In theory, the unlimited number of Thinking-Entities can be considered, set, and run simultaneously in the THINKING-LOOP. However, as the number of Thinking-Entities running in the model increases, the requirements for the robustness of the inference engine also increase. Therefore, more rules need to be added. Second, there may be slight differences of the operating results from different periods in the process of an expert interacting with the model. That is a very interesting phenomenon, and the main reason may be that experts are affected by the cognitive or real-time status of different periods. Therefore, comparing and analyzing the results of experts' practice in different periods will be very meaningful work. However, cold start problems will be encountered in the early stages of practice. Meanwhile, this model is an open human-computer interaction system, which means that the experimental results vary from person to person and have personalized characteristics. How to integrate the personalized results from different experts, and then to draw more guiding conclusions, is a future research direction. Third, the biological and functional properties of the brain require more diverse data to verify, which is a long-term practical process. While this shortfall did not have an impact on the power required for our primary analysis, it does attest to the challenges of conducting research related to brain, behavioral and cognitive sciences.

C. PROSPECTS

A study on human-in-the-loop systemic neurosciences will attract more and more widespread attention because of its ability to integrate the advantages of both human intelligence and multi-layer fusion of data, information and knowledge,

which can often lead to more novel and solid results. Faced with this emerging field, a representative conceptual model that takes into account the power of three-layer fusion of data, information and knowledge has been proposed in existing research, namely Data-Brain, which is a typical model with static characteristics for systematic brain informatics [6]. However, these theories and methods ignore the important role of human beings as a non-negligible factor in the process of knowledge discovery, which has significant dynamic characteristics. In this paper, the integrated advantages of collective wisdom from the published information sources and personal wisdom through human-computer interaction are given full play in the proposed THINKING-LOOP, which provides a feasible solution for systematic methodological research. Although a representative case has been proposed to demonstrate the current model in the field of brain cognitive science, its other directions are worthy of attention.

1) HIGH FLEXIBILITY OF MULTI-VIEW TRANSFER

The advantage of domain transfer brings broad prospects to the THINKING-LOOP, that is, the current model is not limited to be applied in the field of brain research. Considering the conceptual framework for the *KnowL* is a domain-specific ontology model, which guides the construction and computation of semantic vectors in computers. Hence, it will be very convenient to implement the domain transfer of the model by changing the conceptual ontology model in other fields. Obviously, such a domain transfer usually brings about changes in the *InfoL* and *DataL*. In addition to the changes mentioned above in the inter-domain transfer of the *KnowL*, the intra-domain-multi-view transfer is also necessary in the *InfoL* and *DataL* for achieving more reliable verification. For example, switching and fusion among different information carriers of text, graphics, sound and video with multiple data modalities from multiple views (e.g. Genetics, Imaging, and Praxeology) need to be given special attention.

2) HIGH ELASTICITY OF INTERACTION DESIGN

Human-in-the-loop is a very important mechanism of the THINKING-LOOP in which human intelligence assists and drives the never-ending learning of the model. In this process, communication between people and computers can be achieved through a variety of human-computer interaction technologies, including voice interaction, image interface interaction, somatosensory and so on. In the future, with the development and integration of these human-computer interaction technologies, the interaction process will be smoother, and the personal experience will be greatly enhanced.

VI. CONCLUSION

This paper has proposed a semantic vector-driven closed-loop model, namely THINKING-LOOP, for brain computing to systematically investigate the complex brain cognitive functions and its information-processing mechanisms. The details of the operational, computable, and comparable semantic vectors with the two human-computer

interaction schemes (including top-down and bottom-up procedures) and the three-layer fusion of data, information, and knowledge mechanisms are described. Three fMRI experiments for emotion, human reasoning, and problem-solving were performed and analyzed for validating the rationality and effectiveness of the model. It can be seen that the model can not only realize the mining and verification of brain patterns from the perspective of top-down thinking, but also realize the understanding and analysis of brain cognition from the perspective of bottom-up thinking, and realize the mutual supervision of the two decision-making processes. Moreover, the completion of a decision-making process does not mean to stop forever, but the beginning of a new round in this closed-loop model. Some interesting and innovative results will be continuously discovered during the never-ending learning process.

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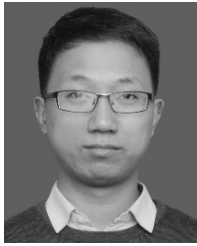
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