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Data-Brain Driven General Intelligence Model with Smart Health Applications
データブレインドリブン汎用知能モデル及び知能健康への応用

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Abstract

Human brain, as the critical information-processing and control center, exhibits activity's specificity underlying the various patterns coupled with specialized functions, behaviors and health status. One of the key ideas is that we understand enough about the brain intelligence, and then we can develop the human-like intelligence approach towards human-level AI society. Another key idea is that decoding brain health could push forward the progress of smart health applications. With the convergence of artificial intelligence, big data and cognitive neuroscience, brain computing has rapidly advanced our understanding of the frontiers on brain intelligence and brain health.

This dissertation presents a novel brain computing approach, building a Data-Brain driven general intelligence model to realize human-level collective intelligence and develop brain-inspired intelligent technologies towards multi-dimensional wisdom services. The model is stitched together from the three-layered Knowledge (K) – Information (I) – Data (D) architecture to process knowledge at the top layer, information in the middle layer, and data at the lowest layer, with the capabilities of reasoning, computing and learning: 1) a conceptual Data-Brain at the top of the K-I-D architecture is developed to systematically represent the characteristics and context of the human thinking and behaviors, with respect to all major aspects of the Brain Informatics methodology surrounding systematic modeling of brain functions, systematic design of cognitive experiments, systematic management of brain data, and systematic data analysis and simulation; 2) the semantic vector in the middle of the K-I-D architecture is designed to realize traceability and provenance of analysis and data, building bridges between the knowledge layer and the data layer; 3) a sample library at the lowest of the K-I-D

architecture is constructed to integrate brain big data resource as the extensional representation of human thinking and behavior. Based on the K-I-D architecture, a K-I-D loop is realized to carry out never-ending learning, supporting design and implementation of systematic cognitive experiments, the KID and DIK-driven dual-directed inference, and evidence combination and fusion computing towards problem solving of the complex brain. Meanwhile, the human-in-the-loop paradigm is covered to provide the thinking-supported AI, connecting human with the model before, during and after learning processes. Hence, the general intelligence model can enhance learning performance by using previously learned knowledge and experience, followed by empowering subsequent learning abilities and habits, continuously.

One focus of Data-Brain driven general intelligence model is placed on understanding human intelligence towards human-level AI society, which is studied by analyzing brain information-processing mechanisms from both perspectives of functional segregation and integration. On the one hand, the task-state functional magnetic resonance imaging data are computed to explore the information-processing capacities of brain regions through both univariate and multivariate pattern analysis methods. On the other hand, the data are computed to explore the characteristics of functional connectivity between connected nodes from different brain regions through the graph theoretical approach, focusing on the role of regional nodes in large-scale brain networks. These brain computing results are identified as different evidential types with dynamic weights, which are further fused into such a never-ending learning paradigm to obtain uncertainty distributions for quantitative assessment and interpretations of brain functions. Experiments demonstrated the use of quantifying uncertainty distributions, by which we could obtain multi-level brain patterns to infer their contributions to a specific or multiple functional domains. In this study, the general intelligence model is used to interpret the specificity of human reasoning within the brain region of interest (i.e., the dorsolateral prefrontal cortex) as well as the other control brain regions. In the KID inference process, the model fuses the task-driven brain encoding results. It validated the hypothesis that the dorsolateral prefrontal cortex is highly related to inductive reasoning. Reversely, in the DIK inference process, the model fuses the data-driven brain decoding results. It showed that the dorsolateral prefrontal cortex has a strongly support to inductive reasoning. Thus, multi-aspect analyses based on the proposed general intelligence model suggest that the dorsolateral prefrontal cortex may play a causal role in inductive reasoning. It should be mentioned that the model also makes it possible to generate new hypotheses about the mapping between inductive reasoning and several regions such as left middle temporal gyrus, right inferior temporal gyrus, fusiform gyrus and bilateral angular gyrus, which were identified by the whole-brain exploratory analysis. Additionally, several functional circuits such as the fronto-striatal circuits (including the key brain regions in the prefrontal cortex and caudate) were detected by functional connectivity analysis, which were not reported in previous studies. These results may act as new potential hypothesis, and inspire us to design and run new experiment to test them.

Another focus is placed on the smart health applications of Data-Brain driven general intelligence model, which are studied to promote our understanding of the brain-mental health by integrating the computational cognitive neuroscience methods. The general intelligence model-aided classification system is constructed to promote progress in the field of translational research. On the basis of uncertainty distributions learned from the human intelligence scenario, the brain patterns are identified into different levels, and then are input into the classifiers. On the one hand, the system realizes the classification of the groups with mental disorders and healthy controls under different task states, taking into account the regional brain patterns from the functional segregation perspective. On the other hand, the nodal networks with different-level uncertainty distributions, together with various functional networks from the proposed brain atlas, are constructed as the connected brain patterns to estimate their contributions for the classification performance and verify the role of various functional networks on mental disorders. Experiments were performed to evaluate characteristics of the learned brain patterns on convergent, robustness and specificity. In this study, the greater accuracy for the recognition of the samples with major depressive disorder is achieved by leveraging the benefits of the general intelligence model and ensemble learning methods. Meanwhile, the selected brain patterns indicate the similar robust degree aligned to the functional networks of default mode, fronto-parietal, sensorimotor and visual. Moreover, the selected brain patterns also indicate the similar specific degree aligned to the functional networks of salience, limbic lobe, ventral attention, dorsal attention, subcortical and cerebellum.

More broadly, this study advances the machine intelligence paradigm for decoding the complex cognitive functions and mental disorders within the human brain. While the single-view learning is necessary, it is of limited use in systematic understanding and multi-aspect interpretations of brain intelligence and brain health. As such, the understanding of future directions in brain investigation will explode with never-ending learning, using evidence combination and fusion computing. Towards the goal of intelligent society, we will focus on brain and mental health by investigating intelligent health technology that comprehensively utilizes health-centered physical, mental and social big data within artificial general intelligence system. We will systematically respond to the lifestyle-related diseases such as mental disorders, diabetes, cancer, stroke and cardiovascular disease, providing ubiquitous services of the health-disease management throughout the life cycle and the integration of “health-medical-welfare”. By integrating brain big data as the extensional representation of the human information-processing system, the Data-Brain can be used as a bi-directional decoder between the inner brain information and the outer brain information by connecting brain and network with big data; an energy converter between brain science and artificial intelligence; and an engine from systematic brain-machine intelligence research to new AI industry chain in the connected world. The Data-Brain driven general intelligence model would be considered as a core part to fit different scenarios on brain intelligence, brain health, and brain Internet.

Keywords: Brain Informatics, Brain Computing, Data-Brain, Web Intelligence, General Intelligence, Never-Ending Learning, Evidence Combination, Fusion Computing, Translational Research.

研究内容要約：

「データブレインドリブン汎用知能モデル及び知能健康への応用」

近年の人工知能技術と脳科学を組み合わせることによって、人間思考のメカニズムの解明による認知症やうつ病の治療及び人間の学習や推論モデルを応用した人工知能の開発が期待されている。

それに対し本研究では、脳情報学方法論に基づいて、人間の脳をひとつのビッグデータを持つ情報処理システムとみなし、階層化された知識(K)-情報(I)-データ(D)アーキテクチャに基づくネバーエンド学習をしながら、「体系的な脳機能の研究; 多目的に活用する体系的認知実験の設計と実施; 知識ベースを考慮した体系的ビッグデータの管理; 体系的ビッグデータの分析; 汎化知能モデルによる知的サービスの提供」という機能を提供するデータブレインを開発し、革新的な脳ビッグデータコンピューティング方法を提案した。また、認知症・うつ病の病理の解明、治療、予防や、AI ・ウェブインテリジェンス(WI)の新たな可能性を示した。具体的には、次に４つの主な研究成果を挙げる。

１．階層化された知識-情報-データビッグデータセンター、すなわち K-I-D アーキテクチャ

知識層 K：脳機能、実験タスク、データ管理及び分析方法の視点から体系的な脳機能研究プロセスを表現するための複数のナレッジグラフ。

情報層 I：セマンティックベクトルの形式でリソースの多面的な情報を記録するマルチ情報ウェアハウス。

データ層 D：マルチ課題の脳機能画像ビッグデータを中心として、マルチモーダル・マルチスケールのビッグデータの体系的な管理。

２．データブレインドリブン汎化知能モデルとするネバーエンド学習 NEL エージェント

ネバーエンド学習は、人間のように、何年にもわたる多様な主に自己監督の経験から、以前に学んだ知識を使用してその後の学習を改善し、プラトーを回避するための十分な内省を備えた多くの種類の知識を学習しながらパフォーマンスが向上する。K-I-D アーキテクチャに基づいて、思考空間としての K-I-D ループを構築し、人間のように機能するネバーエンド学習(NEL：Never-Ending Learning) で革新的な脳ビッグデータコンピューティング方法を提供する。

３．多目的に活用する体系的認知実験の設計と実施

まず脳認知機能研究の目的に応じて主な実験タイプと補助実験タイプ、及び各実験タイプの関連性の推論ルールを制定し、体系的な実験の設計と実施のテンプレートグラフを作成する。次に脳ビッグデータセンターから新しい実験タスクをサンプリングし、データブレインモデルと推論ルールを組み合わせて、新しい実験タスクの属する補助実験タイプを識別し、設計した実験タスクを実験テンプレートグラフに記入する。すべての実験タイプが設計されるまで、上記の手順を数回実行する。この技術により、体系的な高次脳機能の研究のため、人間参加型（HITL : Human-in-the-Loop）の体系的な脳ビッグデータの収集、多面的な解析・理解が可能となる。

4．ネバーエンド学習による課題 fMRI 脳ビッグデータの融合と体系的分析

まず主な実験と補助実験、各実験間の推論ルール、証拠の重みを含む実験テンプレートグラフを制定する。次に実験テンプレートグラフに従って、脳ビッグデータセンターから解析が必要なデータ・情報・知識を取得し、K-I-D ループにおけるマルチ課題 fMRI 脳機能画像を多面的に解析しながら、複数の証拠に基づいた不確実性推論や融合的計算を通じて、複雑な脳機能の解明、心理状態の解読、神経難病や精神病態の診断を行う。

本論文では、全 7 章から構成されており、その概要は以下の通りである。第 1 章では、序論として研究の背景と方向性及び枠組みについて示した。第 2 章では、人間の認知と機能障害、脳を対象とする fMRI 技術と脳情報学方法論を活用し、世界範囲の重大な脳研究の現状に関して 4 つの側面から整理した。第 3 章では、データブレインドリブン汎化知能モデルを提案し、K-I-D アーキテクチャ、ネバーエンド学習、人間参加型の AI 開発、体系的認知実験の設計と実施ルールなどについて述べた。第 4 章と第 5 章では、脳機構の機能分離の観点から単変量及び多変量パターン分析法、脳機構の機能統合の観点から中心性などを定量化する脳機能的ネットワーク指標の評価法について、それぞれを開発し、さらに提案した汎化知能モデルは人間の帰納的推論の神経メカニズムの解明に応用し、提案した汎化知能モデルの有効性を示した。第 6 章では、橋渡し研究として、提案法のうつ病患者の脳機能異常の解明や知能健康への応用を試みた。第 7 章は総括であり、申請論文の研究成果をまとめ、今後研究や社会実装に向けた解決すべき問題について展望した。

Contents

List of Figures

List of Tables

Chapter 1

Prologue

Chapter 1 starts with the background introduction to understand complexity in the human brain and the motivation for accelerating the use of new techniques and methods in such cross-cutting areas. Following with the objectives to be addressed, the theme of the thesis is to investigate and design efficient intelligence approach of realizing brain computing with translational applications. We then summarize the research contributions and present the organization of this thesis at the end of the chapter.

1.1 Introduction

The big brain controls most of the activities of the human body and contributes the intelligence capability that is related to various brain functions such as perception, attention, emotion, memory, language, calculation, reasoning, planning, decision-making, problem-solving, learning, discovery and creativity. Exploring the human brain is an interesting and important work, especially from the information-processing system perspective to study brain mechanisms corresponding to the essential functions of the brain, ranging from perception to thinking. In this context, the segregated and integrated brain activity patterns are investigated by the measures of regional activation and functional connectivity.

As two sides of the same coin: the healthy brain contributes the normal capability that involves various cognitive functions such as reasoning, calculation and problem solving; however, the brain abnormality increases general risk of neuropsychiatries such as depression, mild cognitive impairment and dementia. On the basis of basic cognitive neuroscience, another key focus is to explore the relationships between the normal brain function and dysfunction towards smart health applications. The complex brain and its multifaceted role have created an increasing need for translation research, by which brain intelligence can be developed systematically from multiple aspects, and at the same time, build bridges between it and clinical practice.

To measure brain functions among cognition, emotion, disease, and their relations, the multi-dimensional view has been inspected by integrating various data, methods, techniques and tools, for example: from the macro-scale view, the cognitive ability could be quantitatively measured by behavioral experiments (such as "hypothesis testing" and "observational" forms) and cognitive tests (such as the Cambridge Cognition Examination, the Montreal Cognitive Assessment and the Cognitive Abilities Screening Test); from the meso-scale view, the neuroimaging techniques are commonly used to study human brain functions in vivo, such as functional magnetic resonance imaging (fMRI) and electroencephalography (EEG); from the micro-scale view, the functions could be explained by the cellular and molecular diversity, such as genomics, protein, and axis- and cell-type. For example, from a single investigation view, a brain data obtained by a specific cognitive experiment and neuroimaging technique is collected, processed and analyzed to test hypotheses about the relationships between brain structure and cognitive function. Over time, such brain data at various scales are collected continuously to obtain the big data characteristic, providing evidence for demonstrating the complex brain with the interwoven characteristics of mental processes, experimental design, data states and analytical details. For this, the fusion computing approach, when compared to its commonly analysis strategy from the single view, becomes more urgent to integrate multi-aspect brain data for systematic understanding of brain intelligence and brain health. Such approach led on naturally to relevant thinking, concerning how to systematically cope with a brain science problem, how to systematically design multiple experimental tasks, how to systematically integrate brain big data, and how to systematically compute the brain data with complex contexts. To meet those challenges, the general intelligence model, together with the never-ending learning and human-in-the-loop mechanisms, is studied to build a bridge from the basic cognitive neuroscience to translational study, serving as a basis towards smart health. This thesis is centered around enhancing comprehension of the open question about the complex brain function-structure relationships and their extensible translational applications towards smart health. As one of the most important neuroimaging techniques, the fMRI will gain more visibility, which has produced revolutionary advances in brain science from its inception.

1.2 Motivation

With the progress of big data and artificial intelligence, brain investigation has embarked upon a new phase with motivations to pooling efforts in the three representative directions.

1.2.1 Challenges in the Brain Big Data Era

When it comes to big data in the field of brain science, big neuroimaging will undoubtedly be the most representative aspect (e.g., human neuroimaging studies with very large subject numbers and amounts of data). In general, the neuroimaging datasets for a specific study may not pose major difficulties for processing and analysis using existing machine learning algorithms and statistical methods [1]. Once the brain data is processed and analyzed from multi-level multimodal viewpoints in large-scale datasets, however, considerable challenges emerge. For instance, investigators explore the big brain by using (non) invasive technologies at various spatiotemporal scales and their possible integration [2-5]. The bulk of the work seeks to observe brain activities using advanced neuroimaging and electrophysiological technologies, such as fMRI, ERP (Event-Related Potential), MEG (Magnetoencephalography), fNIRS (functional Near-Infrared Spectroscopy), PET (Positron Emission Tomography) and LFPs (Local Field Potentials), as well as other sources like eye-tracking, wearable, portable micro and nano devices. Some labs/institutes are dedicated to accelerating understanding of neural tracks, shapes and their functions at a microscopic level, and trace substructures of cells and monitor molecule dynamics with nanoscale precision [6, 7]. Such new experimental techniques, such as toto imaging, deep tissue imaging, optogenetics and dense-electrode recording, are also generating massive amounts of brain data at very fine spatial and temporal resolutions. Others are working to overlay gene-expression patterns, electrophysiological measurements and other functional data on those [8-13]. These approaches involve different technical means – all create big data from different research perspectives. As the ultimate goal of most investigators is to advance scientific knowledge, it would be ideal to use multi-source information from large multimodal datasets at various spatiotemporal scales to inform multi-aspect interpretations. Hence, the “fusion science” or “data fusion” from multiple perspectives needs to be further concerned.

As discussed earlier, understanding the complex big brain from different views has produced all kinds of brain data, which has the significant characteristics with big data. In the previous, the data from different brain studies are distributed throughout various sites/centers from local and global sides. It is difficult to produce more energy towards the overarching goal of considering multi-aspect brain data systematically, simultaneously and continuously. Open science promotes the new progress of brain science, especially making it easier to observe, integrate, reproduce, re-use and share brain resource at various scales. In this case, neuroscience is entering a collaborative era in which the scattered data are integrated by large scientific projects in any countries [14, 15]. For example, the powerful vision of global collaboration has motivated multiple large-scale brain initiatives across the United States (the Brain Initiative [16] generally and the Human Connectome Project [17] specifically), the European Union (the Blue Brain Project [18] and Human Brain Project [19]), Japan (Japan's Brain/ MINDS project [20]), Korea (Korea Brain Initiative [21]), China (the China Brain Project [22]), Canada (Brain Canada [23]) and Australia (Australian Brain Initiative [24]).

Integrating multiple data sources is the fundamental work, which is concerned about not only data management and sharing in the era of open brain science, but also needs to meet the requirements of systematic fusion computing. In particular, when faced with the multimodal and multi-scale brain data from different research communities and projects with various contexts and purposes, more practices would be welcomed. To data, many platforms, systems, databases, standards and tools have been developed to embrace the brain big data era, which support our endeavors towards these goals of better data integration and computing. For example, a growing number of platforms are used to integrate brain data at various scales, such as the raw data scale (such as

OpenfMRI/OpenNeuro [25, 26], fMRIDC [27, 28] and FCP/INDI [29, 30]), the statistical maps scale (such as NeuroVault [31]), the coordinate-based data scale (such as NeuroSynth [32] and BrainMap [33, 34]) and the mixed scales (such as HCP [17] and ADNI [35]).The multimodal brain data are also integrated by collaboration from various populations, such as UK biobank [36, 37], CoRR [38], CMI-HBN [39], ABIDE [40, 41] and ADHD-200 [42]. For details, Table 1.1 reviews several standards, tools and platforms related to neuroimaging and associated data in the era of open brain big data. Although a variety of means have been provided to deal with brain big data, the core goal is still placed on the basic functions, such as brain big data storage, management, dissemination and visualization. The exploration to address core issues of grasping brain big data to the purpose of the systematic fusion computing is still running on the road. For example, the brain big data related to the multi-domain cognitive functions and multi-aspect cognitive experimental tasks are entwined to increase complexity of brain data, thereby increasing such difficulty of systematic fusion computing. For this, the key is to investigate the novel brain big data integration architecture, which needs: multi-dimensional knowledge graph to represent the whole brain investigation lifecycle at the knowledge granularity, including concepts and their relations about cognitive function, experimental task, data collecting and processing details; a warehouse to describe properties and parameters of the brain data and study results at the information granularity; the multi-source brain data collected from the local and global side at the data granularity. Within this architecture, the computing operations could be carried out in the legally separated layers of knowledge, information and data. Meanwhile, the fusion computing operations could also be realized by driving these three interconnected layers. In the current work, such a layered data integration architecture is studied.

Table 1.1: Overview of standards, databases, tools and platforms in brain big data era.

Name	Description
BIDS [43]	The BIDS (Brain Imaging Data Structure, https://bids.neuroimaging.io) is a standard for organizing, annotating and describing data collected during neuroimaging experiments. It is based on a formalized file/folder structure and JSON based metadata files with controlled vocabulary.
BrainMap [34]	The BrainMap (http://www.brainmap.org) is a database of published functional and structural neuroimaging experiments with coordinate-based results, which provides tools and services to the sharing and meta-analysis of the human functional brain-imaging studies.
CBRAIN [44]	The CBRAIN (Canadian Brain Imaging Research Platform, https://amnesia.cbrain.mcgill.ca) is a web-based collaborative research platform, which offers transparent access to remote data sources, distributed computing sites, and an array of processing and visualization tools.
ConnectomeDB [45]	ConnectomeDB (https://db.humanconnectome.org) is a data management and dissemination platform where users can access, explore and download the latest datasets (including multiple modalities of MRI and MEG data along with associated behavioral data) from the Human Connectome Project. It is a highly customized instance of the XNAT imaging informatics platform.
EBRAINS [46]	EBRAINS (https://ebrains.eu) is a platform providing services and tools that assist scientists to collect, analyze, share and integrate brain data, and to understand human brain function and disease.
fMRIDC [28]	The fMRIDC (fMRI Data Center) is a publicly accessible database to facilitate progress in understanding cognitive processes, which seeks to collect, archive and openly disseminate the neuroimaging data (including raw, processed, results brain images and study metadata) from published fMRI studies.
Neurosynth [32]	The Neurosynth (https://neurosynth.org) is a platform that uses text-mining, meta-analysis and machine-learning techniques to realize synthesis of human neuroimaging data and mappings between neural and cognitive states.
NeuroVault [31]	The NeuroVault (https://neurovault.org) is a web-based repository that allows researchers to collect, store, share, visualize and decode the unthresholded statistical maps of the human brain.
NIDM [47]	The NIDM (Neuroimaging Data Model, http://nidm.nidash.org) is a semantic web-based metadata standard that helps capture and describe experimental data, analytic workflows and statistical results via the provenance of the data.
OpenNeuro [48]	The OpenNeuro (previously OpenfMRI, https://openneuro.org) is an open platform that consists of the frontend, database and execution engine to enable the dissemination and reproducible analysis of neuroimaging data.
XNAT [49]	The XNAT (Extensible Neuroimaging Archive Toolkit, https://www.xnat.org) is an informatics platform designed to facilitate common management, exploration, dissemination and productivity tasks for neuroimaging and associated data.

1.2.2 Challenges in Systematic Brain Computing

Human brain, as the critical information-processing and control center, exhibits activity's specificity that occurs in various brain patterns coupled with specialized functions, behaviors and health status. Benefiting from the development of cognitive neuroscience and brain measurement technology, such specificities are able to be objectively assessed by noninvasive and invasive methods, under conditions of various cognitive experimental tasks. In this sense, a fundamental work is to explore the latent interrelations between brain pattern and function, such as human brain mapping [50] and connectome [51] followed by clinical settings and decision-making [52]. Figure 1.1 highlights several key issues of brain computing and their complex relations with brain investigation and smart health.

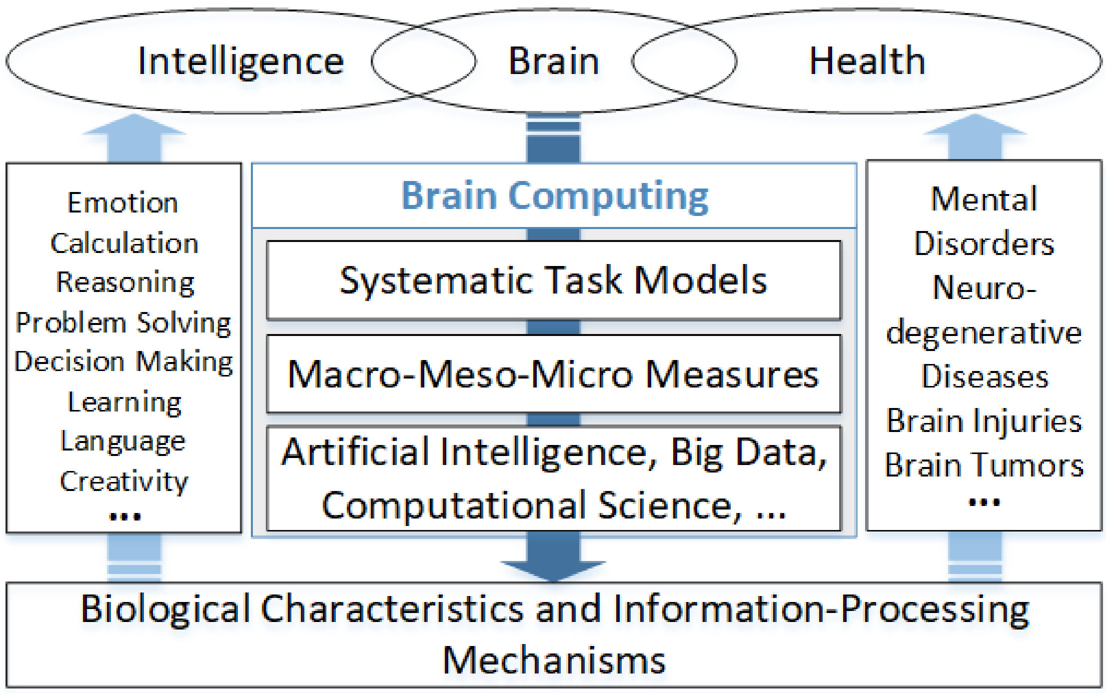


Figure 1.1: Systematic investigation of brain intelligence and brain health from the Brain Informatics perspective.

More specifically, how to handle multi-task models is one of the most core issues to drive brain investigation combined with both higher cognitive functions and functional neurological disorders. To address such a problem, the multi-task flattening analysis strategies [53-57] have become increasingly popular, that is, these studies mainly focus on the comparative approaches of multi-task data separately. However, it overlooks the differential contributions of each task as the evidence for evidence combination and inference, which imposes increasing demands on brain computing with systematic fusion.

Brain big data not only brings huge challenges to the organization and analysis of multi-source heterogeneous brain data, but also potentially puts higher demands on computing power. There are two key drivers for the computing requirements that deserve special attention: the high-dimensional computation and the brain–machine interface. Brain can be understood as a prototype of dynamic systems with structural and functional complexities, which is a high-dimensional computation problem. Its high-dimensional characteristics are mainly related to the complexity of the brain, including the following three aspects and their integrations:

- Brain computing in the structural complexity needs to face more than 80 billion neurons in the human brain with many different sizes and shapes that communicate information in trillions of connections through electrophysiological and chemical signals. On larger scales, the brain is also made up of many specialized regions and divided into several lobes, which consist of a lot of nodes with very complex topological characteristics.
- Brain computing is associated with the functional complexity in understanding the brain information-processing mechanisms related to human thinking-related higher cognitive functions (such as, reasoning, calculation, problem solving and creativity)

and emotion-centric cognitive functions, and their interaction with other basic functions such as perception, attention and memory [58].

- The dynamic complexity in the human brain can be identified with distributed units and network modules organized by excitatory and inhibitory neurons, and their interactive patterns accompanied by high-frequency, time-dependent pattern conversion. Brain computing for dynamic mechanisms needs to consider both structure- and function-related complexities.

Moreover, the brain simulation requires the integration of structural, functional and dynamic aspects from a systematic point of view, which is regarded as the most challenging task of high-dimensional brain computing. With the advancement and development of the information and communication technologies, investigators also have more pursuits and expectations for advanced brain detection techniques and analytical methods that support the brain–machine interface. The software technologies and hardware platforms with superior computing power are needed [59]. For instance, if one considers the increases in state-of-the-art neuroimaging data (e.g., ultra-high spatial and temporal resolution), the computational challenges will appear in the hardware device side for the rapid data acquisition and in the software system side for the real-time data processing, such as the compression and reconstruction of ultrahigh resolution images by the MR system. Meanwhile, we also need new emerging technologies to support the particular computing requirements, such as the accelerated parallel processing technology-based graphic processing units for designing and running deep neural networks. In the current work, the novel brain computing methods are studied to compute brain big data, information and knowledge systematically, exploring the complex human brain from the perspectives of structural patterns and cognitive functions.

1.2.3 Challenges in Artificial General Intelligence

"Human-level AI will be achieved, but new ideas are almost certainly needed, so a date cannot be reliably predicted-maybe five years, maybe five hundred years. I'd be inclined to bet on this 21st century."

—John McCarthy, From here to human-level AI, 2007.

The positive review, so poetically described by John McCarthy, gives us great confidence, but it also involves some serious issues, that is, where the new ideas come from and how to use these new ideas on the road of reaching human-level AI or artificial general intelligence. In his article [60], McCarthy captures the essence of a debate ongoing in the 20th century, and possibly earlier, surrounding two views of reaching human-level AI. One view posits that we understand enough about how the human intellect works, and then we can simulate it, whereas another view is that we can write intelligent programs for the intelligence present in the world. The multidisciplinary supports from cognitive science, artificial intelligence, computational science and big data are strong tools to aid in this effort, which help us to understand how the human brain works, and to accelerate neuroscience development and disorders (see Figure 1.2). Here, we use the term AI in the widest possible sense, including the works related to statics, machine learning and the AI research that aims to build intelligent machines [61]. For a long time, these statistical methods [62], the computational approaches [63], and the model-based methods [64] are considered to perform certain specific brain decoding task. Although these approaches are optimized continuously, the results obtained by them are usually seen as the local optimum.

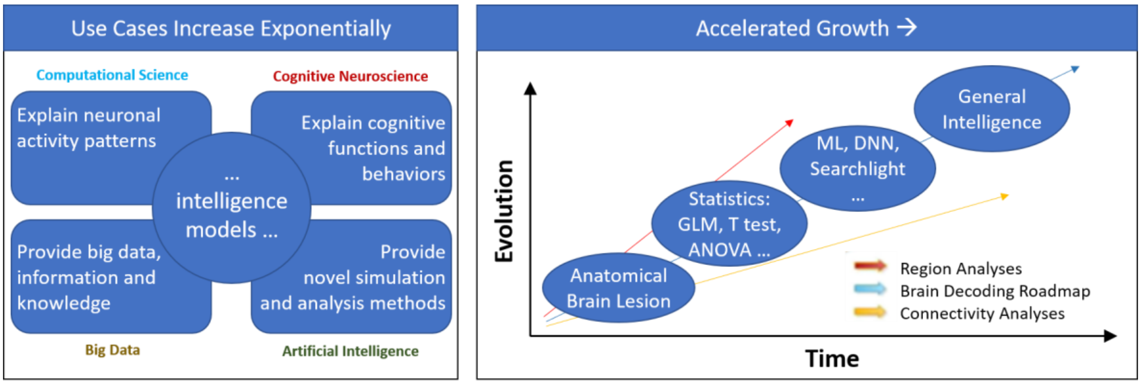


Figure 1.2: Artificial Intelligence meets Brain Science: broader context and roadmap.

Recently, using complementary information from the various approaches to cross reference motivates the development of general intelligence model that can process task broadly and intellectually. In the scenario of brain investigation, one of the most pressing challenges for a general intelligence model is to respond to knowledge, information and data in the brain big data era, systematically. Another urgent need for a general intelligence model is that it can handle multiple computing views from both views of brain region and connectivity, systematically. In addition, a general intelligence model is also expected to adapt to different scenarios, by which the results from one field can be transformed and applied to other fields. For this, the translational research is focused in recent years. By meeting artificial intelligence and neuroimaging, the computational models have been widely applied to various clinical practices, such as prediction, treatment, diagnosis and assessment for the P4 (Predictive, Preventative, Personalized and Participatory) medicine [65]. Therefore, a general intelligence model should consider how to map various discoveries in basic cognitive neuroscience to the computational models with different requirements. In the current work, the general intelligence model is studied to respond to the multi-source data processes, the multi-view computing requirements, and translational research towards the smart health applications.

1.3 Objectives

As explained earlier, the single brain investigation task we usually perform today limits the interpretations of results, not only due to the complex nature of brain science problem itself, but also due to the complexity of various factors such as cognitive experiment, data state and analytical details. In systems neuroscience, the detail of each stage during the process of brain investigation is considered. Recently, most of the works in systems research focus on the parallel comparisons and associative discoveries of various components, but it seems less consideration has been given to the cumulative effect over time. Therefore, it is crucial to study such an intelligence model, both in theory and in practice, to understand complex brain mechanisms coupled with multi-aspect applications. Thus, the main objectives of this study are to understand and answer following questions:

1. How to understand brain intelligence and brain health from neural microcircuits to macroscale intelligence systems, supported by connecting network and brain with big data: investigating a brain big data model to integrate knowledge, information and data systematically from the multi-source local and global sites.
2. How to utilize the power of human brains and man-made networks to create a better-connected world towards human-level AI society: constructing a general intelligence model to perform systematic brain computing like human beings through modeling human investigation behavior during such a never-ending learning process.
3. How to realize human-level collective intelligence as a big data sharing mind on the social-cyber-physical-thinking space by developing brain inspired intelligent technologies to provide wisdom services: developing computational models to bridge basic cognitive neuroscience with smart health applications.

1.4 Contributions

In the pursuit of answers to the above research questions, we make contributions to the following area.

1. Hierarchical knowledge (K) - information (I) - data (D) big data model, that is, the K-I-D architecture.
   - Knowledge Layer **K**: Multiple knowledge graphs are constructed to represent systematic brain investigation processes in dimensions of brain function, experimental tasks, data management and analytical methods.
   - Information Layer **I**: A multi-information warehouse that records multifaceted information of resources in the form of semantic vectors, supporting provenance and computing.
   - Data Layer **D**: Multi-task functional neuroimage-centric systematic management within a multi-modal and multi-scale brain big data center. (Kuai et al. Journal of Computational Science, World Wide Web Journal)
2. Never-ending learning (NEL) agent as a Data-Brain driven general intelligence model.

   Never-ending learning, like human beings, is enough to use previously learned many types of knowledge to improve subsequent learning and avoid plateaus from years of diverse, primarily self-supervising experience. Based on the K-I-D architecture, it builds a K-I-D loop as a thinking space and provides an innovative brain big data computing approach to realize brain-inspired and human-liked neve-ending learning. In addition, human beings directly interact with this loop to extend the ability of never-ending learning, namely human-in-the-loop. (Kuai et al. An International Journal of Information Fusion, World Wide Web Journal)

3. Design and implementation of systematic cognitive experiments for multipurpose investigations and applications.

   The main and supplementary experiment types, as well as the inference rule of their relationships between experiment types, are established according to the purpose of the brain cognitive function investigation, followed by an experimental template graph that is created and implemented to systematic experiment design. At the method level, an experimental task is planned to perform the data sampling from the brain big data center. The Data-Brain model and inference rules are combined to identify the new experimental task to which the supplementary experimental type belongs, and the designed experimental task is mapped into the template graph. By performing the above method several times, all experiment types would been designed. This method enables the systematic integration of multi-source brain data and the multifaceted analysis for the systematic investigation of cognitive functions. (Kuai et al. An International Journal of Information Fusion)

4. Never-ending learning based evidence combination and fusion computing for systematic investigation using task-state fMRI-centric brain big data.

   An experiment template graph is designed and established that includes the main experiments and supplementary experiments, inference rules among various experimental types and the weight of evidence. According to the experimental template graph, the data, information and knowledge that need to be analyzed are acquired from the brain big data center. As the multi-task fMRI data are analyzed in the K-I-D loop for evidence combination and fusion computing, we can obtain the uncertainty distribution for systematic interpretations of the complex brain functions. Such evidence combination and fusion computing promotes our systematic understandings of complex brain functions, systematic reading of psychological conditions, and systematic response to mental disorders. (Kuai et al. An International Journal of Information Fusion, IEEE Access, BI2021, BI2019)

1.5 Organization of the Thesis

The main contents of this thesis consist of seven chapters that are organized as shown in Figure 1.3.

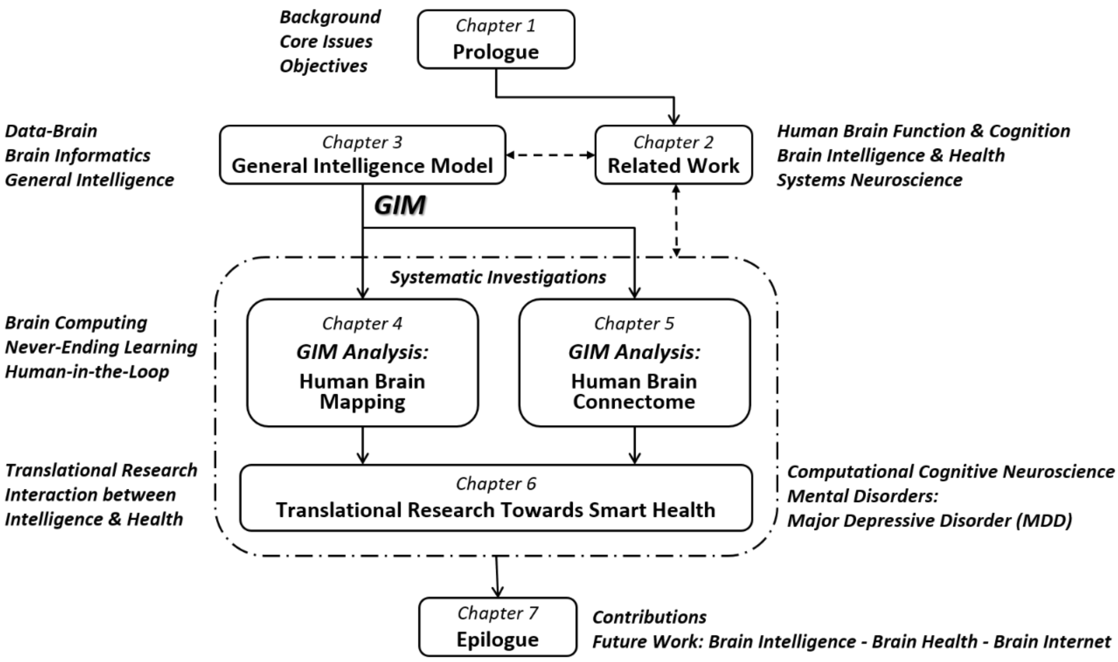


Figure 1.3: Organization of this thesis. This thesis consists of seven major chapters.

Chapter 2 introduces related works, including the theoretical foundation to the functional segregation and integration that are two core directions in the human brain researches; the new progress of basic cognitive neuroscience, especially for the function magnetic resonance imaging (fMRI) that was employed as the main approach in this thesis; an overview about translational research from brain intelligence to brain health; and the brain investigation from the systems science perspective.

Chapter 3 describes the general intelligence model, including: the problem statement and preliminaries surrounding systematic brain computing; the basic theories with Brain Informatics, web intelligence and general intelligence for cognitive neuroscience research; the study of the Data-Brain driven general intelligence model with evidence combination and fusion computing towards never-ending learning coupled with human-in-the-loop; and the prospective about the model as the core of a global platform supporting the whole systematic Brain Informatics research process and its real-world applications.

Chapter 4 elaborates the brain activity patterns underlying the higher-order mental processes, such as inductive reasoning, calculation and emotion, by using the general intelligence model from the functional segregation perspective.

Chapter 5 focuses on the brain mechanisms of functional integration to investigate the inductive reasoning process, and proposes a model to explain the crucial nodes and topological characteristics within the large-scale brain network.

Chapter 6 delineates a computational model to distinguish the disease group and healthy controls, focusing on different-level brain patterns learned by the general intelligence model. This chapter also focuses on the robustness of brain patterns for recognition capability and convergence performance of the model, and their translational effect on the major depressive disorder.

Finally, Chapter 7 concludes this thesis. It discusses contributions and some topics for future researches on brain intelligence, brain health and brain internet.

Chapter 2

Related Work

Chapter 2 discusses the technology, methodology and applications on systematic brain computing. We begin by introducing two principles of functional organization that are extensively explored in the human brain studies: functional segregation and functional integration. Then, the translational research related results are reviewed to promote better practices from brain intelligence to brain and mental health. The opportunities of brain investigation in the big data era are discussed, especially in the face of complex content and context of brain data. Lastly, we review a series of brain investigation methods from the systems science perspective.

2.1 Functional Segregation and Integration in the Brain

The functional segregation and integration are two critical principles of organization in the human brain: the former emphasizes the functional specificity of discrete brain regions (or nodes), whereas the latter stresses the brain connectivity patterns of the interactions among regions or nodes [66, 67]. The study on human brain function is an interdisciplinary field, overlapping with disciplines such as behavioral science, cognitive psychology, computational science and neuroscience. Especially, cognitive neuroscience as an important branch makes great contributions to the development of brain investigations, which combines experimental strategies and computational paradigms to actually examine how brain function supports mental activities [68].

From the two fundamental perspectives of human brain mapping and connectome, the broad strategies are presented to understand the functioning of brain organization. Early works focused on the brain lesions study for understanding of brain function, which provided a comparable starting point on regards to healthy and fully functioning brains [69, 70]. Furthermore, the development of task-dependent closed-loop approaches such as brain stimulation can demonstrate casual functional relations between various brain organizations, which has gained popularity to the brain function study [71-73]. In addition to the above-mentioned techniques, the advantages of modern functional neuroimaging techniques yield major breakthroughs for brain investigations in recent years. On the one hand, the functional neuroimaging techniques (such as fMRI and positron emission tomography) are widely used to measure the brain activity of the focal brain regions during behavioral or cognitive operations, by which various ROI analysis approaches are performed to further understand brain function they participate [74]. On the other hand, from the connectivity perspective, the interaction mechanisms are investigated in the human brain, in which a number of brain structures are linked into pathways or circuits such as reward circuits and limbic system [75-78]. Moreover, graph-based network analyses reveal meaningful information about the topological architecture of brain network, such as small-worldness, modular organization, and highly connected or centralized hubs [79-82].

2.2 Basic Cognitive Neuroscience

2.2.1 Brain Function Study

While the research in cognitive neuroscience combines many levels of neuroscientific and psychological analyses, the image technology and methodology have given us enormously detailed information about the brain activity patterns of complex function [83]. However, the evidence generated by neuroimaging studies also cusses understandings of uncertainty, especially for brain activity patterns involved in higher cognitive function [84]. One fundamental problem to cognitive neuroscience is to interpret the complex brain structural-functional relationships, the broad discussion of which includes functional domains, brain structures and their interactions.

For functional complexity, the cognitive functions are usually divided into three primary subsystems, including the basic cognitive system (such as perception, attention and memory), the higher cognitive system (such as reasoning, calculation, problem-solving, decision-making, learning and language), and the system for social processes (such as emotion processing, self-representation, social communication and social dominance) [85]. On the one hand, the functions within each of cognitive system show the intra-correlated characteristic. For example, the human reasoning as a higher-order cognitive function can be divided into three basic forms of inference, including induction, deduction and abduction [86]. Furthermore, for inductive reasoning, it can also be involved in various sub-components, such as rule identification and extrapolation [87]. On the other hand, the functions across three cognitive subsystems shows the inter-correlated characteristic. For example, the studies about influences of emotion and basic cognitive functions on higher-order cognition (such as reasoning and decision making) provide substantial evidence for interpreting the interactive effect between them [88].

For structural complexity, brain regions are organized into cytoarchitectonically distinct areas, each cytoarchitectural configuration of which has structural properties with different implications for computational functions [89]. On the large scale, the brain is divided into several lobes from the anatomical classification perspective, such as frontal, parietal, occipital, temporal, insular and limbic [90]. Furthermore, the human cerebral cortex is subdivided into 52 cortical areas from the Brodmann’s mapping with various cognitive and behavioral functions [91]. For the smaller scale, the human brain parcellation (including criteria of architecture, function and connectivity) approaches are developed to create human brain atlases with the finer-grained brain regions and sub-network architectures.

2.2.2 Cognitive Experimental Design

Apart from the above-mentioned complexity of brain function, in-depth consideration to design and application of different experimental tasks is also given to increase the power of study, which directly affects the response of mental processing [92]. More specifically, the complexity to design cognitive experiments need to consider variables and how they are related within a specific testable hypothesis. Additionally, implementations of such cognitive experiments also need to consider various subjects and groups, either between-subjects or within-subjects, as well as the means to measure these dependent and independent variables. These factors increase the difficulties of experimental design, at the same time, increasing the difficulties of experimental selection to test the hypothesis related to different cognitive functions.

The many-to-many complexity appears not only in the interactive scenarios of brain function and structure, but also in the interactive scenarios of brain functions and cognitive experiments. Firstly, the experimental tasks with different paradigms can be used to investigate a specific cognitive function. For example, the tower of Hanoi task, the sequence complement task and sudoku puzzle task are usually used to study the reasoning mechanism. Secondly, one experimental strategy may be considered to test different cognitive functions from different perspectives. For example, from one view, some investigators used the facial emotions task to study the perceptual skills. However, from another view, some investigators also used the similar experimental task to judge the social ability. Thirdly, while some of experiments seem to vary significantly, they induce a similar brain response. Moreover, a dual-task experiment can obviously induce multiple mental processes [93]. The complex interactions have motivated us to develop solutions that can efficiently organize these experimental details and their relationships, such as the cognitive paradigm ontology (CogPO) and the cognitive atlas. In CogPO, the experimental paradigms are categorized by various concepts about the stimulus presented to the subjects, the requested instructions, and the returned response [94]. These concepts are connected by a set of relationships such as "has stimulus", "has contrast", "includes condition" and "related to". In the cognitive atlas, a knowledge base was developed to collect and manage terminology about experimental tasks and mental processes [95].

2.2.3 Brain Data Science

The field of functional brain data has substantially advanced as a big data science in the past decade, thanks to the development of open science [96-99]. Handling large-scale brain data faces many challenges, especially in the transmission, storage, and dissemination of the functional neuroimaging with complex experimental characteristics as mentioned above [100]. Moreover, how to quickly extract a or multiple satisfactory data from the data ocean constructed by tens of thousands of brain data to meet the needs of systematic brain computing has become urgent in the brain big data era.

Currently, numerous strategies have been developed to regulate the identification, representation, interpretation, operation and integration of various data-typing brain data. For open and FAIR neuroscience [101], on the one hand, some common principles are developed towards the goal of best practices, such as the DICOM and NIfTI data standards [102, 103], BIDS (Brain Imaging Data Structure) [43] for organizing neuroimaging and behavioral data, and MIDS (Medical Imaging Data Structure) extended to multiple modalities and anatomical regions. On the other hand, some databasing approaches, ontologies and data models are constructed to improve usability and readability of brain data, such as BrainMap [33], NIDM (Neuroimaging Data Model) [104], NEMO (Neural ElectroMagnetic Ontology) [105], NeuroML [106] and Computational Neuroscience Ontology [107]. However, the current strategies are limited to data and analysis provenances, as a planner aimed at the decision-making process of data integration and reuse, which ignore the direct impact of defined factors on the brain computing results. As such, the mental processes, experimental design and data acquisition details increase the complexity, not only for data archiving, management and sharing, but also for the fusion computing of resources at various granularities of brain data, information and knowledge (such as the raw data, parameter mapping and localized coordinates in the brain). For this, it is becoming an urgent need to enhance data integration and brain computing simultaneously.

2.2.4 Brain Computing Methods

By integrating artificial intelligence and computational science, various brain computing methods are developed to decode complex brain functions. Here, we review representative approaches that are already having profound effects and will continue to play a critical role in brain science, towards the goals of uncovering two principles of functional organization.

Localization exploration of brain functions is one of the most fundamental works in cognitive neuroscience, which is investigated to determine the location of brain activity or to produce functional/parametric brain mapping by correlational methods (such as ROI analysis) and connectional methods (such as the role of part of brain region in the whole brain) [84, 108]. In recent years, benefit from the advantages of functional neuroimaging techniques, many methods are developed to decode the complex brain function, such as statistical analysis, representational analyses and computational methods [2]. For example, the functional brain images are analyzed by the standard univariate approach such as statistical parametric mapping (SPM) to examine differences of brain activity recorded during functional neuroimaging experiments in regions of interest (ROIs) [109, 110]. Under the SPM framework, the statistical effect of each voxel is observed by combining with the general linear model (GLM) [111]. Apart from the statistic-based univariate analysis approach, the multivariate pattern analysis (MVPA) uses machine learning methods to examine the multidimensional relations between brain activity patterns, such as classifier-based and pattern-similarity MVPA [112]. As another approach that directly decodes the relations between psychological contents and brain function, representational similarity analysis (RSA) is introduced [113]. Furthermore, model-based approaches, such as reinforcement learning, play a critical role in our understanding of brain function [114].

In contrast to such local specialization, brain connectivity refers to the integration characteristics among distinct units, which is measured by anatomical links (structural connectivity), statistical dependencies (functional connectivity) or causal interactions (effective connectivity) [115, 116]. For example, the structural connectivity patterns are determined by directly observing links such as synapses, circuits or fiber pathways [117, 118]. The statistical dependencies between brain regions or nodes can be measured by cross-correlation analysis, coherence analysis or mutual information from the functional connectivity perspective [119]. The casual interactions can be investigated by granger causality (GC), dynamic causal model (DCM) and Bayesian network (BN) from the effective connectivity perspective [120]. Furthermore, complex network metrics are examined by regional nodal parameters (such as centrality, betweenness and participant coefficient) and global network parameters (such as clustering coefficient, local efficiency and global efficiency) [121, 122]. More specifically, there are many functional networks to be recognized in the human brain, which act with various functional characteristics, such as the primary sensory and motor networks, the language network, the default network (DN), the salience network (SN), the attention networks (ANs), the control networks (CNs) [123-125].

2.3 Translational Research in Cognitive Neuroscience

As the control center of human body, the brain plays a key role in perception and regulation of the mental and physical health status. Especially the development of translational research in brain science, the shift from basic neuroscience discoveries to the public health applications has advanced progress towards precision medicine [131] and the P4 medicine [65]. For example, the basic brain research has linked the presence of brain abnormalities to a variety of symptoms and signs, including major depressive disorder (MDD) [126, 127], mild cognitive impairment [128], dementia/Alzheimer's disease [129], epilepsy [130], and so forth.

On the one hand, many studies have demonstrated the brain functional abnormalities in regions is associated with the symptoms of patients with psychiatric disorders [132]. For example, some studies showed the abnormal regions in the amygdala, insula, dorsal anterior cingulate cortex, dorsal striatum and dorsolateral prefrontal cortex in individuals with major depressive disorder than in healthy subjects [133]. The bipolar disorder shows the abnormal activation in the bilateral inferior frontal gyrus, bilateral insula extending into the striatum, right superior frontal gyrus (SFG), superior temporal gyrus (STG), bilateral precuneus, left cerebellum and left anterior cingulate cortex (ACC) [134]. Schizophrenia shows the abnormal information processing in the prefrontal cortex, amygdala and hippocampal [135, 136]. On the other hand, the symptoms of mental disorders are also associated with the abnormal characteristics on the brain functional connectivity [51]. For example, network dysfunction underlies core cognitive and affective abnormalities in depression [137]. The default mode network and medial prefrontal cortex connectivity abnormalities are found in bipolar disorder and schizophrenia [138-140].

Currently, the integration of computational science and neuroimaging techniques has surpassed expectations in the field of the brain-related translational research, which has been widely applied to various clinical practices [63, 141]. For example, prediction and treatment of mental disorders [142], diagnosis and assessment of neurological diseases [143], brain tumor detection [144], as well as assessment for epilepsy surgery [130]. More specifically, computational approaches to psychiatry could be divided into two views: one is the data-driven approach (such as machine learning and standard statistical methods), and another is the theory-driven approach (such as biophysically realistic natural network models, algorithmic reinforcement learning models and Bayesian models) [145, 146].

The machine learning and pattern recognition methods has shown the potential to transform the role of neuroimaging in clinical applications [52, 129, 147-149].

2.4 Systems

Systems science is an interdisciplinary field concerned with understanding systems– from simple to complex – in nature, society and cognition, which brings together techniques and methods from ontology, similarity comparison and so forth [150]. As its one interdisciplinary instance, systems biology develops the integrative strategies to investigate complex interactions within biological systems, using a holistic approach (holism instead of the more traditional reductionism) to biological research [151]. With the development of cognitive neuroscience, the integration of brain science and systems science has become more frequent, evolving into systems neuroscience as a subdiscipline of neuroscience and systems biology [113]. One of the significant domains which benefit from systems science is brain informatics, complying with the "Top-Down" principle to decode complex brain functions from perception to thinking [152, 153]. From the systematic view, brain computing changes from single to fusion, chasing the balance of multifaceted factors about cognitive function, experimental design, data state and analytical details. Furthermore, general theory plays a key role in systems research, which is about developing broadly applicable concepts and principles [154]. Combining with general theory, a smart health application means that a system and/or model learns systematic thinking, knowing itself completely, what happened (facts), why it happened (causes) and how to accomplish (actions) [155]. More specifically, it can realize transformation across multiple scenarios, relying on translational study.

On the consistency of the traditional brain investigation approach, systems neuroscience focuses on the interrelated factors covered by cognitive functions, experimental designs, data collections and analysis strategies. More specifically, under the process of understanding human thinking, the thinking-centric higher cognitive functions and relevant basic functions need to be explored systematically. Furthermore, such a systematic investigation strategy guides the systematic design of multiple cognitive experiments, the systematic collection and management of multiple brain data, and the systematic analysis and simulation for an in-depth understanding of the brain information-processing mechanisms, as well as the intra- and inter-element relations within and among themselves (see Figure 2.1 and the diagrammatic representation for systems neuroscience).

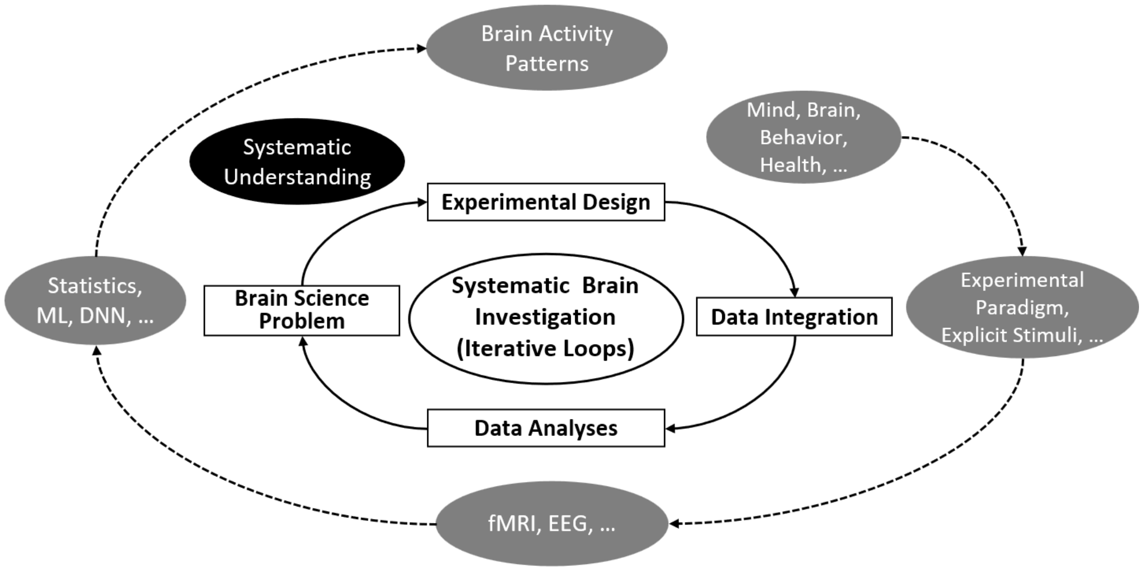


Figure 2.1: A diagrammatic representation of goals and approaches of systematic brain investigation. (1) the outer spiral with dotted arrows depicts some factors within a brain investigation process, which involve detailed parameters during the whole life cycle of brain data including functional domains, experimental details, data state, algorithmic selection and interpreted views, and (2) the inner circle with solid arrows shows iterative process of brain investigation from a systematic perspective, which includes the following: systematic investigation of brain science problems, systematic design of cognitive experiments, systematic brain data collection and integration, and systematic brain data analysis and simulation. For a goal hypothesis, each iteration refines the brain computing results through a combination of practice from the previous and current loops, and deepens our understanding of the brain activity patterns. Ultimately, such models may be used in a predictive mode towards human health-care and clinical practices.

Given the most common brain research process, an initial hypothesis to a brain science problem must first be given. Then, a specific cognitive experiment is designed to collect the limited brain data. Finally, we may try the strict methods to test the hypothesis we mentioned earlier. Obviously, this strategy is essential to understand the one-to-one relationship between brain structure and cognitive function from a single perspective. But when we want to consider the many-to-many interactions among several cognitive functions, this strategy is not enough. For example, on the one hand, as the largest of the lobes in human brain, the frontal lobe is further divided in various functional areas, including the motor cortex, the prefrontal cortex and Broca's area. The frontal lobe plays a key role in a broad scope of cognitive functions from movement to intelligence, such as memory, reasoning, decision-making, problem-solving, language and emotion regulation. On the other hand, as a basic component to human intelligence, human reasoning reflects different ways of thinking logically, including inductive, deductive and abductive approaches. The inductive reasoning is further divided to various cognitive sub-components, such as rule identification and application, which are related to other cognitive functions, such as memory and calculation. Some studies suggest that the inductive reasoning is not only related to the prefrontal cortex, but also precuneus, inferior parietal lobule, superior occipital gyrus and so forth. We can find that it is difficult to clear the complex brain structure-function relationships, which is still an open question in the field of brain science. Hence, it is becoming an urgent need to change our views from the independent brain investigation to systems.

2.5 Conclusion

In this chapter, we cover the related works on brain investigation with translational research in the big data era. We review two research views of the functional segregation and integration that are two important organization principles in the brain. The basic cognitive neuroscience is introduced around the brain function study, cognitive experimental design, big data science and brain computing methods. We then review the neuroscience-centric translational research and the necessary of systems research for brain science.

Chapter 3

Data-Brain Driven General Intelligence Model (GIM)

In this chapter, the Data-Brain driven general intelligence model and its multi-aspect applications are introduced. This model is designed and constructed by combining several components surrounding the represent knowledge, inference engine, brain computing, never-ending learning, human-in-the-loop and an interpreter for uncertainty. The model, as a thinking machine, performs systematic cognitive experimental design and implementation, and systematic brain big data analytics and fusion computing from multi-aspect task-state functional neuroimaging sources. This chapter was prepared for understanding (1) what drive the emergence of the general intelligence model, (2) how to construct such a Data-Brain driven general intelligence model, and (3) what is the capability of the general intelligence model for understanding brain intelligence and brain health.

3.1 Problem Statement

3.1.1 Complex Brain Computing

The human brain often casually described as the most complex system (with functional, structural and dynamic characteristics) in the universe, for which different brain computing methods are developed to uncover the biological characteristics and information-processing mechanisms [156-159]. Typical investigation processes include formulating goal hypotheses, designing and carrying out cognitive experiments, collecting and analyzing brain data, and generating scientific reports with various findings. During such a process, numerous factors will be considered to solve a particular brain science problem by carefully selecting experimental paradigms, measured techniques and analytical methods to reduce the impact of intervening factors and increase confidence level of hypothesis testing. As a result, such carefully thinking and practical behaviors contribute to the urgency of implementing brain computing with systematic fusion. Meanwhile, such many-to-many uncertainty mapping on brain structure-function relationships increases the difficulty in interpretations of brain functions.

As an example, understanding human thinking itself is the key step towards human-level AI, for which purpose the thinking-centric higher cognitive functions and relevant basic cognitive functions need to be explored systematically. That is to consider multiple cognitive functions, simultaneously or continuously, for an in-depth understanding of brain information-processing mechanisms and their biological characteristics, as well as the intra- and inter-construct relations within and among themselves. Such a systematic consideration drives the systematic design of multiple cognitive experiments, the systematic collection and management of multi-angle brain data, and the systematic analysis and simulation of multi-source brain data [152, 153, 160-162]. This example inspires us that 1) multi-aspect factors should be coupled with each other, and need to be treated by systematic consideration. If they are separated or only a particular aspect is observed, it is difficult to capture the brain specificity, and give rational interpretation and evaluation; 2) models for fusing multi-sourcing of data, information and knowledge should cater for the joint investigation among cognition, emotion and disease from a systematic perspective. Taken together, the practice goal is achieved through continuous brain computing and learning.

3.1.2 Systematic Behavioral Modeling

An important idea is to build a machine through modeling of human thinking and behaviors, promoting the transparency and interpretability of brain computing results. Hence, the behaviors of investigators and the operations of machines can be interchangeable in a whole cycle of brain investigation, which constitute various strategies to achieve his/her investigation goals. One of the most core challenges is how to make a machine present a brain data with the complex context. In this case, characteristics (the complex context from functional domain, experimental design, data state and analytical detail) of a brain data need to be marked by a descriptor, and make it traceable in data ocean constructed by the interconnected and interrelated resources (see Figure 3.1). The reason is: the confounding of cognitive processes produces the urgent need to a standardized definition for cognitive processes and their relationships; the ambiguous terminology makes it difficult to test the utility of these resources for large-scale annotation of data, search and query, and knowledge discovery and integration; gaps and conflicts make it difficult to combine brain resources for interpretations of multi-aspect data [95, 163]. Just like human beings, a machine also needs to recognize the complex context of various brain data to response to requests rightly. Hence, an identifier

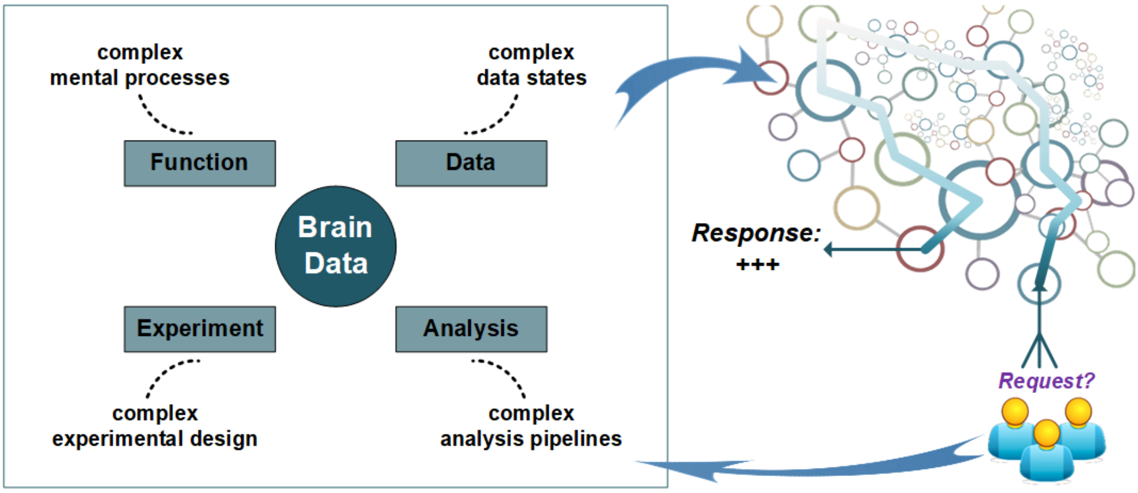


Figure 3.1: Systematic behavioral modeling interacts with brain big data towards never-ending learning.

is needed to systematically demonstrate the complex data for meeting the requirements of storing, computing, analyzing and interpreting.

Furthermore, the complexity of brain science problem makes it impossible to uncover the nature of cognitive processes, observed from only one angle such as a single brain data obtained by a single experimental task and decoded by a single analytical strategy. Such like human beings to address a brain science problem by performing many different types of experiments from diverse hypotheses for a long time, even throughout one's whole life, a machine needs to acquire multiple functions or data models from multiple datasets in responses to a user request continuously and permanently. The core challenge is how to identify the goal-matching resources obtained by different experiments for a machine to address a specific brain science problem, which is also involved with behavioral modeling (see Figure 3.1). In particular, the thinking behaviors present the complex relations of brain data, corresponding to the behaviors of the inner system. However, the practical behaviors present the sampling of complex brain data in the big data era, corresponding to the behaviors of the outer system. Thereby, an intelligence model is authorized to intelligently select different types of brain resources, and systematically fuse them for providing the thinking-support investigation.

3.2 Basic Theories

3.2.1 Brain Informatics

Brain Informatics (BI) is a rapidly evolving interdisciplinary and multidisciplinary research field that focuses on studying the mechanisms underlying the human information processing system (HIPS) with big data [152, 153]. It investigates the brain information processing mechanisms with respect to the essential functions of human brain, ranging from perception to thinking, such as perception, attention, memory, reasoning, calculation, decision-making, problem-solving, language, learning, creativity, planning and discovery. Brain Informatics has opened up an avenue for investigating the complex brain science problems systematically, integratively and intelligently, by leveraging the benefits of cognitive neuroscience, artificial intelligence, and information and communication technology in the big data era (see Figure 3.2).

The core issues in the Brain Informatics methodology are systematic studies from the following four aspects: systematic investigations of complex brain science problems, systematic design of cognitive experiments, systematic brain data management, and systematic brain data analysis and simulation [161]. Such a methodology guides the design, development and operation of the intelligent model for systematic brain investigations. One of the core strategies in Brain Informatics is to model the many-to-many structure-function relationships of the brain at the logic level, depending on a directed labeled graph such as knowledge graph. Directed by the Brain Informatics methodology, the systematic brain investigations can be executed in multiple directions of cognition, emotion and disease, respectively, as well as their joint investigations from

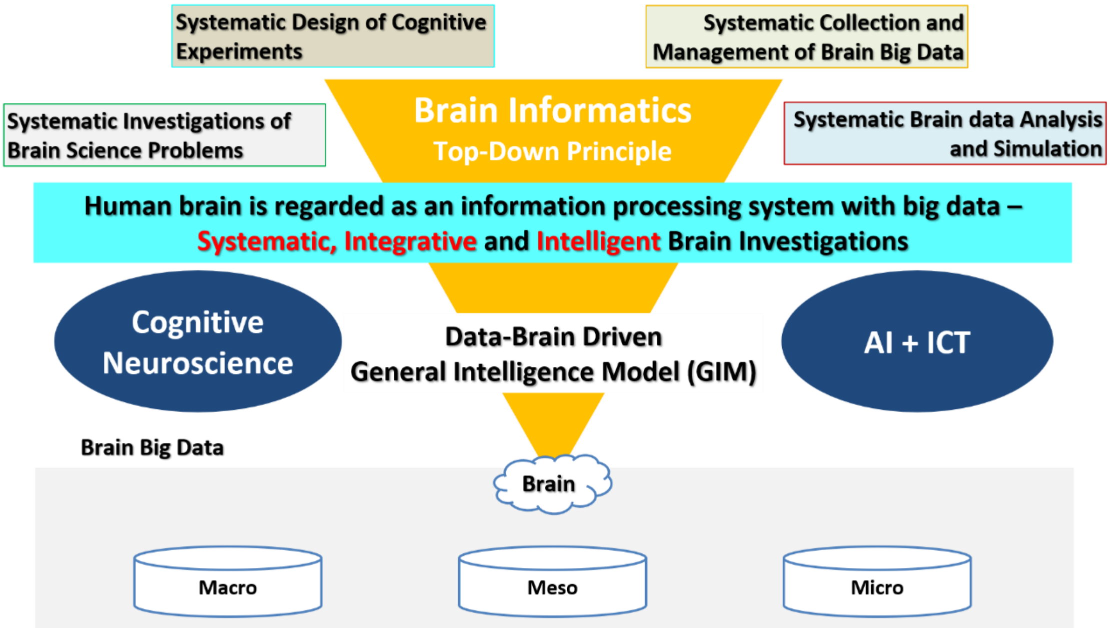


Figure 3.2: The Brain Informatics methodology. Brain Informatics is an interdisciplinary and multidisciplinary research field with joint efforts from neuroscience, cognitive science, medicine and life sciences, data science, artificial intelligence, neuroimaging technologies, and information and communication technologies (ICT). It provides five research tracks with respect to: cognitive and computational foundations of brain science; human information processing systems; brain big data analytics, curation and management; informatics paradigms for brain and mental health research; and brain-machine intelligence and brain-inspired computing, for investigating big brain in the era of big data.

the basic cognitive neuroscience to translational research. Another core strategy in Brain Informatics is the top-down priority principle, which focuses on the systematic study about the full-scale data of human brain in vivo with cognitive tasks for seeking a complete comprehension of human intelligence and health. Following this principle, the processes of decoding brain are specified to map investigating behaviors from macro- and meso- scales to micro-scale. For instance, we can first observe the macro-scale characteristics for a full brain function by testing behavioral experiments. Then, we can observe the meso-scale characteristics in the local brain and functional connectivity, depending on a series of functional neuroimaging techniques. Next, we can observe the micro-scale characteristics for a type of neuron within a brain region of interest obtained at meso-scale. Finally, such investigated results from the macro-meso-micro brain are integrated to an evidential chain to promote our systematic understanding and multi-aspect interpretations of the biological characteristics and information-processing mechanisms.

The Brain Informatics highlights the systematic brain computing, contributing to the need of the general intelligence research. To develop the general intelligence-oriented problem-solving and decision-making as well as knowledge discovery systems with human-level capabilities, we need to better understand how human beings complete adaptive, distributed problem solving and reasoning. As a result, the linkages between the classical AI study and the biological brain study for problem-solving and reasoning need to be defined and elaborated. It puts forward the higher requirements for advanced computing techniques in the connected world.

3.2.1 Web Intelligence

Web Intelligence (WI) is now a cutting-edge research field on exploring fundamental roles and practical impacts of artificial intelligence and advanced information technology (IT) on the Web and the next generation of Web-empowered wisdom services [164, 165]. It aims to achieve a multidisciplinary balance among research advances in theories, methods and applications usually associated with collective intelligence, data science, human-centric computing, knowledge management and network sciences. With an eye on the future, Web Intelligence begins a new chapter around the theme of

“Web Intelligence = AI in the Connected World”.

Here, we use the term “AI” in the widest possible sense, including the works related to statics, machine learning and AI research that aims to build intelligent machines [166].

The core of this process is to both deepen the understanding of computational, logical, cognitive, physical and social foundations of the future human-level AI society, and enables the development and application of intelligent technologies. More specifically, these topics could be tracked to investigate how intelligence is impacting the Web of People, the Web of Data, the Web of Things, the Web of Trust and the Web of Agents in this era of the rapid development of information and communication technologies.

The social interactions, cyber correlations, physical perceptions and thinking communications can be intertwined in the ubiquitous things' interconnections, which realize a perfect integration of the social-cyber-physical-thinking spaces. Connections with variable effect characteristics, including virtual and real connections, are the most common forms of dynamic structure in these spaces. In this context, brain computing in the connected world is not only supported by the interactions and integration of data, information and knowledge in a general intelligence model, but also the interconnections related to the Web of People, the Web of Data, the Web of Things, the Web of Agents, the Web of Trust and the Web of Security with respect to Web Intelligence.

- The Web of Data (WoD)

  The WoD focuses on the organization, management, allocation and computation of loose resources and system platforms in the cyber space, in which different data objects will be distributed and centralized through the existence of links. For this, the knowledge graph and graph database techniques could be integrated into the general intelligence model, which is expected to achieve a more natural data ecosystem by using the native graph storage and processing modes. Changing the type of data transmission, from data containing multiple messages to the information extracted from multiple data, will greatly improve the efficiency of data communication and dissemination in the connected world. Hence, the loose data can be processed at the terminal. The combination mode of edge computing and distributed computing is considered in the general intelligence model, and technical and service supports are provided through the cloud platform. On the one hand, multi-source heterogeneous data bring huge challenges to the integration and fusion of resources, such as the polycentricity problem widely existing in the field of neuroscience. Through edge computing technology, the massively heterogeneous data that previously tended to be processed centrally is now being processed by edge nodes for initial processing to make original data more standardized. These isomorphic information and metadata during the entire life cycle of data are transferred and shared, which will greatly improve application efficiency. On the other hand, the situation of the massive data processing is inevitable in the era of brain big data, which cannot be solved by the computing resources of an organization or a group. Hence, the distributed computing technology is applied to a general intelligence model to solve the large-scale brain computing problems by collaboratively managing increasing resources. In addition, a general intelligence model may provide the hierarchical and personalized data computing services through the virtualization technology, which can quickly meet the needs of different tasks.

- The Web of Things (WoT)

  Physical objects of real world are established into the interconnected mode via the various communication technologies and remote collaboration means, which form the WoT in the cyber-physical space. In the WoT, all objects can be perceived and controlled by sensors and actuators, in which they are connected by the Web/Internet of Things technology to achieve dynamic interaction and autonomous management.

Its core research challenge brought by the connected world is to realize the organic amalgamation and harmonious symbiosis among ubiquitous objects, i.e., to make everything smarter, intelligent, and smooth communication. To achieve the goal, the Wisdom Web of Things (W2T) has been developed as a core of the WoT with big data in the social-cyber-physical spaces. For instance, the physical objects themselves not only can adaptively process and analyze data, but also can sense the status of other sensors and respond autonomously to the surrounding environment. The actuators are not only the performers who send and receive action instructions, but also have the ability to organize and manage autonomously by themselves. For instance, these actuators can interact dynamically through adaptive modes and collaborate to accomplish specific tasks and goals in the complex environments. Throughout the W2T, a general intelligence model may act as the overall control center to provide the intelligent solutions and global services in the connected world. It can not only receive the global-scale information transmitted by the Web technology to perceive the real-time status of physical objects, but also timely analyze the dynamic changes to generate a set of control instructions that can be interpreted by physical objects. In addition, a general intelligence model also can be personalized as a local node to participate in the construction and operation of the local services. Such interactions of models from the global and local sides build the collective learning and mutual support mechanisms of physical objects in the WoT. Some main communication and networking technologies are applied to the interactive mode between a general intelligence and the cyber-physical environment, such as virtual reality techniques, 5G, radio frequency identification, Bluetooth, ZigBee, Wi-Fi, global positioning system and radar sensor network.

- The Web of Agents (WoA)

  The characteristics and mechanisms of biology in the thinking space, including behaviors and activities, are integrated into the connected world to form the new generation of network modes called WoA. The thinking agents in the WoA are not equivalent to the virtualization of entities in the cyberspace. The latter mainly rely on virtual and digital signals for information exchange and dissemination. More importantly, the thinking and organism themselves are the important component of an agent in the current network, which directly participates in the dynamic changes of the network characteristics through the physiological signals and functional mechanisms. For instance, the social brain communication is an emerging direction formed by the combination of the ICT and brain-machine interface technologies. It aims to achieve synergy among individuals through the direct brain-to-brain connections, thereby cooperating to accomplish goals that one cannot achieve. For this, a general interface is considered to build the bridge between organisms and intelligent agents through the Web technology, which is the driver and engine of the WoA development. In addition, the human information-processing mechanisms decoded by the web agents are developed to provide the brain-like computing methods, forming the core element of an intelligent agent that performs like human beings. Meanwhile, human thinking directly participants in the learning of agents, connecting the biological end with other spaces to realize the human-agent interaction within human-in-the-loop.

- The Web of Trust (WoTr)

  Trust plays a significant role in the connected world to maintain the stable and sustainable relations, as well as dynamic balance among humans, machines and things. Authenticity is the cornerstone of trust, which is the premise for ensuring reasonable decision-making, publicizing authoritative information and so forth. Hence, the authenticity of data, information and knowledge requires special attention to provide the trusted services. The method and technical discussions surrounding it are usually classified into two groups from the perspectives of acquisition and application. In particular, the various combinations of these processes (including true acquisition with true application, true acquisition with false application, false acquisition with true application, and false acquisition with false application, respectively) can produce different results and effects. Obviously, obtaining real resources with the right methods and applying them to suitable scenarios are the ultimate goals, which are most likely to achieve the results we expect. In this case, the streaming data derived from real states of an entity under dynamic environments need to be accurately captured through progressive software and hardware techniques in real time. For instance, the ultra-high-field technology is applied to brain investigation for more realistically restoring the time-space response and more effectively capturing the functional specificity. The compression tools are developed to address the high-throughput data problem for future undistorted reconstruction. Furthermore, the batch data derived from historical states of various entities need to be unmistakably detected, which is the fake detection issue. For instance, in the social-cyber space, the authenticity of social elements in the different directions is concerned, such as filtering of spam email, detection of fake social media behaviors, detection of fake online reviews and news, and detection of fake software and websites. Moreover, in the social-physical space, various biometrics are applied to detect hiding true emotion and determine liveness from the iris, fingerprint, face, eye, brain and so forth. In view of the above observations, a trustworthy intelligent model in the WoTr is not only the generator of the open data, information and knowledge that must be authentic and convincing, but also the detector of fake resources that must be faced in the social-cyber-physical spaces.

- The Web of Security (WoS)

  Security is another issue of broader concern in the connected world, including but not being limited to personal data acquisition and analysis, which is closely related to privacy. An important view is to ensure that the resources generated by people, computers, sensors and agents within the social-cyber-physical spaces have their appropriate locations through the constraint of laws and regulations, followed by realizing the secure communication among them while taking individual privacy into consideration. To achieve such the WoS, a range of technologies, methods, strategies, mechanisms and regulations needs to be merged into the general intelligence model. For instance, the decentralized blockchain technology, which provides anonymity and data integrity without any third-party control, is considered to ensure the security of data management. Another way is to extend data storage, processing, computing and application services to the edge of the network, especially for end users, such as the fog computing and edge computing modes. Besides, for any entity in the social-cyber-physical spaces, the ultimate way of protecting the individual privacy and data security is not to open and share their data. In our increasingly interconnected world, however, it is obviously neither desirable nor realistic to confine individuals in isolated nodes, and not allow them to interact with each other. In this case, the federated learning, first proposed by Google in 2016, provides a solution that allows us to participate in the Internet feast more efficiently and effectively while maximizing the protection of the individual data and privacy. In the federated learning framework, each device in the network is used as a computing node performing training tasks on its local data instead of logging it to a data center for training. The privacy-preserving federated learning method is integrated into the developing process of an intelligent model, which is expected to provide more security solutions in the WoS.

In the face of complex brain science problems, Web Intelligence provides the technical support for such systematic brain computing in the connected world. Different from the conventional expert-driven approach, a systematic brain study integrates a powerful brain data center and various IT techniques within a general intelligence system. A brain big data center, as the extensional representation of human information-processing system, systematically organizes multi-level brain data to support the whole systematic brain research process. The Web Intelligence research, such as wisdom web of things [153, 167], provides a novel vision for computing and intelligence towards systematic brain research. A general intelligence model on the wisdom Web is developed to enable high-speed, large-scale, distributed computing, and new ways towards the integrations of data, information and knowledge. The W2T extends the wisdom Web in the connected world (Internet/Web of Everything), by which each thing in the social-cyber-physical spaces can be aware of both itself and others to provide right service, for right object, at the right time, and in the right context.

3.2.2 General Intelligence

The overarching problem in artificial intelligence is that we do not understand the intelligence process well enough to enable the development of the human-level computational models [61, 168]. Much work has been done in artificial intelligence over the years at lower levels, particularly, deep learning that has gained an unprecedented impact across research and industry communities [169, 170]. As a result, machine learning tools have been widely adopted to help computing and decision-making in various real-world scenarios. However, a big part of what has been missing involves the high level, abstract, general nature of intelligence. The gap needs to be addressed by developing a model with general intelligence.

Brain computing is widely studied to provide inspiration and support for studies of general intelligence. It is the multidisciplinary fields from cognitive neuroscience, big data, computational science to medicine and life sciences [171-173]. From the perspectives of brain intelligence and health, several typical directions are explained as follows:

- Firstly, as the biological basis of intelligent behavior, the human brain has long served as a source of inspiration for artificial intelligence and computational science [174]. For instance, the biological characteristics of the brain are studied to develop new algorithms [175, 176], neural inspiration models [177, 178] and neuromorphic computing [179, 180], as well as verify theories [181]; and the processing mechanisms of the brain are designed in chips to make computing more efficient and effective [182, 183]. Additionally, how to make intelligent agents perform like human beings with cognitive capabilities and social expectations is regarded as a key step on the road of reaching ultimate artificial intelligence [184, 185]. For instance, many advances have come from the area of explainable artificial intelligence to provide more transparency to their models [186-188].
- Secondly, as the control center of human body, human brain plays a key role in perception and regulation of the mental, physiological and physical health status.

Research has linked the presence of brain abnormalities to a variety of clinical outcomes, including cognitive impairment [189], dementia [129], psychiatric disorders [145], neurological disorders [190], and so forth. Owing to individual differences, the computational method for human brain is studied to realize precision medicine [131] and the P4 (Predictive, Preventative, Personalized and Participatory) medicine [191]. For instance, computational neuroscience has been widely applied to various clinical practices, such as prediction and treatment of mental illness [142], diagnosis and assessment of neurological diseases [143], brain tumor detection [144], as well as assessment for epilepsy surgery [130].

With the development of brain big data and open science, brain computing is rapidly moving towards using systematic fusion from perspectives of multi-aspect, multi-domain and collective efforts. This thesis is centered around advancing the frontier of both artificial intelligence and brain science in systematic learning and fusion computing. By meeting Brain Informatics and Web Intelligence, the novel machines can be built to perform brain computing approaches, learning and thinking like human with general intelligence. As shown in Figure 3.3, we believe a general intelligence model should include the represent knowledge and an inference engine, together with various learning strategies to realize decision-making and interact with the user in the continuous loops. In each iteration, the model receives input from the user and maps the queries to its internal algebraic representations by using the represent knowledge. The inference engine then carries out rule-based inference in experimental and analytical factors to predict user behaviors, and choose matched actions to execute evidential learning, fusion computing and decision-making. Thus, a goal of this thesis is to build a unified framework that provides a common thinking space for never-ending learning and inferring, together with

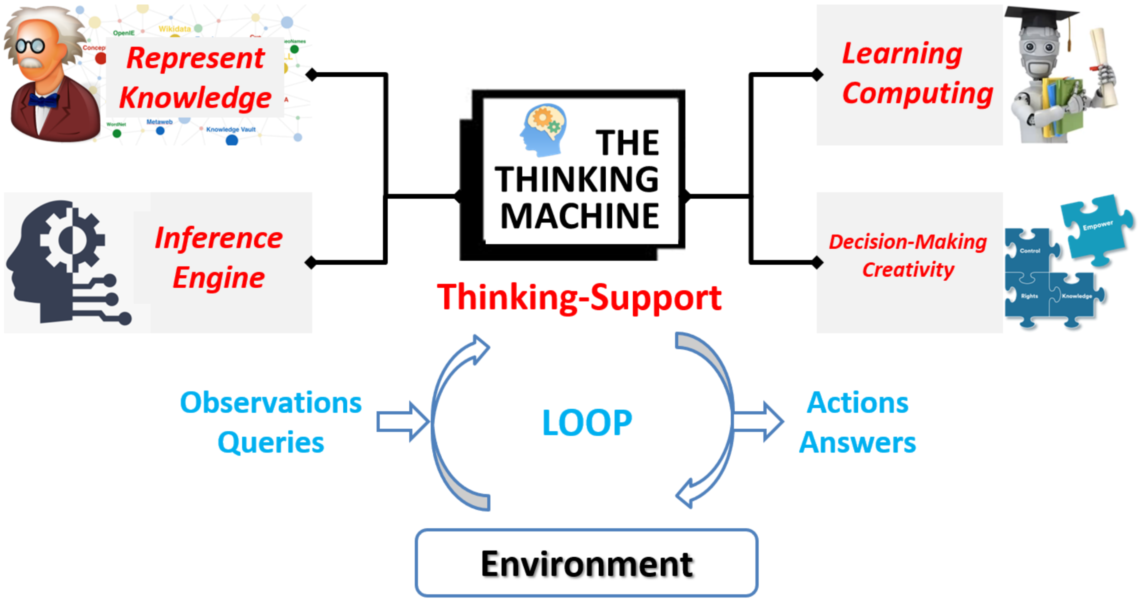


Figure 3.3: A model of general intelligence, which consist of the correlative knowledge, inference engine, learning paradigms and decision-making. The correlative knowledge serves as the basis of actions within model to represent human behavior, mapping from real-world goals to their internal representations. The inference engine is powered by rule-based reasoning that guide the model to walk in the huge graph to select, integrate and compute resources.

human-in-the-loop. By developing multi-factorial representations that generalize across scenarios, it can be adapted to help address the brain science problem around human brain mapping, human brain connectome and translational research.

3.3 Preliminaries

3.3.1 The Conceptual Data-Brain

Directed by the systematic Brain Informatics methodology stated in Section 3.2.1, a conceptual model is proposed, namely Data-Brain, to present and model the whole process of brain investigations. The conceptual Data-Brain provides a thinking space to serve as systematic brain computing, which is constructed as the interconnected four dimensions in knowledge graphs, including function dimension, experiment dimension, data dimension and analysis dimension:

- The function dimension provides a conceptual model of mental processes for supporting systematic brain investigations with structural constraints of cognitive elements. More specifically, it focuses on the conceptual modeling of the constituent elements on cognition, emotion and disease, as well as the intra- and inter-element relations within and among themselves. For instance, in order to understand human intelligence, the thinking-related cognitive functions need to be explored and explained systematically. The conceptual modeling of such cognitive functions is often divided into three primary systems, including the basic cognitive systems (such as perception, attention and memory), the higher cognitive systems (such as reasoning, calculation, problem-solving, decision-making, learning and language), and the systems for social processes (such as self-representation, emotion processing, social communication and social dominance) [192]. Moreover, a human reasoning-oriented mental process, as part of the higher cognitive system, can be further divided into three various aspects of reasoning (including deduction, induction and abduction). Hence, the function dimension guides the systematic organization of functional domain, at the same time, impacting the subsequent processes within the systematic experimental design, the systematic data sampling, and the systematic analysis and simulation of brain big data for understanding brain patterns and information-processing mechanisms in depth.
- The experiment dimension provides a conceptual model of experimental design for supporting systematic testing of research purposes that are also involved in the function dimension. As a conceptual model of the systematic experiment design during various periods of implementing experiments, the experiment dimension needs to represent the different factors of cognitive experiments, including

experimental paradigms, task types, measuring instruments, subjects and so on. Meanwhile, the conceptual relations among these experimental tasks and task-related parameters are defined rationally. For instance, in order to investigate inductive reasoning related information-processing (neuro) mechanisms, multiple tasks related to various explicit stimuli of numerical, figural and sentential materials may be considered comprehensively to test a cognitive function from multiple perspectives. We also can test and retest the same type of experimental tasks such as the numerical serial complement task to increase the reliability. Additionally, one task also can be used to test different cognitive hypotheses, such as the sudoku task used to test reasoning and problem solving.

- The data dimension provides a conceptual model of brain data for supporting multi-source systematic integrations of brain big data as the extensional representation of the human information-processing system. As a conceptual model of the brain data, the data dimension needs to represent the different aspects of heterogeneous data with multi-modal and multi-scale characteristics. For instance, increasingly neuroimaging techniques used to various brain research processes have accelerated the emergence of more data types and structures. Because of the differences of data organization strategy in the connected world, it is difficult to achieve simple hard fusion for the investigating requirements of complex brain science problems. For these reasons, the data dimension covers various information granularities and data roles such as original data, processed data and reorganized data from the internal and external sources. Here, the internal source refers to the local resources that are stored on local servers, usually obtained by our own research team, and the external source is organized from the global open sources (such as published results and sharing datasets) through data cooperation. These multi-source data can be mapped to the same semantic space in the way of soft fusion for the dissemination and utilization of brain big data.

- The analysis dimension provides a conceptual model of analytical methods for supporting multi-aspect systematic analyses of brain data that are organized in the data dimension. As a conceptual model of the systematic analysis and simulation, analysis dimension needs to represent the different aspects of analytical methods and their parameters, such as analysis tasks, analysis pipelines, analysis tools and algorithms. For instance, in a neuroimaging-oriented analysis task, brain images could go through preprocessed and postprocessed pipelines, during which they are processed by using a specific programming language under a specific algorithmic framework. During postprocessed process, the comparison and integration of multiple analysis methods may be considered, such as ensemble learning [193], multi-view learning [194] and comparative analysis [195, 196]. The core issue is how to combine a group of suitable methods for the right data object at the right context. A systematic methodology can guide the fusion computing of analytical results to give multiple interpretations from various methods and analytical aspects. Following these requirements, the concepts and their relations of analysis methods related to multi-scale brain data (such as brain image from the brain regions and connectivity perspectives, and neuron from the axon and dendrites perspectives) are defined in the analysis dimension to guide the systematic brain computing.

All of the four dimensions stated above are interlinked together in the conceptual Data-Brain as shown in Figure 3.4, supporting the extensional representation of the human information-processing system and providing the traceable provenances in the thinking

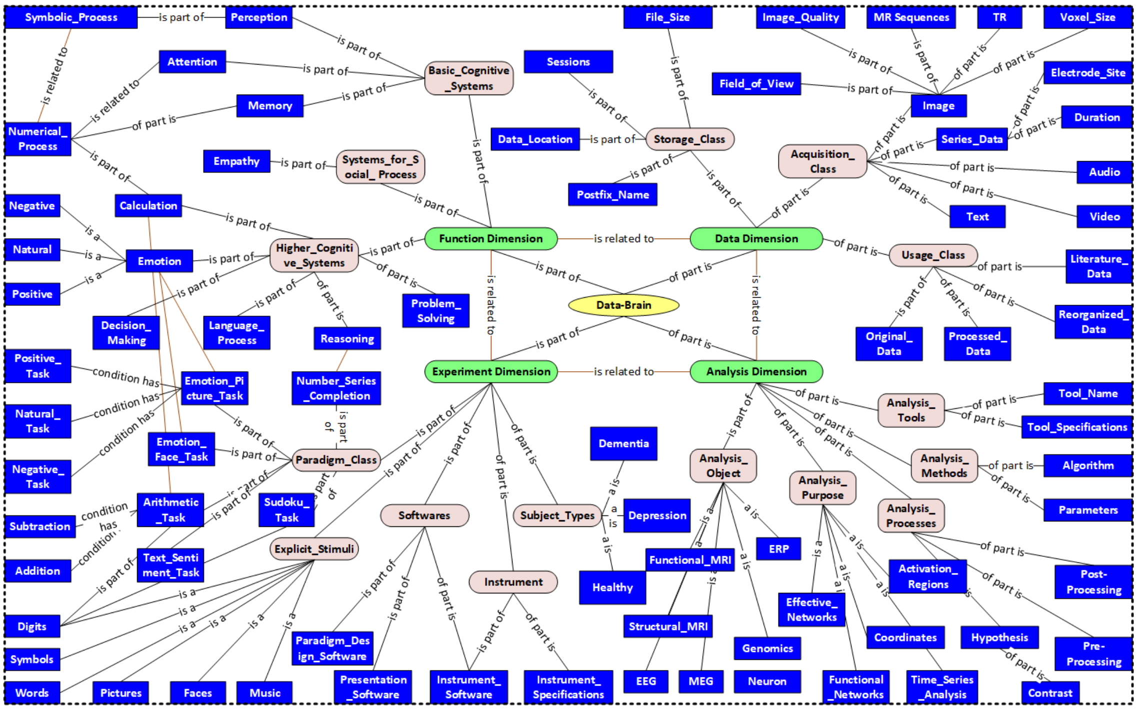


Figure 3.4: The conceptual Data-Brain. The green-shaded nodes indicate the four dimensions of the conceptual Data-Brain from the function dimension, experiment dimension, data dimension and analysis dimension; the pink-shaded nodes indicate the subclasses of those dimensions with respect to various scopes; the blue-shaded nodes indicate more characterized subclasses for modeling multiple aspects of the systematic Brain Informatics methodology.

space combined with various evidential chains of "Function domain – Experimental design – Brain data – Analytical method – Computing result" towards systematic brain computing. On the one hand, the core elements of the conceptual Data-Brain are firstly designed by experts from different fields, owing to the complexity of brain investigation. On the other hand, other existing ontologies and data models such as cognitive paradigm ontology [62] and cognitive atlas ontology [63] can be further linked to expand and enrich the conceptual Data-Brain. Such a collaborative learning mode can support scientists coming from different backgrounds to contribute their wisdom for advancing, exchanging and developing knowledge, as well as best practices around brain investigations.

3.3.2 The Sample Library

The sample library is created to integrate the multi-layered brain resources, as the basic of brain computing, corresponding to multiple sources of data, information and knowledge. In this library, a complete description of provenances is designed to the neuroscience studies from raw data to the final results including all the details in-between. In the sample library, each sample is represented as a chain of evidence that contains the data and its context such as the research purpose (such as function domain and medical problem), experimental details, data properties, processing methods and computed results. We restricted some scopes to the factors and attributes that are crucial for systematic brain computing. Hence, this limited the number of categories that are illustrated in Table 3.1. The factors of each category can be deleted, updated and extended as needed.

Depending on the data integration standard, as illustrated in Table 3.1, the brain data are normatively organized in the sample library. Such a standard not only enhances the readability for a machine, but also improves the interpretability and transparency to support data sharing and data reuse. Additionally, the computability is equally important, which is often overlooked in the previous studies. For example, the existing data integration architecture is mainly to provide a complete description of data objects, and describes their relations from the qualitative perspective. Such data integration architectures are able to participant in the sampling process of brain data, but indirectly affect the computing results. In the current study, the sample library extends the capability of conventional data integration architecture by mapping various samples to the conceptual Data-Brain with various weights. Hence, the relations among multiple samples can be quantitatively described to directly affect the brain computing results, because their weighted properties participant in computing processes themselves.

Table 3.1: Fifteen categories of neuroimaging entities are defined to represent the neuroimaging data and results. These entities indicate key factors in the neuroimaging study, and can be used to evidence combination and fusion computing.

Category	Description
Human Intelligence Problem (HIP)	The human intelligence problem is related to function domain that is an ability of the brain to process reasoning, calculation, problem-solving and so on.
Human Health Problem (HHP)	The human health problem is related to an abnormal symptom of individuals, such as depression, mild cognitive impairment and dementia.
Region of Interest (ROI)	A region of interest is a subset of a brain image identified for a particular purpose.
Functional Subnetworks (FSN)	The functional subnetworks represent very strong functional connections, such as default mode network, salience network and executive control network.
Experimental Task (TSK)	The experimental task is a cognitive task that the subject needs to complete during the neuroimaging study, such as serial complement task.
Experimental Paradigm (EPM)	The experimental paradigm is an experimental setup (i.e. a way to conduct a certain type of experiment) that is defined by certain fine-tuned standards and often has a theoretical background, including categorical designs, parametric designs and factorial designs.
Experimental Protocol (EPL)	The experimental paradigm involves the management of variables, their presentation, the assignment of respondents, and the statistical procedures of analysis and especially for event-related design, block design and mixed design.
Explicit Stimulus (ESI)	The explicit stimulus is a kind of sensory channel of subjects presented by stimuli during the neuroimaging study.
Subject Type (SUB)	The mental health conditions of a person who is suffering, commonly divided into various types of healthy control and populations with disorders.
Data Modal (DAM)	The data modal indicates the brain data that is collected by various techniques, such as fMRI (functional magnetic resonance imaging), EEG (electroencephalogram) and PET (positron emission tomography).
Data State (DAS)	The data state indicates the processed degree of a brain data, including the original raw data, derived data, the results of outputs, and the DOI if it has been published.
Data Acquisition (DAA)	The data acquisition involves a series of parameters that involves the properties of original raw data, such as MRI equipment, MRI pulse sequence and voxel size.
Analytical Method (ANM)	The analytical tool and method are the data analytical algorithm or software, which is used to mine experimental data during the neuroimaging study.
Activation Region (ACR)	The activated feature is a kind of brain responses that is mined from experimental data during the neuroimaging study, include the peak of the activation coordinate, the cluster size and so forth.
Brain Connectivity (BRN)	Brain connectivity refers to a pattern of anatomical links ("anatomical connectivity"), of statistical dependencies ("functional connectivity") or of causal interactions ("effective connectivity") between distinct units within a nervous system.

3.3.3 The Semantic Vector

As mentioned above, the novel data integration standard provides a machine-readable representation to make data more understandable and computability. However, not all understandable data are needed, especially in big data era. Another core work is to develop a container that models human behaviors to select needed data with respect to a specific research goal. The semantic vector (SV) is a dynamic container, conveying interactive messages from the real-time service request to the internal representation of the request in system. Its core purpose is to provide the right sample for the right object at the right time and context towards the flexible data and analysis provenances. The semantic vector includes five objects surrounding research purposes (SV-ORP), experimental details (SV-OED), objective data (SV-OOD), processing methods (SV-OPM) and computed results (SV-OCR), interacting with the categories of entities defined in the data integration standard of the sample library. Figure 3.5 demonstrates the details and workflows of the semantic vector, centered on a specific example.

As shown in Figure 3.5, the semantic vector receives the service requests from users who can set up parameters of categories of interest defined in Table 3.1. Then, the semantic vector derives five objects to recognize parameters of each sample in the sample library, followed by measuring their matching degree to the service requests. At the same time, the selected samples are compared and sequenced on the basis of matching degree from big to small. Such actions are performed iteratively like the experimental designing behaviors of investigators. During this process, a list of samples can be obtained to serve as the systematic investigation purpose. For instance, during the system operation, the user requests are first translated to the four dimensions in the knowledge layer, and then multi-aspect provenances can be generated in the information layer to retrieve, organize,

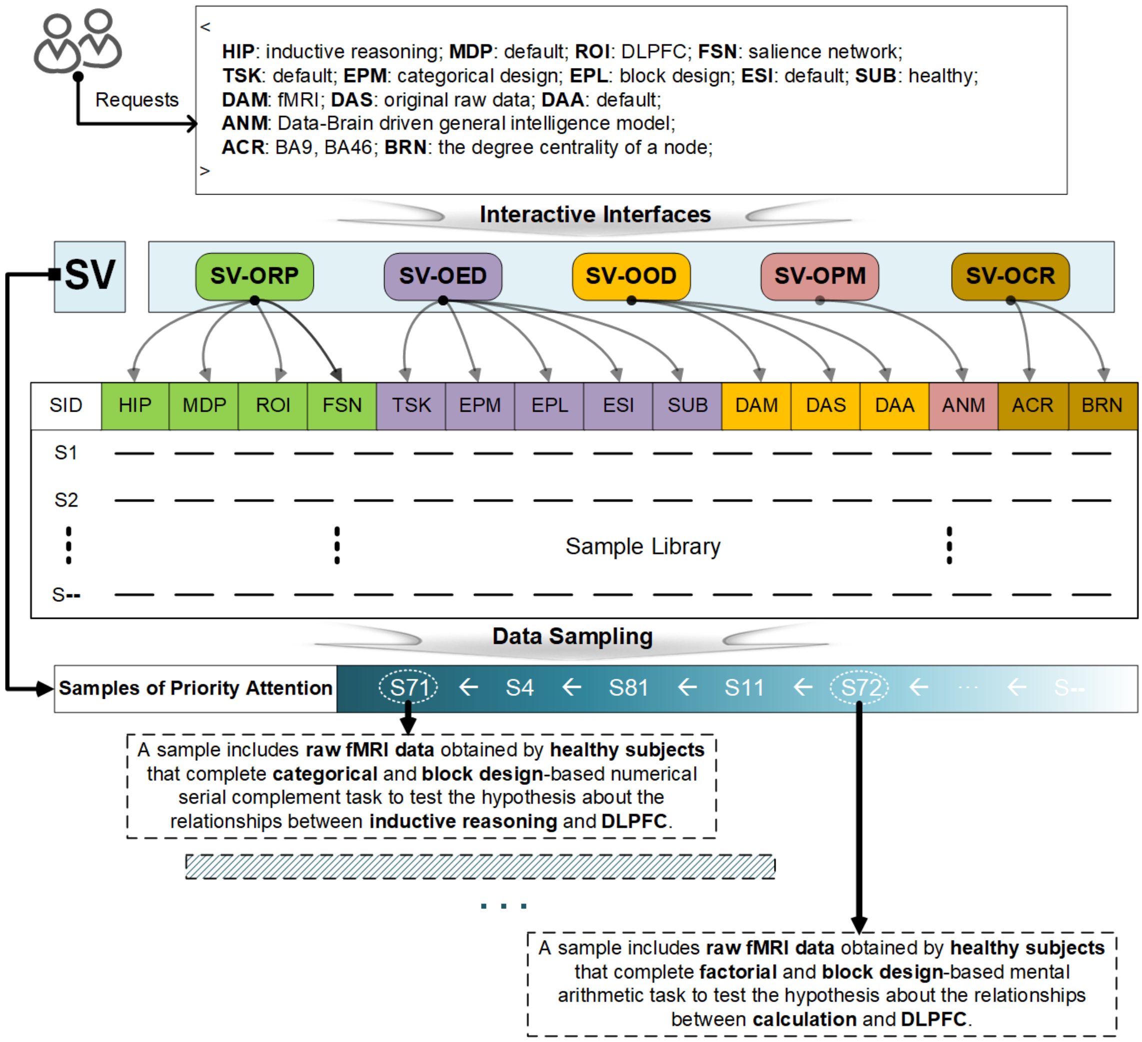


Figure 3.5: The details and workflows of the semantic vector (SV). The SV transforms user requests (for example, the human intelligence problem “inductive reasoning”, the experimental task “the categorical and block design-based numerical serial complement task”, the data modal “fMRI data”) from the human-understandable terms to the machine-readable commands with respect to various objects of research purposes (SV-ORP), experimental details (SV-OED), objective data (SV-OOD), processing methods (SV-OPM) and computed results (SV-OCR) through interactive interfaces. Then, the SV runs the sampling operation to extract potential brain data from the sample library, at the same time, give the priority of matched samples. Such sorted brain data are given by the general intelligence model continuously, meeting the requirements of systematic brain computing.

process and analyze data until the end of the whole learning processes. During these processes, brain data are processed through a loop that extracts core values of the data in various abstract degree to meet needs for different purposes - going through the loop of data, information and knowledge (or the K-I-D loop for short) - from both bidirectional knowledge-driven and data-driven processes to systematic brain computing.

3.4 Framework of the GIM

The general intelligence model (GIM) models human intelligence-inspired problem-solving capability, thereby enabling the systematic learning among different components (such as represent knowledge, inference engine, decision-making, and brain computing based on never-ending learning and human-in-the-loop) on the road of reaching human-level AI society. Couple with these various components, the global picture of Data-Brain driven general intelligence model is illustrated in Figure 3.6.

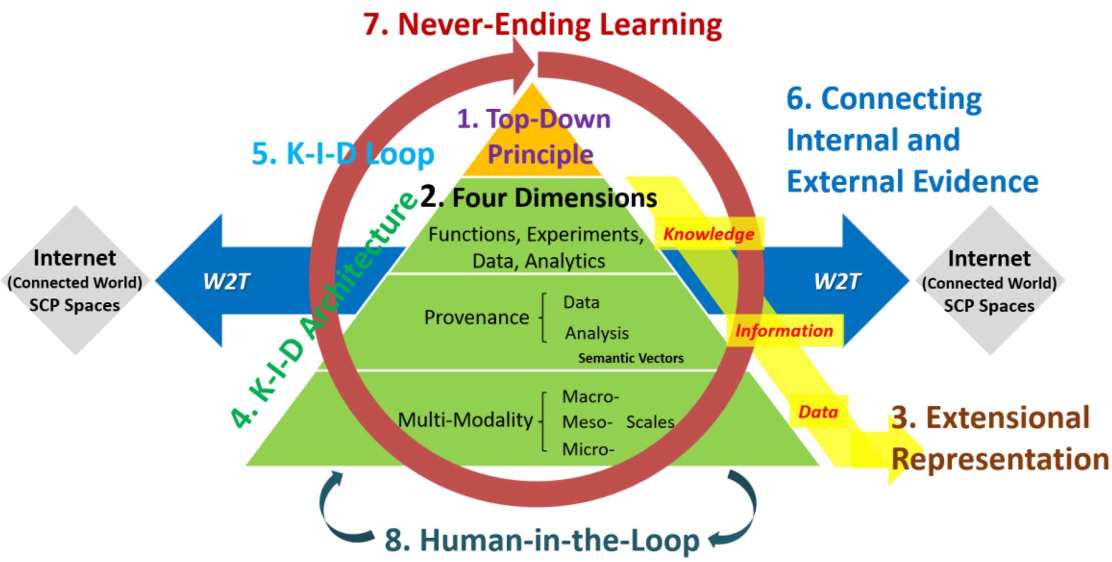


Figure 3.6: The global picture of Data-Brain driven general intelligence model (GIM). The GIM consists of the conceptual Data-Brain, the sample library as the extensional representation, K-I-D architecture, K-I-D loop, the wisdom web of things (W2T) related algorithmic development to connect internal external evidence, never-ending learning and human-in-the-loop, depending on the Top-Down principle to investigate the brain.

To aid in this effort, several key points can be identified to construct such a general intelligence model, including:

- Top-Down principle: a principle maps the development processes from the high-level abstract to the bottom-level details that guide us to develop such a general intelligence model;
- Conceptual Data-Brain: a conceptual model to systematically represent brain data from various dimensions and their many-to-many relationships, with respect to all major aspects of the Brain Informatics methodology;
- Extensional representation: the explicit expression of human intelligence by representing brain big data from the perspective of the human information-processing system (HIPS);
- K-I-D architecture: a multi-source data integration architecture integrates knowledge representation at the top, information in the middle, and data at the lowest level;
- K-I-D loop: the KID and DIK schemes are connected into a cycle as the thinking space for supporting dual-directed inference, computing and problem solving;
- Connecting internal and external evidence: an evidence combination and fusion computing method to learn the internal evidence as the main source (such as the first-hand raw data resources), aided by the external evidence (such as the second-hand paper resources) to serve as the same brain computing goal;
- Never-ending learning (NEL): a learning mechanism drives the continuous iteration and evolution of the model and computing results, and achieves multi-dimensional interconnections in the social-cyber-physical space;
- Human-in-the-loop (HITL): an interactive mechanism provides the multi-aspect support to connect human with the model before, during and after learning processes.

By integrating brain big data as the extensional representation of the human information-processing system, Data-Brain driven general intelligence model can be used as a bi-directional decoder between the inner brain information and the outer brain information by connecting brain and network with big data; an energy converter between brain science and artificial intelligence; and an engine from systematic brain-machine intelligence research to new AI industry chain in the connected world. As two important directions, such a model could be awakened by a series of tasks from brain intelligence and brain health. On the one hand, such a general intelligence model can help capture and explore brain functions from the basic cognitive neuroscience perspective. On the other hand, from the perspective of translational research, such an intelligence model can be used as an important tool in the era of digital transformation towards smart health society. The following sections provide the methods and technical details of how to construct such a general intelligence model, and how to use such a model to provide multi-aspect wisdom services.

3.4.1 K-I-D Architecture

Benefiting from the progress of open science in the brain big data era, increasing evidence gives the opportunity to interpret brain intelligence and health systematically. Towards the systematic brain investigation, the whole process of brain investigation can be implemented by integrating multi-modal and multi-scale brain big data from systematic design of cognitive experiments in our own research team and global open sources. The core issue is how to integrate and sample knowledge, information and data for meeting needs of systematic brain computing. Consequently, the layered K-I-D architecture of Data-Brain driven general intelligence model is constructed to support such a systematic integrating and computing method as illustrated in Figure 3.7.

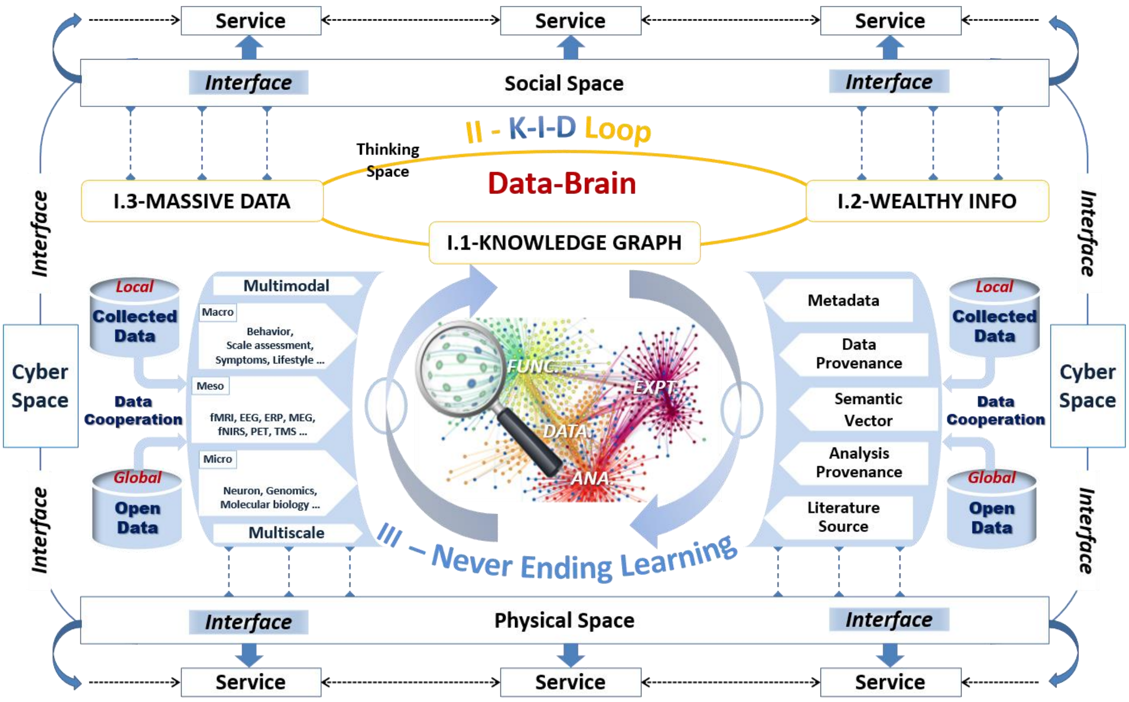


Figure 3.7: The K-I-D architecture of Data-Brain driven general intelligence model. The brain big data resources are organized into a three-layer K-I-D architecture with knowledge graphs (K), wealthy information (I), and massive data (D). On the basis of K-I-D architecture, the KID scheme and the DIK scheme are connected into a cycle as the thinking space, namely the K-I-D loop, for systematic brain investigation. The never-ending learning mechanism based on the K-I-D loop drives the continuous iteration and evolution of the model. The interfaces ensure human-in-the-loop that achieves multi-dimensional interconnections in the social-cyber-physical-thinking spaces.

The following parts give an exhaustive illustration of the three-layered K-I-D architecture in Data-Brain driven general intelligence model, including:

- *Knowledge Layer*

  By modeling the four aspects of the systematic Brain Informatics methodology stated in Section 3.2, the knowledge layer at the top of the K-I-D architecture is mainly presented as the four dimensions of the conceptual Data-Brain, that is, function dimension, experiment dimension, data dimension and analysis dimension, as well as their relations in knowledge graphs. Such prior knowledge-based four dimensions form a thinking space to link the sample library and semantic vector, thereby providing holistic conceptual schemata for various Brain Informatics provenances. In turn, the newly transformed Brain Informatics provenances generate the new rules to enhance semantic inference and brain computing for updating the conceptual Data-Brain. The knowledge layer also provides the wisdom service for users, that is, the new knowledge from the brain big data center will be produced when users utilize the general intelligence model, and become one part of the new round of knowledge-generated cycle. On the one hand, the knowledge layer consists of the represent knowledge, such as facts, beliefs and experience for the interpretations of the brain mechanisms on function, structure and dynamics. Through the learning and inference processes within the general intelligence model, some explicit knowledge will be discovered to be integrated into the factual knowledge base for forming new knowledge and raising awareness. On the other hand, 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.

- *Information Layer*

  The information layer in the middle of the K-I-D architecture is the bridge connecting the knowledge layer and the data layer, cooperating with the semantic vectors for the data provenance and the analysis provenance. The "provenance" means that the data and analytical histories of a data object can be fully tracked and interpreted within a particular request, and can be organized to respond to needs of various workflows flexibly. The informatics technique is the core to support the construction of information layer. Towards the whole lifecycle of systematic brain investigation, the semantic information is given to different forms of brain data obtained from various sources to enable the systematization of measuring, collecting, modeling, transforming, managing, mining, interpreting and explaining. The information layer includes various entities that are instantiated from the four dimensions of the knowledge layer, and their corresponding attributes and values to represent the whole lifecycle of each data object in the data layer. For instance, it records explicit parameters about how the experimental data were acquired and processed, the timing and order of the stimuli presented in the task, the demographic information of subjects selected for analyses, the storage location of experimental data from each selected subject, the intermediate results of data analysis and so forth. Meanwhile, such semantic vectors with operational and computational modes are used to view, query, add, delete and modify instances in the sample library through the on-line and off-line learning during the internal and external processes. Internally, the metadata, data processing details and analytical results produced by the local sources are recorded and converted into the sample library. Externally, the global open sources are continuously searched to extract the information for specific user requests. Such extracted information is also integrated into the sample library by semantic vectors, which complements and improves the internal information.

- *Data Layer*

  The data layer at the lowest of the K-I-D architecture merges full-scale brain big data that are systematically collected and integrated to reveal essences of brain intelligence and health, modeling their extensional representation. A full-scale perspective indicates a holistic consideration about the brain-related resources that advocate an integration of wide-ranging investigations from macro-, meso-, and micro- scales. At the macro-scale, the data layer integrates resources about behavioral responses (such as accuracy and reaction time) and other physiological/non-physiological information such as demographic attributes, scores of psychological and mental questionnaires, to support human mind study directly via external phenomena. At meso-scale, the data layer integrates resources with respect to the electrophysiological, hemodynamic and endocrine measures to support brain studies in neural mechanisms and their relationships with external behavior. Especially, the current model focuses on the systematic integration of function-related brain data obtained by both resting-state (task-free) and task-states. At micro-scale, the data layer integrates resources on the infrastructural units, such as neuron, synapse, protein and genome, to support cellular and molecular studies. Furthermore, the data layer responds to the multi-modal and multi-scale brain big data obtained from various data objects that are both physical and virtual. It is involved with not only integrating resources produced by various measuring instruments and sensing devices, but also integrating resources from the shared datasets and published results in the connected world. The data layer is also involved with various data management and processing technologies as well as application services, including data collection, cleaning, integration, storage, sharing and so on, for completing the whole process of the data cycle from both internal and external requests.

3.4.2 Systematic Experimental Design

The purpose of systematic experimental design is to produce the experimental plan towards systematic brain investigation, modeling the human behavior to understand human intelligence and health. More specifically, a systematic experimental plan is performed to further guide data sampling, analyzing and fusing, which are designed through the combination of multi-type experiments and rules. As mentioned earlier, cognitive experiments are designed to test hypotheses about the relation between neural mechanisms and cognitive function. Our goal is to investigate which neural mechanisms support a specific cognitive function, and which cognitive functions may affect the activity of a specific neural mechanism. Considering an ideal experiment designed to test the goal and its related multiple hypotheses, it should consist of multiple tasks, conditions and contrasts that reflect comprehensive views. However, this strategy is restricted by many practical factors, such that investigators may have difficulties in contributing to such complex tasks that are easily executed by a single participant in one session. In practice, such an experimental strategy is often divided into multiple stages to be executed and follows some systematic design rules. For instance, investigators design an exploratory task as the main experiment that is used to directly test the goal hypothesis, followed by a series of supplementary experiments that are designed to test relevant cognitive hypotheses with the main experiment. Such differences of designing factors between the main experiment and the supplementary experiments are mainly from both dimensions of function and experiment related to the conceptual Data-Brain. As these progresses, the growing evidence is provided continuously to improve the interpretability of goal hypothesis, which has obvious the multi-task and sequence characteristics.

The characteristics of systematic experimental plans challenge the behaviors of systematic experimental design, that is, how to design the next experiment based on the heuristics from the previous and current experiments. To address such problems, we distinguish various types of experiments with differences of factors in the function dimension and the experiment dimension, followed by linking them into such an experimental template graph based on various matching rules. Here, the main experiment (T_{mae}) that corresponds directly to the goal hypothesis, as a starting point for systematic experimental design, and supplementary experiments that are inspired by the main experiment, as continuous supporting for evidence combination and fusion computing. The supplementary experiments are further defined as various experimental types, including the similar experiment (T_{sie}), the parallel experiment (T_{pae}), the deeper experiment (T_{dee}), the inspired experiment (T_{ine}), the missed experiment (T_{mie}) and the sub-processing experiment (T_{spe}). On the basis of the four dimensions defined in the conceptual Data-Brain, the characteristics of various experimental types are described as follows:

- If an experiment is identified as the main experiment, its task corresponds directly to the goal hypothesis and includes the well-matched factors in the function dimension and the experiment dimension.
- If an experiment is identified as the similar experiment, its task shares the similar factors with the T_{mae} in the function and experiment dimensions. However, the T_{sie} and the T_{mae} share the different parameters in the data dimension, such as the difference of the brain image parameters from multiple data centers.
- If an experiment is identified as the parallel experiment, its task shares the similar factors in the function dimension with the goal hypothesis-oriented T_{mae}, but has different factors in the experiment dimension, such as the difference of explicit stimuli on digits and symbols.
- If an experiment is identified as the deeper experiment, its task is used to further explore the hidden mental processes related to the T_{mae}, but corresponding to different cognitive hypotheses defined in the function dimension. For instance, the calculation related cognition activity is able to be studied through arithmetic tasks. However, such a task is not only relevant to calculation processing, but also related

to the numerical and symbolic processes that need to be further investigated by designing the T_{dee}.

- If an experiment is identified as the inspired experiment, its task is used to test the goal hypothesis that involves different factors in the function dimension from the T_{mae} but shares the similar factors in the experiment dimension with the T_{mae}.
- If an experiment is identified as the missed experiment, its task does not satisfy the aforementioned criteria but evokes similar brain activities (such as patterns and indicators) with the T_{mae}.
- If an experiment is identified as the sub-processing experiment, its task is used to test the goal hypothesis-related single aspect within a dual-task paradigm. For instance, an experiment designed for association study of emotion and calculation may be regarded as two separate tasks to test the emotional and calculation hypotheses, respectively.

The different types of experimental tasks in such a process of systematic experimental design are illustrated in Figure 3.8, by which multiple tasks are coupled with each other to match an experimental template graph with various rules and contributions. In Figure 3.8, the T_{mae} and $SET = (T_{sie}, T_{pae}, T_{dee}, T_{ine}, T_{mie}, T_{spe})$ indicate the main experiment and supplementary experiments, respectively. The $\{R_i | 1 \leq i \leq 6\}$ indicates the matching rules that are used to design the experimental tasks, and then select the related brain data in the following processes of systematic experimental design. The $\{\varepsilon_i | 1 \leq i \leq 6\}$ indicates the similar degree of the samples obtained by the main experiment and the various supplementary experiment from the experimental design perspective, which are given by the experimental similarity evaluation, impacting the results of the evidential sampling.

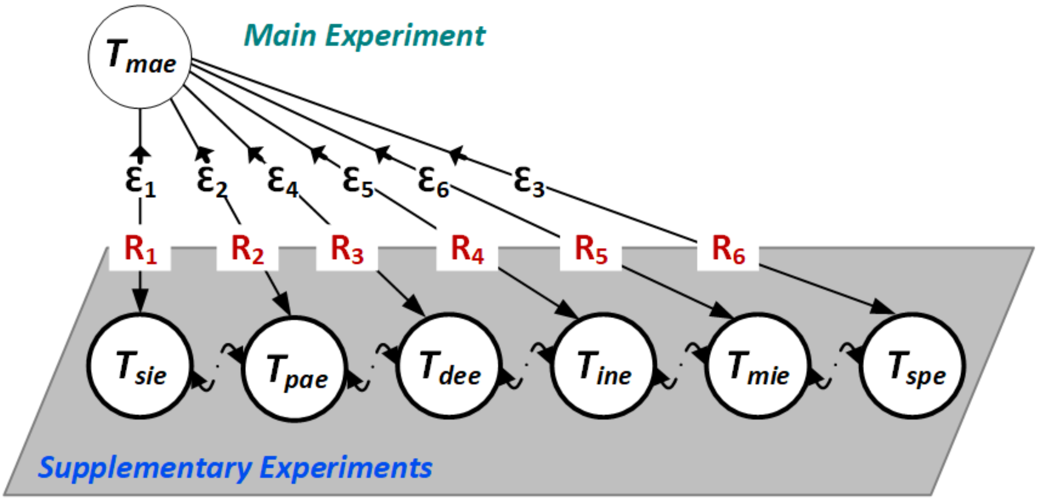


Figure 3.8: The template graph of systematic experimental plans.

Suppose there is a request from systematic experimental design to integrate multi-task brain data for filling with the experimental template graph defined in Figure 3.8 towards systematic fusion computing. Two types of factors in the function dimension (FD) and the experiment dimension (ED) are concerned. At a future point, to match the next experiment T_{next} represented in such a template graph with respect to a systematic experimental plan, the $T_{next} - Call$ rules are defined as follows:

$R1. IF \left(FD(T_{next}) = FD(T_{mae})\right) AND \left(ED(T_{next}) = ED(T_{mae})\right), THEN\ \Phi(T_{next}) = T_{sie};$

$R2. IF\ (FD(T_{next}) = FD(T_{mae}))\ AND\ (ED(T_{next}) \neq ED(T_{mae})), THEN\ \Phi(T_{next}) = T_{pae};$

$R3. IF \left(FD(T_{next}) \neq FD(T_{mae})\right) AND \left(Relation\left(FD(T_{next}), FD(T_{mae})\right) \neq \emptyset\right)$

$AND\ (ED(T_{next}) = ED(T_{mae})), THEN\ \Phi(T_{next}) = T_{dee};$

$R4. IF \left(FD(T_{next}) \neq FD(T_{mae})\right) AND \left(Relation\left(FD(T_{next}), FD(T_{mae})\right) = \emptyset\right)$

$AND\ (ED(T_{next}) = ED(T_{mae})), THEN\ \Phi(T_{next}) = T_{ine};$

$R5. IF \left(FD(T_{next}) \neq FD(T_{mae})\right) AND \left(Relation\left(FD(T_{next}), FD(T_{mae})\right) = \emptyset\right)$

$AND \left(ED(T_{next}) \neq ED(T_{mae})\right) AND\ (Results(T_{next}) \cap Results(T_{mae}) \neq \emptyset),$

$THEN\ \Phi(T_{next}) = T_{mie}.$

Furthermore, for an experimental paradigm within the mixed methods that is designed to explore the mutual effect between multiple cognitive processes, such a T_{mae} can be directly divided into multiple sub-processing experiments (such as the T_{mae}^{i} and the T_{mae}^{j}) that are matched based on the following $T_{next} - Call$ rule:

$$R6.IF\ \Big(\big(FD(T_{next}) = FD(T_{mae}^{i})\big) AND\ \big(ED(T_{next}) = ED(T_{mae}^{i})\big)\Big)\ OR$$

$$\Big(\big(FD(T_{next}) = FD(T_{mae}^{j})\big) AND\ \big(ED(T_{next}) = ED(T_{mae}^{j})\big)\Big),$$

$$THEN\ \Phi(T_{next}) = T_{spe}.$$

where "=" and "≠" indicates the factors of convergence and divergence, respectively, the Function $\Phi(\cdot)$ is used to identify the experimental type of a task, the Function "$Relation(\cdot,\ \cdot)$" is used to identify the cognitive relevance of two experiments through walking in the conceptual Data-Brain, the Function "$Results(\cdot)$" is used to compute the brain data.

On the basis of a systematic experimental plan, the relevant resources from the sample library are sampled by the semantic vectors to guide the further operations of integrating, computing and analyzing. Considering both views of function and experiment, the procedure of systematic experimental design is shown in Algorithm 3.1. Given a goal hypothesis related to the function dimension (G_{FD}) and the experiment dimension (G_{ED}), the conceptual Data-Brain (CDB), a set of various supplementary experimental types SET, the designing depth (DED) and the $T_{next} - Call$ rules, a systematic experimental plan that organizes multiple tasks in a graph is generated to guide future data sampling, analysis and computing. The SET and DED determine the scale and complexity of an experimental plan. The whole process interacts with the sample library that maintains various information in the function dimension, the experiment dimension, the data dimension and the analysis dimension.

Algorithm 3.1: Systematic Experimental Design (SED)

Input: the goal hypothesis, G_{FD}. ▹ From Function Dimension
the goal hypothesis, G_{ED}. ▹ From Experiment Dimension
the CDB;
the designing breadth, SET;
the designing depth, DED.
Output: the experimental task graph, $T_{SYS}^{G} = \left(Tmae, \left(T_{sie}^{G}, T_{pae}^{G}, T_{dee}^{G}, T_{ine}^{G}, T_{mie}^{G}, T_{spe}^{G}\right)\right)$.
procedure Depth Experiment Designing (DED, SET, G_{FD}, G_{ED}, CDB)
Initializing the designing depth, $DE = 1$;
Initializing a template graph, $T_{temp}^{G}(T_{mae}, SET)$;
G_{FD}^{mae}, G_{ED}^{mae} ← G_{FD}, G_{ES};
Matching a $T_{mae}(G_{FD}^{mae}, G_{ED}^{mae})$ from the sample library;
T_{full}^{G} ← Adding $T_{mae}(G_{FD}^{mae}, G_{ED}^{mae})$ to T_{temp}^{G} at the T_{mae};
$Call$ Breadth Experiment Designing (T_{full}^{G}, G_{FD}^{mae}, G_{ED}^{mae}, SET, CDB);
$T_{SYS}^{G} = T_{full}^{G}$;
DE ++;
while $DE \leq DED$ do
  for Each task T_i in the T_{SYS}^{G} at the depth of ($DE - 1$) **do**
    Initializing a template graph, $T_{temp}^{G}(T_{mae}, SET)$;
    T_{mae} ← T_i;
    G_{FD}^{mae}, G_{ED}^{mae} ← $FD\ of\ Ti$, $ED\ of\ Ti$;
    T_{full}^{G} ← Adding T_i to T_{temp}^{G} at the T_{mae};
    $Call$ Breadth Experiment Designing (T_{full}^{G}, G_{FD}^{mae}, G_{ED}^{mae}, SET, CDB);
    Linking ($T_{SYS}^{G}, T_{full}^{G}$) at the T_i;
  end for
  DE ++;
end while
return T_{SYS}^{G}
procedure Breadth Experiment Designing (T_{full}^{G}, G_{FD}^{mae}, G_{ED}^{mae}, SET, CDB)
for Each $Type$ in the SET **do**
  while T_{next} is $Null$ do
    Getting a task $T(FD, ED)$ from the sample library;
    Inferring the relation between G_{FD}^{mae} and FD based on the CDB;
    Inferring the relation between G_{ED}^{mae} and ED;
    if Matching T_{next}-$Call$ rules **then**
      Adding $T(FD, ED)$ to T_{full}^{G};
    end if
  end while
end for
return T_{full}^{G}

3.4.3 Evidence Combination and Fusion Computing

Couple with systematic experiment design, the evidence corresponding to various experimental types is also selected from the sample library. In Data-Brain driven general intelligence model, the collected samples are computed via two strategies:

- Forward inference: The brain data are computed by the task-driven strategy and the univariate pattern analysis methods such as general linear model with statistics.
- Reverse inference: The brain data are computed by the data-driven strategy and the multivariate pattern analysis methods such as Searchlight.

According to the two brain computing strategies, various brain computing results are obtained from different evidence. The core is how to fuse these computing results of evidence to give the multi-aspect and solid results. We consider the shared brain activation patterns from different functional domains and experimental tasks.

Firstly, we consider the forward inference-based evidence combination and fusion computing. In this approach, the evidence is divided into two different types, including the Type-I evidence and the Type-II evidence, towards different strategies of evidence combination for the fusion computing request.

- The Type-I evidence is related to the intra-evidence combination. The intra-evidence combination means a variety of investigations, in which methods and technologies work within a cognitive functional domain. On the one hand, when two evidence-oriented function domains belong to the relationship of the cognitive component and the cognitive subcomponent, these evidences are identified as Type-I evidence (See Figure 3.9(a) and (b)). In this context, the brain computing results of an evidence can give positive support for the computing results from another evidence. One of the most typical cases is the study on human reasoning, in which the evidence from the rule identification and extrapolation can advance our understanding on the inductive reasoning [87]. On the other hand, when multiple evidences belong to a cognitive function (See Figure 3.9(c)), it can be investigated by the comparative analysis under multiple controlled conditions from the experimental perspective, the comparative analysis under multiple computing methods from the analysis perspective, and the comparative analysis of the multimodal brain data from the data perspective. In such cases, the Data-Brain driven general intelligence model is designed to support the intra-domain multi-aspect analyses from three core functions, including the experimental condition-based analysis function, the computing method-based analysis function, and the multimodal data-based analysis function.

- The Type-II evidence is related to the inter- evidence combination. The inter-evidence combination means a variety of investigations, in which methods and technologies work among multiple cognitive domains (See Figure 3.9(d-g)). It is a multi-domain learning paradigm to leverage the common information contained in multiple related functional domains to help improve the generalization performance of all the domains [197]. For example, according to [198], the relations among decision-making, reasoning, executive functioning and cognitive abilities are investigated simultaneously to reveal the nature of brain intelligence. In this case, the brain computing results of such supplementary experiment-oriented evidence can give opposed support for the computing results from the main experiment-oriented evidence. For example, inductive reasoning and calculation belong to different functional domains, the brain data of which will be analyzed by the inter-strategy. When the human reasoning-related hypothesis is tested, the calculation-related brain computing results will decrease the level of confidence to the given hypothesis.

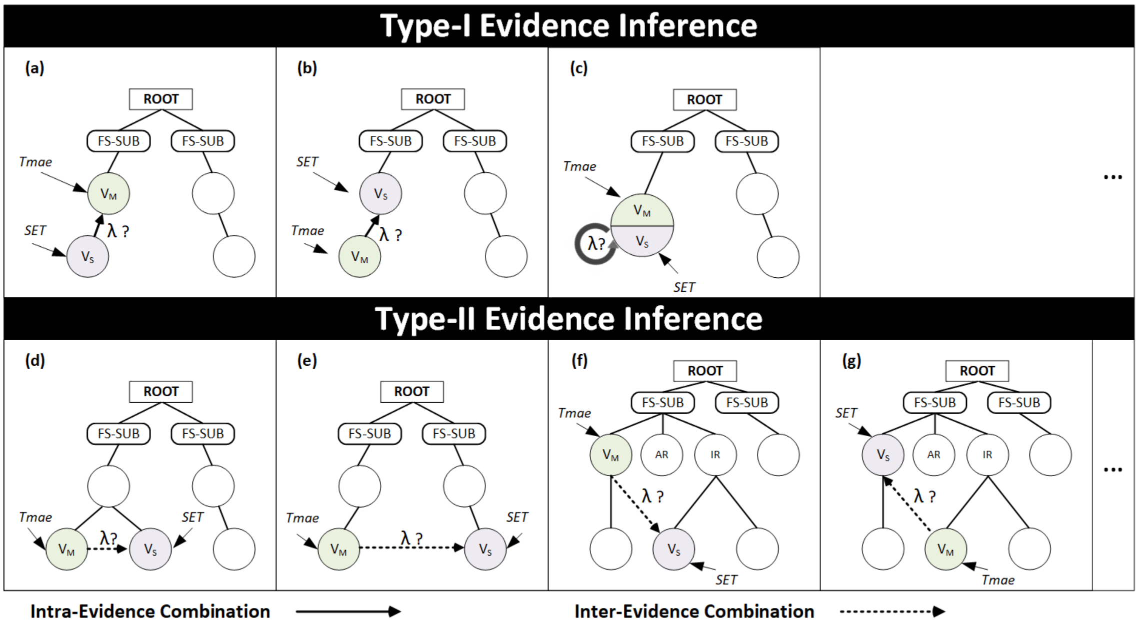


Figure 3.9: The discriminant rule of evidential types. The V_M is the evidence corresponding to the main experiment, while the V_S is the evidence corresponding to the supplementary experiments. The ROOT and FS-SUB indicate the concepts of brain function in the conceptual Data-Brain with the cognitive relevance.

Additionally, considering the differentiated contributions of various supplementary experiments to the main experiment, the evidential degree (λ) is given manually and measured automatically to be merged into evidence combination and fusion computing. Figure 3.10 illustrates the processes of the forward inference-based fusion computing. The brain computing results observed by a supplementary experiment T_{next} are used as the evidence to assess the uncertain distribution of the main experiment T_{mae}'s hypothesis overlapping with that of the T_{next}. It is realized that combining distributed assessment with single-aspect consequents (such as the Z-value) can enable various types of tasks to be incorporated into a hypothesis testing process. In the following, the multi-level uncertainty distribution τ with respect to the brain computing results of the goal hypothesis-oriented main experiment is given by:

$$\tau = \sum_{\substack{T_{next} \in SET \\ R(T_{mae}), R(T_{next}) \subseteq CoR}} \left[\tau\left(R(T_{mae})\right) + \lambda(T_{next}) \tau\left(R(T_{next})\right) \right] \qquad (3.1)$$

where $R(T_{mae})$ and $R(T_{next})$ indicate the brain computing results from the analyses of the main and supplementary experiments, respectively, $CoR = \{R(T_{mae}) \cap R(T_{next})\}$ indicates the overlapping results between paired T_{mae} and T_{next}, $\tau\left(R(T_{mae})\right)$ and $\tau\left(R(T_{next})\right)$ indicate the uncertainty distribution from the main and supplementary experiments, given by the brain computing results.

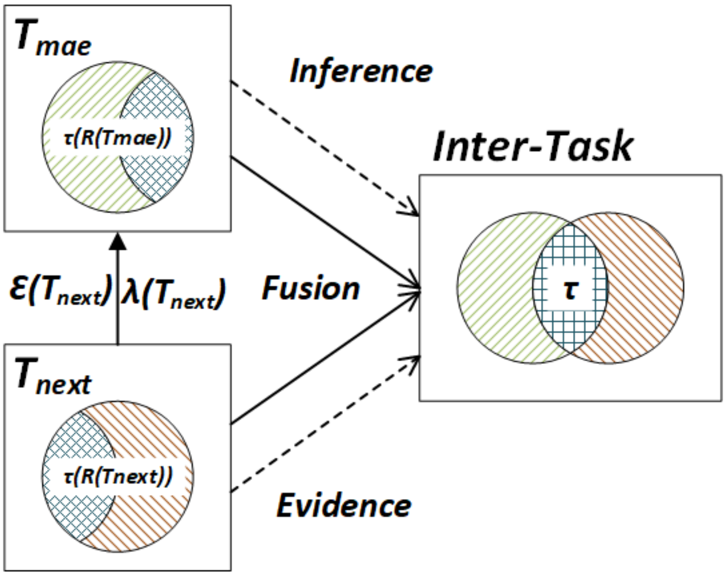


Figure 3.10: The evidence combination and fusion computing approach.

Through the forward inference-based evidence combination and fusion computing, the computed uncertainty distribution helps us understand the subtle relations between brain patterns and cognitive functions, at the same time, providing multi-level interpretations with respect to the goal hypothesis. Given the τ distribution of a brain pattern is greater than zero, the greater the τ distribution of the brain pattern is, the more specific the brain pattern has for a hypothetical brain function. Given the τ distribution of a brain pattern is smaller than zero, the smaller the τ distribution of the brain pattern is, the more general the brain pattern has for multiple hypothetical functions. Given the τ distribution of a brain pattern is equal to zero, the selected brain pattern maintains the high randomness.

Secondly, we consider the reverse inference-based evidence combination and fusion computing. During this learning process, the multivariate pattern analysis is performed to consider spatial patterns of brain activity over ensembles of multiple variates (such as voxels and nodes), recovering what information they represent collectively [63, 112]. The machine learning methods are selected to discriminate between brain patterns associated with different cognitive states. In this case, we carry out the evidence combination and fusion computing from three dimensions of cognitive states, including complexity, condition and component, respectively. For the dimension of complexity, the predictive results are used to test information-processing capability of a brain pattern to various experimental tasks with varied complexity (such as, the complex task vs. the simple task). For the dimension of condition, a brain pattern is tested by discriminating between the same-level component of interest (such as, addition vs. subtraction within the mental arithmetic task). For the dimension of component, a brain pattern is tested by discriminating between the component of interest and baseline component (such as, number induction vs. number judgement within inductive reasoning). On the basis of definition above, the predictive results can be fused by the data-driven reverse inference and weighted fusion computing. Considering that the greater difference between two types of experimental tasks may lead to the greater difference in brain activity patterns, and then impact the classification effects. We need to design the weights with respect to different cognitive states, as follows:

$$\begin{cases} \alpha(X), & if\ X\ =\ the\ complexity\ level\ -\ based\ classification. \\ \alpha(Y), & if\ Y\ =\ the\ condition\ level\ -\ based\ classification. \\ \alpha(Z), & if\ Z\ =\ the\ component\ level\ -\ based\ classification. \end{cases} \tag{3.2}$$

where $\alpha(\cdot)$ indicate the weight, $\alpha(X) \approx \alpha(Y) > \alpha(Z)$, and $\alpha(X) + \alpha(Y) + \alpha(Z) = 1$. Hence, the predictive results of multiple evidences corresponding to the intra-analysis can be fused to answer a question about "the information-processing capability of a specific brain pattern (BRP) to a specific cognitive functional domain (CFD)". It is defined as the support coefficient γ ($0 \leq \gamma \leq 1$), which is calculated as follows:

$$\gamma(BRP \rightarrow CFD) = \sum_{\Phi \in \{X,Y,Z\}} \left(\frac{\sum_{i=1}^{N(\Phi)} \alpha(\Phi) \times \mathrm{P}(\Phi)}{N(\Phi)} \right) \tag{3.3}$$

where $N(\Phi)$ is the number of the Φ predictive mode, $\mathrm{P}(\Phi)$ indicates the predictive results under a cognitive state Φ.

3.4.4 Never-Ending Learning (NEL)

By integrating systematic experimental design with evidence combination and fusion computing, a never-ending learning paradigm is studied to realize such a novel brain big data computing approach. More specifically, never-ending learning [199] is dependent on the K-I-D loop from the continuous iteration and evolution of Data-Brain driven general intelligence model to learn multiple sources of knowledge, information and data, continuously and incrementally, towards providing multi-aspect results and new findings underlying human brain. On the one hand, the never-ending learning paradigm produces the specific brain pattern that is related to a specific cognitive function with more confidence through the task-driven KID inference, which helps us understand the specificity of a function-related brain pattern. On the other hand, the never-ending learning paradigm produces multi-aspect interpretations of brain functions for a specific brain pattern through the data-driven DIK inference, which helps us understand the brain pattern-contributed difference for various cognitive functions. The procedure of the never-ending learning within the K-I-D loop is described in Algorithm 3.2. The implementation process of never-ending learning begins with Algorithm 3.1, during which the experimental task graph T_{SYS}^{G}, the uncertainty distribution τ, and the support coefficient γ are obtained.

Algorithm 3.2: K-I-D Loop (Never-ending Learning in Thinking Space)

Input: the goal hypothesis, G_{FD}. ▹ From Function Dimension
the goal hypothesis, G_{ED}. ▹ From Experiment Dimension
the conceptual Data-Brain, CDB;
the cognitive functional domain, CFD;
the designing breadth, $SET = (T_{sie}, T_{pae}, T_{dee}, T_{ine}, T_{mie}, T_{spe})$;
the designing depth, DED.
Output: the experimental task graph, $T_{SYS}^{G} = \left(T_{mae}, \left(T_{sie}^{G}, T_{pae}^{G}, T_{dee}^{G}, T_{ine}^{G}, T_{mie}^{G}, T_{spe}^{G}\right)\right)$
the support coefficient, γ;
the uncertainty distribution, τ.

```
// Task-driven KID loop
procedure KID (DED, SET, G_FD, G_ED, CDB)
  T^G_SYS = SED(DED, SET, G_FD, G_ED, CDB);
  SVs = Data matching (T^G_SYS, Sample library);
  Data checking(T^G_SYS, SVs);
  R(T_mae) = Data computing (SV of T_mae);
  R(T_next) = Data computing(SV of T_next);
  Initializing τ = [0];
  while DED > 0 do
     T_mae ← The (DED − 1) loop nodes in the T^G_SYS;
     T_next ← The DED loop nodes in the T^G_SYS;
     Computing τ;
     DED --;
  end while
  return T^G_SYS, τ
// Data-driven DIK loop
procedure DIK (DED, SET, G_FD, G_ED, CDB)
  T^G_SYS = SED(DED, SET, G_FD, G_ED, CDB);
  SVs = Data matching (T^G_SYS, Sample library);
  Data checking(T^G_SYS, SVs);
  P(T_mae) = Data computing (SV of T_mae);
  P(T_next) = Data computing(SV of T_next);
  Initializing γ = [0];
  for each CFD in function dimension do
     Computing γ;
  end for
  Prioritization of γ for all CFD;
  return T^G_SYS, γ
```

3.4.5 Human-in-the-Loop Interactive Learning (HITL)

Human-in-the-loop puts humans in never-ending learning that takes into consideration human intents, psychological states, emotions and actions [200]. Such a design method of interactive artificial intelligence systems can be beneficial in solving the computationally NP-hard problem, especially facing the complex brain [201]. By integrating experience and knowledge from human expertise, the human-in-the-loop mechanism can make learning more relevant, effective, transparent and reasonable. In this thesis, we study two views of human-in-the-loop: one is that human-in-the-loop participants in the learning direction of Data-Brain general intelligence model, namely thinking-space construction; another is that human-in-the-loop participants in the interactive learning process, namely human-aided interactive learning.

3.4.5.1 Thinking-space Construction

In practice, the structured constituents of each domain are defined in the knowledge layer of the conceptual Data-Brain that provides the operational interface, and then the multi-task brain data driven by semantic vectors are sampled and mapped to a uniform space for never-ending learning. In Data-Brain driven general intelligence model, human mainly interacts with the thinking space in three ways, including request setting, resource refining and resource screening in such a human-in-the-loop process.

- Firstly, request setting is a reconstruction process of the conceptual Data-Brain. In this stage, investigators constraint scope of functional domains in the function dimension to meet research goal. For example, a human reasoning-centric systematic study may involve inductive reasoning and its subcomponents such as rule identification and extrapolation. Meanwhile, their relational properties are given on the basis of computational principles and personal experience. In the experiment dimension, task-related parameters are given, such as experimental paradigms, experimental protocol and explicit stimuli surrounding interest of investigators. In the data dimension, the data-related parameters are given, such as the data modal of fMRI, the data state of raw data, the subject type of healthy. In the analysis dimension, the computing details are given. For example, general linear model framework-based method is used as the core computing method in such a KID scheme. Hence, these related parameters are given, such as the statistical P value, the corrected methods, the size of cluster selected from the set of $\{10, 20, 30, 50, 100, 150, \ldots\}$. Meanwhile, the Searchlight method is used as the core computing method in such a DIK scheme. Hence, selection of the machine learning methods needs to be concerned. Such reconstructed four dimensions are connected as a computable Data-Brain that is integrated into never-ending learning.

- Secondly, resource refining occurs at updating stages (including add, modify, delete and query operations) of the sample library and the conceptual Data-Brain. For those processes of mapping the internal and external resources to the sample library, human can ensure correctness of information and add missing information. Furthermore, human is indispensable for extending and refine of knowledge surrounding the conceptual Data-Brain. In this process of collective modes, investigator not only participant in their own learning process, but also help shed new light on learning processes from other investigators.
- Thirdly, human also participants in the process of resource screening. In each loop, although brain data can be automatically sampled, computed and fused, the complexity of higher cognitive functions tells us that the fully autonomous learning paradigm is not enough. For example, in the operational procedures of external

evidence, the topic modeling can automatically extract meaning from neuroimaging articles by identifying their themes or topics. However, it is difficult to identify a core topic from a paper with multiple topics, especially in the context of full-text learning. Hence, we need to a further rescreening of the topic-related articles on the basis of an initial screening of the topic modeling.

3.4.5.2 Human-aided Interactive Learning

In this part, we introduce the human-aided interactive learning method within human-in-the-loop. Through this kind of inference mechanism based on the comparative index-matching procedures, this model can select some candidate patterns/indicators and investigate their fruitful meaning for further study. The key mechanism of the human-aided interactive learning is to integrate the actions of human thinking 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 pipeline for the human-aided interactive learning is shown in Figure 3.11.

Investigators operates the interface to interact with various Thinking-Entities ($TEs \geq 3$) in the general intelligence model. A Thinking-Entity is a basic operating unit involved in the whole life cycle of a sample from the sample library, including the optional knowledge unit, TEK, the optional information unit, TEI, and the optional data unit, TED. In details, the TEK options the cognitive concepts from the function dimension of the conceptual Data-Brain; the TEI options the hypothetical brain patterns; the TED options the sampled brain data. The output of the general intelligence model is a list of the association pairs between cognitive concepts in the knowledge layer and patterns/indicators defined in the information layer whose feature properties are observed

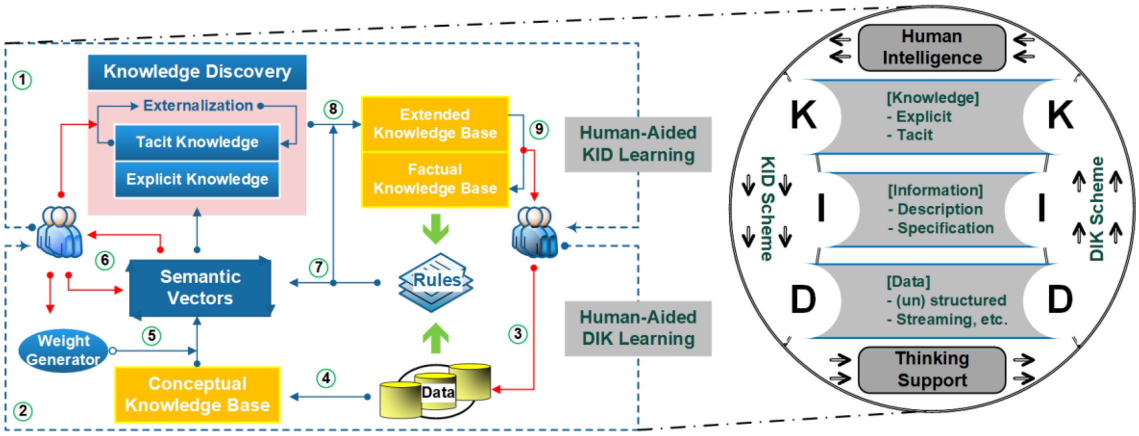


Figure 3.11: The information-processing pipeline of human-in-the-loop. The dotted arrows indicate two schemes from top-down and bottom-up perspectives respectively. The red arrows indicate multiple human-computer interaction processes between human and the model. The blue arrows indicate information 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.

in the data layer, after never-ending learning within the K-I-D loop. In this model, the hybrid knowledge-driven KID and data-driven DIK schemes in learning and inference stages are defined:

- The KID scheme: In the learning stage, the conceptual weights are obtained by users in the TEK of the Thinking-Entity, which are used to measure the relevance between the cognitive function and the sampled brain data. Meanwhile, the metric and/or pattern characteristics of the sampled brain data are measured in the TEI and TED, respectively. In the inference stage, some information is obtained by the learning process from the knowledge layer to the data layer, in the purpose of verifying indicators with stability and measuring patterns with special significance.

- The DIK scheme: In the learning stage, the conceptual weights are obtained by multiple human-computer interaction processes and the metric and/or pattern characteristics of original data are also evaluated concurrently. In the inference stage, some information is obtained by the learning process from the data layer to the knowledge layer, in the purpose of exploring more 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 existing knowledge, but also one that generates hypothetical information to inspire us to carry out the next phase of experimental design and related work. Therefore, the ability of the human-aided interactive learning is continuously improved during the never-ending learning process of human-in-the-loop. Following this learning paradigm, some important issues need to be identified:

- How do we construct various Thinking-Entities towards the integration, processing and computing of multi-source brain resources for systematic brain research;
- How do we implement the Thinking-Entities based interactive learning in the current closed-loop model; and
- How do we make inference and judgment to generate new meaningful and valuable plans, and then guide further experiments for obtaining more evidence towards never-ending learning?

For this, we further explain the connectionist architecture of each element in the human-aided interactive learning process. Their details are described as follows, including the human-aided interactive KID learning method and the human-aided interactive DIK learning method, corresponding to different schemes. For the convenience of readers, a list of essential symbols and abbreviations are shown in Table 3.2.

a: Human-aided Interactive KID Learning Method

Obtaining effective brain patterns and indicator calculation methods is one of the most important directions in the study of cognitive and clinical characteristics. As we all know, there are thousands of definitions and computing methods for existing patterns and indicators. How to choose the quantitative indicators and evaluation methods has become a huge challenge during addressing a specific brain science problem. The purpose of the human-aided interactive KID interactive learning method within human-in-the-loop is to compare, compute and evaluate the effectiveness of different indicators and patterns in the $InfoL$ by utilizing prior knowledge in the $KnowL$ and brain data in the $DataL$, which is similar to the feature or pattern selection processes in machine learning. The main processes in different layers include:

Table 3.2: List of essential symbols and abbreviations.

Category	Description
$KnowL$	A computable knowledge layer, bound by a set of concepts from the conceptual Data-Brain.
$InfoL$	A computable information layer, bound by the definition of patterns (PID) and the computing methods of indicators (PIM).
$DataL$	A computable data layer, consisting of samples that are computed to obtain properties of patterns and indicators.
$DTEK$	The TEK whose weights are predefined from expert or personal inclination, where $DTEK = \{c_1: v_1, c_2: v_2, \ldots, c_n: v_n\}$. Here, ci refers to the i^{th} concept in the conceptual Data-Brain, $vi\ (0 \leq vi \leq 1)$ refers to the value of the weight coefficient corresponding to the i^{th} concept.
$LTEK$	The TEK whose weights are learned from human-machine interaction, where $LTEK = \{c_1: v_1, c_2: v_2, \ldots, c_n: v_n\}$. Here, ci refers to the i^{th} concept in the conceptual Data-Brain, $vi\ (0 \leq vi \leq 1)$ refers to the value of the weight coefficient corresponding to the i^{th} concept.
Sdif	The vector represents the semantic distance among multiple Thinking-Entities.
Kdif	The conceptual difference matrix represents the weight differences corresponding to all concepts among multiple Thinking-Entities.
Ddif	The feature difference matrix represents the significant differences in patterns or indicators among multiple Thinking-Entities.
C_n^m	Combination in mathematics, $\frac{n!}{m!(n-m)!}\ (n \geq m)$.
$ABS\ (X)$	Return absolute value for value X.
$Dist\ (x, y)$	Return the distance between variables x and y by various similarity measurement methods such as the Euclidean distance algorithm and the Hamming distance algorithm.
$Sort\ (sort\_values)$	Return sorts in descending order and their index.
$Zeros\ (m, n)$	Return a matrix of the given shape and type, filled with 0.
$Rand\ (m, n)$	Return a matrix of the given shape with random floats in the interval [0.0, 1.0].

1) Based on the prior knowledge, the concepts in conceptual Data-Brain can be adjusted to $DTEK = \{c_1: v_1, c_2: v_2, \dots, c_n: v_n\}$ by the expert before the learning process. The adjusted $DTEK$ will affect the distribution of concept c_i in the TEK and then affect its dimensions. In addition, a concept c_i defined in the $KnowL$ can be encoded as a value $vi\ (0 \leq vi \leq 1)$ with following rules: the weight of concept is 1, if its corresponding meaning is mostly related to the context of a sample in the Thinking-Entity; otherwise, its weight is 0. At this point, a Thinking-Entity is mapped to a computable vector space with the interval [0, 1] properties, such as $DTEK = \{c_1: 0.1, c_2: 0.5, \dots, c_n: 0.8\}$.
2) Based on the request of investigators, the definition of the brain patterns (PID) and the brain computing methods of the indicators (PIM) could be bounded by the $InfoL$. For example, the effectiveness of the paired $\langle PID_p, PIM_s \rangle$ can be validated by the learning process from the $KnowL$ to the $DataL$. Here, the PID_p may be a network pattern "default mode network", and the PIM_s may be an indicator such as "clustering coefficient", "local efficiency" and "global efficiency".
3) The property values of different indicators and brain patterns defined above are computed in the $DataL$, corresponding to various Thinking-Entities. Then, the values of significant differences between these Thinking-Entities can be obtained by the statistical theory.

The computing operations in the $KnowL$, $InfoL$ and $DataL$ are executed as shown in Algorithm 3.3. The computed results obtained from various layers will be used as input to the rule engine, and then used to select the effective patterns and feature extraction methods by comparative learning strategy. Here, the comparative learning strategy is performed by comparing the difference between paired Thinking-Entities in the $KnowL$

and the $DataL$, corresponding to various brain patterns/indicators in the $InfoL$. Supposing there are three Thinking-Entities, that is, TEi, TEj and TEk, they are predefined by $DTEKi$, $DTEKj$ and $DTEKk$ in the $KnowL$, as well as being computed to achieve their property values (i.e., PVi, PVj and PVk) in the $DataL$, respectively.

- Firstly, based on the predefined $DTEK$ corresponding to various Thinking-Entities in the $KnowL$, their semantic differences among different Thinking-Entities could be computed by $Dist\,(x, y)$, achieving $Sdif = [Dist\,(DTEKi, DTEKj), Dist\,(DTEKi, \;\; DTEKk), Dist\,(DTEKj, DTEKk)]$.
- Secondly, based on the computed property values in the $DataL$, their property differences among different Thinking-Entities could be computed by $Dist\,(x, y)$, achieving $Ddif = [Dist\,(PVi, PVj), Dist\,(PVi, PVk), Dist\,(PVj, PVk)\,]$.
- Finally, the obtained semantic differences $Sdif$ and property differences $Ddif$ are sorted by $Sort\,(Sdif)$ and $Sort\,(Ddif\,)$, respectively. For the paired $\langle PID_p, PIM_s\rangle$ in the $InfoL$, if $Dist\,(DTEKi, DTEKj) \geq Dist\,(DTEKi, DTEKk) \geq Dist\,(DTEKj, DTEKk)$ and $Dist\,(PVi, PVj) \geq Dist\,(PVi, PVk) \geq Dist\,(PVj, PVk)$, the current $\langle PID_p, PIM_s\rangle$ will be recommended.

The KID inference rule is used to infer the learning results obtained by Algorithm 3.3, including the $Sdif$ and the $Ddif$. 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 the $Ddif$ for a row are consistent with that of the $Sdif$, the $\langle PID_p, PIM_s\rangle$ pair corresponding to the current row is output, which is defined in the $InfoL$.

Algorithm 3.3: Human-aided Interactive KID Learning (KID-HITL)

Input: The set of N Thinking-Entities (TEs), $TEs = \{TE1, TE2, \dots, TEk, \dots, TEN | 2 < i \leq N\}$;
The $DTEKs = \{DTEK1, \dots, DTEKi, \dots, DTEKj \dots\}$ with the C concepts and
the predefined weights, corresponding to various Thinking-Entities;
The P pattern definitions and/or Q computing methods from the $InfoL$,
$PASet = \left\{\langle PID_p, PIM_q\rangle \middle| 1 < p \leq P,\ 1 < q \leq Q\right\}$.

Initialize: $Sdif = Zeros\ (1, C_N^2)$;
$Ddif = Zeros\ (P, Q \times C_N^2)$;

Output: $Sdif$ & $Ddif$.

procedure in the $KnowL$ and the $InfoL$

Initialing $l = 1$;
for $i = 1, 1 < N, i++$ **do**
  for $j = i + 1, j \leq N, j++$ **do**
    $Sdif\ [l] = Dist\ (DTEKi, DTEKj)$;
    $l++$;
  end for
end for
Return $Sdif$

procedure in the $DataL$

for $p = 1, p \leq P, p++$ **do**
  for $q = 1, q \leq Q, q++$ **do**
    Calculating property values of TEs based on PID_p and PIM_q, namely PVs
  end for
  for $q = 1, q \leq Q, q++$ **do**
    Initialing $m = 1$;
    for $i = 1, 1 < N, i++$ **do**
      for $j = i + 1, j \leq N, j++$ **do**
        $Ddif\ [p, C_N^2 \times (q - 1) + m] = Dist\ (PVi, PVj)$;
        $m++$;
      end for
    end for
  end for
end for
Return $Ddif$

b: Human-aided Interactive DIK Learning Method

The main purpose of the interactive DIK learning method is to interpret the characteristics of a specific feature pattern, for example, to answer the question about "Is it the limbic system related to emotion". In this interactive procedure, the new semantic vector $LTEK = \{c_1: v_1, c_2: v_2, \dots, c_n: v_n\}$ is acquired by the comparative learning strategy in the $KnowL$. The brain patterns of interest from the $InfoL$ are evaluated on the basis of the comparisons of property values in the $DataL$. Its computational procedure is described in Algorithm 3.4.

Algorithm 3.4: Human-aided Interactive DIK Learning (DIK-HITL)

Input:

The set of N Thinking-Entities (TEs), $TEs = \{TE1,\ TE2, \dots, TEk, \dots, TEN | 2 < i \leq N\}$;

The $LTEKs = \{LTEK1, \dots, LTEKi, \dots, LTEKj, \dots\}$ with C concepts and initial weights, corresponding to various Thinking-Entities;

The P pattern definitions and/or Q computing methods from $InfoL$, $PASet = \{\langle PID_p, PIM_q \rangle | 1 < p \leq P,\ 1 < q \leq Q\}$;

The maximum number of iterations, max_{iter},

The level of marginal significance, P − Value.

Initialize: $Kdif = Zeros\ (C, C_N^2)$;

$LTEKs = Rand(C, N)$;

$Ddif = Zeros\ (P, Q \times C_N^2)$.

Output: $Kdif$, $LTEKs$ with learned weights and $Ddif$.

procedure in the $KnowL$ and the $InfoL$

Initialing $l = 1$;
for $i = 1, i < N, i++$ **do**
  for $j = i + 1, j < N + 1, j++$ **do**
    Randomly initialize $LTEKi$ and $LTEKj$ within 0 to 1;
    while $max_{iter} \neq 0$ **do**
      Convergence conditions analysis with $LTEKi$ and $LTEKj$;
      if Satisfy convergence conditions **then**
        break;
      else
        Step 1: Generating random weight adjustment (enhancement and suppression) symbols by machine for each concept in $LTEKs$;
        Step 2: Changing the adjustment symbols generated in Step 1 by the user based on the information obtained;
        Step 3: Updating weights in $LTEKi$ and $LTEKj$ according to symbols from Step 1 and Step 2;
        $max_{iter} --$;
      end if
    end while
    $Kdif\ [:, l] = ABS(LTEKi - LTEKj)$;
    $l++$;
  end for
end for

procedure in the $DataL$ based on Algorithm 3.1

Difference from the inductive KID learning procedure, their weights (only 0 or 1) in the TEK are set by experts or users before learning processes. In the interactive DIK learning method, however, the weights (from 0 to 1) are obtained during learning processes with multiple iterations. The following steps describe the interactive DIK method in details:

- **Convergence Conditions.** Steps 1 to 3 in Algorithm 3.4 are iterated until the algorithm reaches a predefined stopping criterion. In particular, the procedure is stopped if the statistical significance in the predefined $P-Value$ is reached between $LTEKi$ and $LTEKj$ in an iteration or after a predetermined number of iterations. As mentioned above, a comparative learning strategy is designed in the general intelligence model, that is, comparing the semantic and data characteristics of different Thinking-Entities at each iteration. 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 [202]. 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 [203]. 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 both $LTEKi$ and $LTEKj$ in $LTEKs$, 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 different 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 computing process of the corresponding $LTEKi$ and $LTEKj$; otherwise, it is a positive correlation.

- **Weight Computing.** In Step 1, a control weight vector (CWV) consists of randomly generated three signs '-1', '0', and '1', and is of the same size as $LTEKs$. In this vector, the sign - 1 means that the weight of the corresponding concept in $LTEKs$ will decrease in the next weight updating process; the sign 0 means that the weight will not be changed; and the sign 1 means that the weight of the corresponding concept in $LTEK$ will increase in the next weight updating process. During the interaction process, the user can control the symbol change in CWV by judging the relevance of the concept to each Thinking-Entity, thereby changing the next weight-updating action. For example, users 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. Hence, if a concept ci in $LTEKs$ is considered to be closely related to the Thinking-Entity TEi, but the sign '-1' in CWV is 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 CWV are random. We consider to obtain one CWV for each two Thinking-Entities during the processes of human-computer interaction in Step 1.

Then, how to compute and update the weights of both $LTEKi$ and $LTEKj$ at one time. First, the CWV generated by the computer is set to control the weight-updating process of the $LTEKi$. Then, the CWV of the $LTEKj$ is generated by comparing the semantic distance between the two Thinking-Entities, which includes two cases in Step 2:

- When the semantic distance of both Thinking-Entities is small enough to be considered as positive correlation: If the sign '1' appears in the CWV during an iteration and the current weight of the corresponding position in $LTEKi$ is greater than $LTEKj$, the corresponding position of the CWV for $LTEKj$ is also set to the sign '1'. Conversely, the corresponding position is set to the sign '-1'. If the sign '-1' appears in the CWV during an iteration and the weight of the corresponding position in $LTEKi$ is greater than $LTEKj$, the corresponding position of CWV for $LTEKj$ is also set to the sign '-1'. Otherwise, the corresponding position is set to the sign '1'. In other cases, $LTEKi$ and $LTEKj$ have the same control symbol for the CWV.
- When the semantic distance of both Thinking-Entities is large enough to be considered as negative correlation: if the sign '1' appears in CWV during an iteration and the weight of the corresponding position in $LTEKi$ is greater than $LTEKj$, the corresponding position of the CWV for the $LTEKj$ is set to the sign '-1'. Conversely, if the weight of the corresponding position in $LTEKi$ is smaller than $LTEKj$, the position is set to the sign '1'. If the sign '-1' appears in CWV during an iteration and the weight of the corresponding position in the $LTEKi$ is smaller than the $LTEKj$, the corresponding position of CWV of the $LTEKj$ is also set to the sign '1'. Conversely, the corresponding position is set to the sign '-1'. In other cases, the $CWVs$ of $LTEKi$ and $LTEKj$ have the same control signs.

The weights of concepts in the $LTEKi$ and $LTEKj$ are calculated based on these signs after obtaining the CWV in Step 3. In combination with the above,

$$w(t+1) = \begin{cases} w(t) + \frac{1-w(t)}{RIN}, & sign\ in\ CWV = 1 \\ w(t), & sign\ in\ CWV = 0 \\ w(t) - \frac{w(t)}{RIN}, & sign\ in\ CWV = -1 \end{cases} \tag{3.4}$$

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 interactive DIK 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.

Through the above learning process, we can get the $Kdif$, the $LTEKs$ with learned weights and the $Ddif$. 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 be entered into the inference engine and then generate new information and knowledge based on rule constraints. The DIK inference rule is used to infer the learned results obtained by Algorithm 3.4. The elements of the $Kdif$ and the $Ddif$ for each row are 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 $\langle PID_p, PIM_s \rangle$ pair with concept is given and output by using a form of $\langle\langle PID_p, PIM_s \rangle, \text{concept}\rangle$ pair, where the concept is from the $LTEKs$. Through this kind of inference mechanism based on the comparative index-matching procedures, the general intelligence model can select some candidate patterns/indicators with fruitful meaning in the knowledge layer for further study.

3.5 The Systematic Brain Computing with HITL-Aided NEL

The pipeline of the systematic brain computing approach is shown in Figure 3.12, which is formalized as a loop towards the human thinking-supported never-ending learning of the brain and translational research. More details regarding such a systematic brain computing approach are introduced as follows, including the conceptual Data-Brain setup, systematic experimental design, evidential type inference, evidence combination and fusion computing, towards never-ending learning:

- Conceptual Data-Brain Setup. At the beginning of such a systematic brain computing process, people interact with the general intelligence model through the conceptual Data-Brain setup. The conceptual Data-Brain [161, 204] provides a thinking space, which includes multiple knowledge graphs to represent the systematic brain investigation processes from four dimensions related to brain functions, experimental tasks, data organization and analytic methods. It describes different scopes and their relations (including "include" and "related-to") at the conceptual level. For example, if we solely consider the "include" relation in the subgraph of function, this graph will become a tree structure with "Function Dimension" being the root node. During this human-in-the-loop process, people assign various factors of interest such as experimental factors and analytical factors, corresponding to various questions and hypotheses. Here a question may be to explore which neural structures support a specific cognitive function, and which cognitive functions may be related to a specific neural structure.

Furthermore, such factors also directly impact the intra- and inter- analytical strategies, the computing processes and interpretations of results.

- Systematic Experimental Design. Systematic experimental design indicates that the model knows how to design the next experiment based on the heuristic from the previous experiments, depending on experimental types with similarity assessment through experiment dimension of the conceptual Data-Brain. The experimental types can be identified by the $T_{next} - Call$ rules stated in Section 3.4.2. To assess the experimental similarity ε between two samples, it is necessary to describe the experimental profile such as paradigm- and stimuli-related factors, by which the design process is quantifiable. Here, we give an example to realize this process, which is related to about three representative factors stated in Table 3.1. These three factors include experimental paradigm (EPM), experimental protocol (EPL), explicit stimulus (ESI). Hence, the experimental similarity assessment can be realized on the basis of these experimental factors, $\Theta = \{EPM, EPL, ESI\}$, which is given by:

$$\varepsilon(T_M, T_S) = \frac{1}{the\ size\ of\ \Theta} \sum_{\theta_i \in \Theta} BIN(T_M^{\theta_i}, T_S^{\theta_i}) \tag{3.5}$$

where ε indicates the experimental similarity, T_M indicates the main experiment, T_S indicates a certain supplementary experiment; θ_i is the i^{th} variable which indicates various factors in Θ; $T_M^{\theta_i}$ indicates the factor properties of T_M at θ_i, $T_S^{\theta_i}$ indicates the factor properties of T_S at θ_i; $BIN(T_M^{\theta_i}, T_S^{\theta_i})$= 1 if $T_M^{\theta_i}$ is consistent with $T_S^{\theta_i}$.

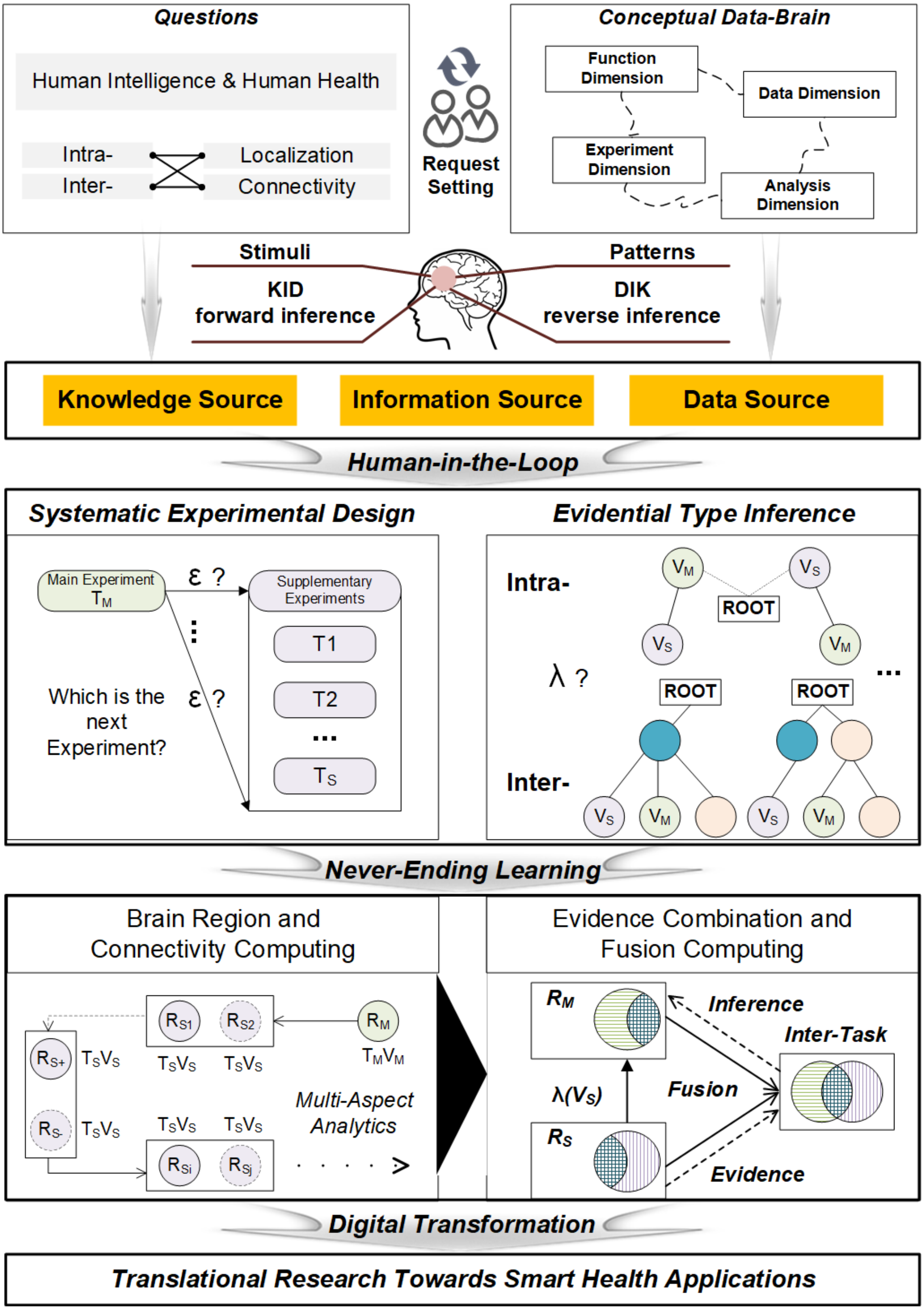


Figure 3.12: The schematic diagram of the systematic brain computing approach. A conceptual Data-Brain is constructed to guide systematic investigations of complex brain science problems,

systematic design of cognitive experiments, systematic brain data collection and management, as well as systematic brain data analysis and simulation stated in the Brain Informatics methodology. The hierarchical experimental design, evidential type inference, and evidence combination and fusion computing are performed to realize never-ending learning and translational applications.

- Evidential Type Inference. These evidences are classified into different types with the evidence weight coefficient λ, namely Type-I and Type-II evidence, which are identified by the discriminant rule of evidential types stated in Section 3.4.3. Here, the Type-I evidence is learned to increase the level of confidence to the given hypothesis, conversely, the Type-II evidence will decrease the level of confidence to the given hypothesis. For example, the evidence V_M and V_S are corresponding to the main experiment and the supplementary experiments, respectively. If the evidence V_S is identified as the Type-I evidence, it indicates that the functional domain of V_S can be the "ancestor" or "descendants" relationship of V_M, according to function dimension of the conceptual Data-Brain. Inversely, if V_S is identified as the Type-II evidence, the functional domains of V_M and V_S belong to other relationships that are different from the Type-I evidence, such as the "sibling" relationship. The λ coefficients are determined as follows: (1) if the functional domain of the V_S is the "descendants" relationship with that of the V_M in function dimension of the conceptual Data-Brain, $\lambda = 1$; (2) if the functional domain of the V_S is the "ancestor" relationship with the V_M, $\lambda = \prod \frac{1}{degree\ of\ node}$, where the $node$ is in the shortest path from the functional domain of the V_S to the parent of that of the V_M in function dimension; (3) if the V_S belongs to the Type-II evidence, $\lambda = -1$.
- Evidence Combination and Fusion Computing. The integrated evidence is firstly computed on the basis of predefined methods in analysis dimension. Different from the approach stated in Section 3.4.3 that focuses on combination and fusion in a single loop, the extended approach concerns about computed results across multiple loops towards never-ending learning. Hence, the computing results of these evidence

are fused continuously to measure the uncertainty distribution τ of brain functions on various patterns (such as brain regions and/or network nodal information) underlying the goal hypothesis [162], which is given by:

$$\tau_{loop} = \sum_{i=1}^{N_{loop}} \lambda(Vi) \times Mask(GH_P) \times R(Vi) \tag{3.6}$$

where N_{loop} is the number of evidence that will be fused by the intersection of computing results in a loop, $\lambda(V_i)$ indicates the weight coefficient of the i^{th} evidence, $Mask(GH_P)$ indicates the mask of patterns of interest from the goal hypothesis, $R(V_i)$ indicates the computing results of the i^{th} evidence.

- Never-ending Learning (NEL). The never-ending learning is realized by the human-centric K-I-D loop to meet multi-aspect brain computing requirements. During this process, the new experiments, together with new evidence, are designed and analyzed by evidence combination and fusion computing to test the goal hypothesis continuously. More specifically, along with iteration and evolution of the loop, the τ distribution is calculated and updated to interpret the multi-layer specificities of the brain functions on various patterns, which is given by:

$$\tau_{NEL} = \sum_{loop=1}^{\infty} \tau_{loop} \tag{3.7}$$

where τ_{NEL} indicates the τ distribution obtained by the cumulation of τ_{loop} from various loops. Theoretically, as the brain data is continuously acquired, the learning process can be performed forever. In addition to this mechanism, an end condition is also designed to ensure expected results that can be observed. For more details, the τ distribution obtained by the Type-II evidence in a certain loop is used to exclude those parts where there is overlapping with the cumulative τ_{NEL}, until the τ_{NEL} is empty.

- Translational Applications. Considering to the potential relationships between brain patterns and clinical outcomes, the learned multi-aspect patterns from the general intelligence model might provide insights into brain mechanisms of disease arises. Hence, it can support to develop individualized diagnosis and treatment plans for different groups with various substates of cognitive impairments. Furthermore, the learned brain patterns could guide feature extraction and selection, combining with computational neuroscience methods to realize the prediction and recognition of abnormal conditions.

3.6 Prospective

An intelligence system is concerned with not only self-learning and evolving capabilities, but also realizing interactions within and across different domains/scenarios. Figure 3.13 illustrates the collaborative mechanisms and applications of the proposed general intelligence model in the connected SCP spaces. More specifically, the basic model provides the initial mode and interface that can be personalized in different scenarios. People can fill the content of interest and set personalized parameters in such a basic model. For example, the resources organized in the K-I-D architecture can be adjusted to match never-ending learning of other scenarios. The goals and hypotheses can be designed to drive model learning, through binding the scope, concept and parameter of the conceptual Data-Brain. In the future, these personalized models can be interconnected into a network. Owing to the same mode, they can realize smoother interactions and more productive collective learning. It involves different developing directions: the systematic brain computing for brain investigation and the multi-dimensional services in the connected world.

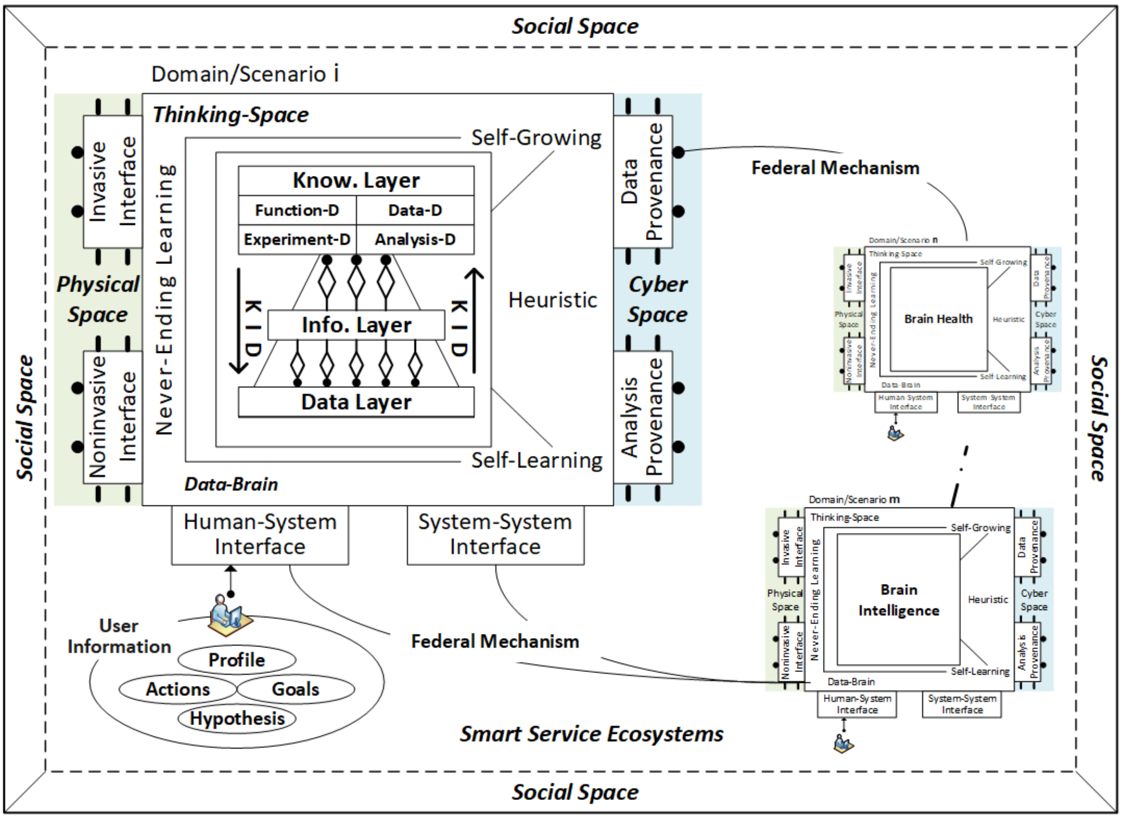


Figure 3.13: Collaborative mechanisms and multi-dimensional services of the general intelligence model. The multiple sources are organized into a three-layered architecture surrounding knowledge graphs, wealthy information, and massive data; the KID and DIK schemes are connected into a cycle as the thinking space, namely the K-I-D loop, for brain computing with conceptual Data-Brain driven systematic fusion; the never-ending learning characteristic hidden in the K-I-D loop drives the continuous iteration and evolution of the platform; the social-cyber-physical interfaces ensure interactions within and outside the platform, and working collaboratively across multiple domains/scenarios to provide the multi-dimensional smart health services.

3.6.1 Systematic Brain Computing Based on the GIM

The self-process of learner reflects the ability to work and learn independently. As shown in Figure 3.14, the general intelligence model-based brain computing platform provides such never-ending learning ability that generates new knowledge and findings through active learning and heuristics in the thinking space. Its working processes are as follows: during the online phase, the brain computing platform responds to user input, including the goal hypotheses provided by an investigator. A systematic experimental plan is generated based on Algorithm 3.1, followed by integrating data, information and knowledge from multiple sources for multi-aspect analysis and inference. On the basis of the above, the multi-level uncertainty distribution τ is computed and inferred; the support coefficient γ is given; and more new experimental plans are continuously recommended to meet requirements of an investigator. During the offline phase, the systematic experimental plans are automatically designed to explore brain specificity for a certain hypothesis based on random combinations of factors in function dimension and experiment dimension from the conceptual Data-Brain. Alternatively, a systematic experimental plan can also be expanded based on the data-driven approaches that rely on the local storage data and linked external data sources.

Furthermore, the general intelligence model is composed of the KID and DIK schemes that constitute the complementary mechanism for never-ending learning. Under the KID scheme of knowledge-driven learning, the knowledge layer guides the systematic processes from experimental designing to acquisition, combination and inference of relevant evidence at the data layer (including the first-hand data of remaining original states) and the information layer (including second-hand data of published results and electronic medical records). Conversely, under the DIK scheme of data-driven learning, the brain computing results of data and information layers are regarded as the clues to inspire new systematic experimental design for further analysis and practice.

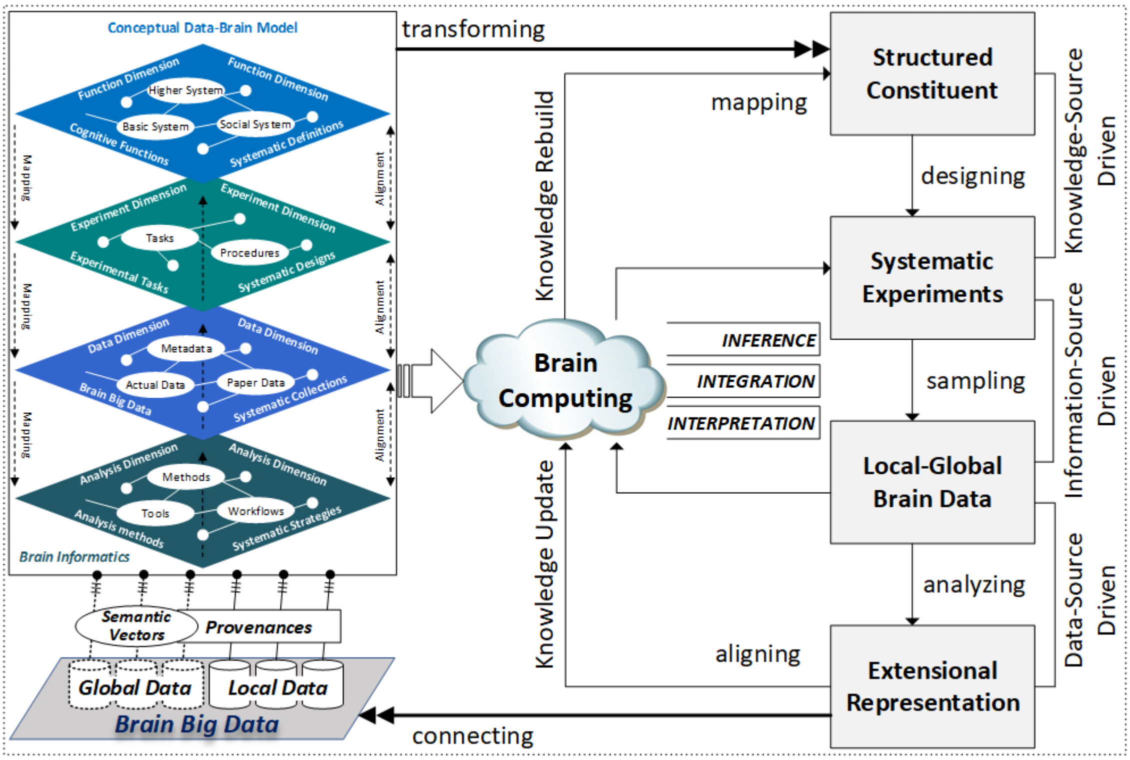


Figure 3.14: The architecture of the multi-source brain computing platform. The conceptual Data-Brain is organized by interconnected four dimensions from the function, experiment, data and analysis; brain big data is organized into semantic vectors with provenances for meeting dynamic requirements of brain computing; multi-source knowledge, information and data are driven by three operations, namely designing, sampling and analyzing, for implementing systematic experimental plans, systematic data sampling and fusion, as well as systematic analysis and inference with uncertainty, respectively.

3.6.2 Multi-dimensional Services in the Connected World

We present two scenarios of the wisdom service within the virtual world including the brain cloud platform and the healthcare assistant system, as shown in Figure 3.15. Cloud computing promotes globally cooperative mechanisms and resource-sharing arrangements to generate and test theories of brain function and dysfunction for accelerating brain science discovery [205]. For instance, the IEEG.org provides a cloud platform for sharing, visualizing and analyzing of data from multiple file formats (e.g., imaging data combined with electrophysiological data and patient metadata) [206]. The

MRICloud provides cloud-based services for automated brain MRI segmentation and analytical tools for quantification via distributed client-server remote computation and Web-based user interfaces [207]. When Data-Brain driven general intelligence model meets cloud computing as a brain cloud platform, a greater power will be exerted [161].

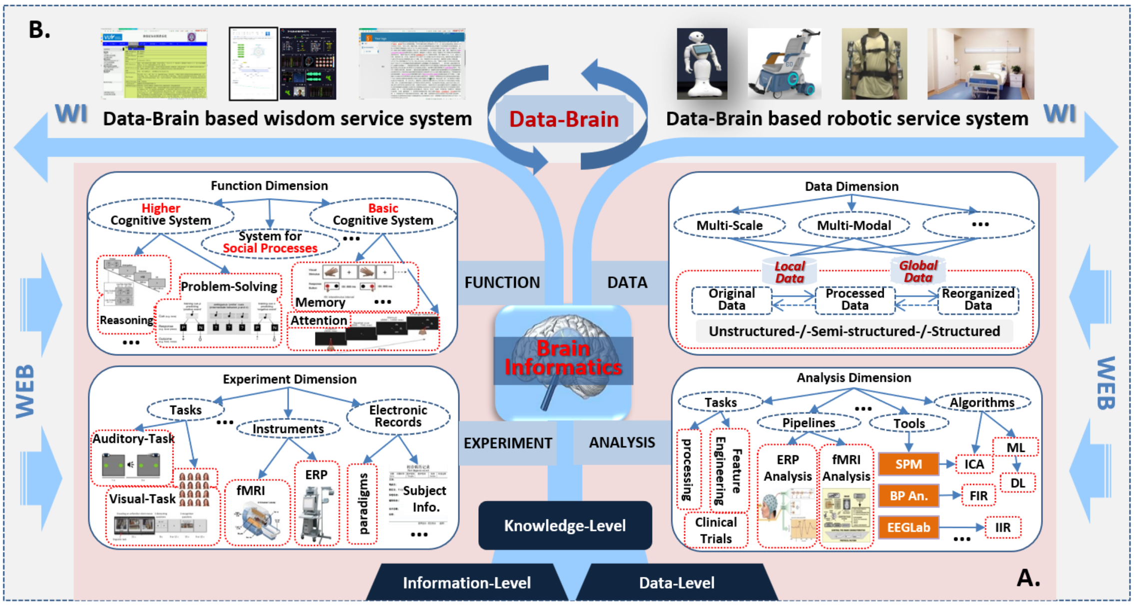


Figure 3.15: The multi-dimensional services of Data-Brain driven general intelligence model. The services are provided from two perspectives: A. The Data-Brain-supported systematic brain investigations, and B. The Data-Brain-supported versatile services.

In the current scenario, the brain cloud platform covers the multidimensional service modes supported by Data-Brain driven general intelligence model with the Data-Information-Knowledge-Wisdom hierarchy and intelligent agents in different circumstances, which is the extended version of the Wisdom as a Service (WaaS) in the W2T architecture [167]. Its five service dimensions are described as follows:

- Data as a Service (DaaS) provides services based on both the historical data and ongoing data streams, in which the data is the raw or preprocessed quantities and text, as well as data in multi-media, multi-modal and multi-scale collected, stored, and transmitted throughout the whole life cycle;

- Information as a Service (IaaS) provides services by using both static display and dynamic response modes, in which the information is a collection of interpreted, structured or organized items that are significant and useful for a certain specific request;
- Knowledge as a Service (KaaS) provides services with respect to existing and will-be-refined explicit knowledge, such as knowledge graphs, user models, facts, truths or principles gained through a specific request;
- Thinking as a Service (TaaS) provides services to support various human creativity related activities, in which the thinking is sagacity, discernment or insight to know what is true or right for making correct judgments, reasoning, decisions and actions;
- Robot as a Service (RaaS) provides customized, personalized and collaborative services for various physical scenarios, in which the robot can perceive the internal/external context and make intelligent responses autonomously.

The social interactions, cyber correlations, physical perceptions and thinking communications can be intertwined in the interconnections among ubiquitous things, which realize a smart fusion of the SCP spaces. Brain computing in the connected world is supported by not only the interactions and integration of data, information and knowledge, but also the interconnections related to the web of people, things and machines with respect to WI. In this context, brain computing with the thinking space should consider its role in the SCP spaces to develop multi-dimensional services, including human–human, human–machine and machine–machine interactions, which are described as follows:

- Human–Human Interaction (HHI). For physical interactions, the multi-person non-invasive direct brain-to-brain communication is presented to increase human performance by sharing intelligence [208] or drive collective intelligence for collaborative problem solving [209]. For thinking interactions, the ideas spread among people through social behaviors, which are affected by brain activity and structure [210].
- Human–Machine Interaction (HMI). For physical interactions, interfacing brain-inspired devices with the real brain is established to restore and enhance organ function in vivo through the neurobiohybrids [211]. For thinking interactions, the humanin-the-loop mechanism is used to create natural artificial intelligence algorithms and models, by which the learning and simulation processes leverage the power of machine and human intelligence [201].
- Machine–Machine Interaction (MMI). As machines have no thinking and ethics like human beings, stricter control is required to address the challenges of privacy protection and data security. Machine–machine interactions usually occur in the processes of data fusion that reflects the multi-dimensional characteristics, such as the data exchange among multi-center/multi-site [212]. Currently, federal learning may be the best practice to mitigate the possible risks caused by data behaviors between machine and machine [213, 214].

To achieve the goal, the Wisdom Web of Things has been developed as a core of interconnections among the ubiquitous things with big data in the social-cyber-physical spaces. As a wisdom aspect, the current brain computing platform can be an application in individual smartphone to dynamically access health information, by which the personalized models are constructed and the collective intelligence is realized by the interconnected people. For another, by leveraging the systematic Brain Informatics methodology and integrated data, information and knowledge from the interconnected virtual or/and physical entities, the current brain computing platform has achieved multi-source fusion on evidence level for decision-making support. Taken together, these applications have provided great expectations to be involved in the revolutionary process from traditional health to smart health, as well as meet healthy ecosystem demands intelligently.

3.7 Conclusion

In this chapter we theoretically study the important problem of the general intelligence for brain science. We show that handling complex brain comping tasks need the systematic behavioral modeling. Likewise, a Data-Brain driven general intelligence model is proposed to give multi-aspect understanding of brain function and health, directed by brain informatics and general intelligence theories. We believe that the general intelligence model will be widely applied to various scenarios and promote the progress of brain intelligence and health.

Chapter 4

GIM Analysis I: Functional Segregation in the Brain

In Chapter 4, we apply the general intelligence model to analyze the brain information-processing mechanism from the segregation perspective. In the experimental part, the human reasoning-centric brain patterns are investigated to validate the model performance. Neuropsychological investigations have traditionally divided human reasoning into two categories, induction and deduction, based on the type of relationships between the premise and the conclusion. Here, the inductive reasoning mechanisms is investigated by using Data-Brain driven general intelligence model.

4.1 Introduction

Reasoning is one of the uniquely human cognitive processes, using existing knowledge to draw conclusions, make predictions, or construct explanations [215, 216]. Three classes of reasoning separately represent different problem-solving strategies, including the inductive, deductive and abductive approaches. More specifically, the inductive reasoning involves inferring underlying relations from observations that are limited in scope, which is a process from special instances to general rule [217]. The deductive reasoning requires inferring a guaranteed conclusion from given information, which is a process from general rule to the specific application [218].

Recent advances in neuroimaging have augmented numerous findings in the human reasoning process but have yielded varying results. Based on neuroimaging methods and mental model theory, Osherson et al. revealed diverging brain region activations for inductive (such as, right-sided posterior and bilateral frontal activation, visual cortex, right superior parietal lobule and thalamus) and deductive (such as, left dorsolateral prefrontal cortex and right insular cortex) reasoning [219]. Goel and colleagues showed that inductive tasks mainly engage the left medial frontal gyrus, the left cingulate gyrus, and the left superior frontal gyrus (Brodmann areas 8, 9, 24, 32), whereas deductive tasks draw on the left inferior frontal gyrus (Brodmann areas 45, 47), indicating mainly prefrontal differences between reasoning types [220, 221]. Parsons and Osherson discovered hemispherical differences between reasoning types, showing that inductive reasoning engages the left hemisphere (specially for the prefrontal areas and the cerebellar Bergmann glia) and deductive reasoning engages the right hemisphere (activation in the language-dependent areas and the limbic system) [222]. Moreover, meta-analyses have been conducted, showing that several regions (such as, the left inferior frontal gyrus, the precentral gyrus, the superior frontal gyrus, the bilateral middle frontal gyrus, the bilateral superior parietal lobule, the right precuneus, the left inferior parietal lobule, the right superior occipital gyrus and the left frontopolar cortex) were reported to be actively involved in inductive reasoning [216, 217, 223]. The quantitative meta-analysis method of neuroimaging studies has also been conducted to investigate deductive reasoning, showing that the right middle frontal gyrus, the left medial frontal gyrus and the bilateral posterior parietal cortex were actively involved [224].

4.2 Problem Statement

Although reasoning has been studied for the past 70 years, its brain information-processing mechanisms are still not sufficiently understood [225]. One of the most fundamental questions is to answer the core neural underpinnings of a specific reasoning type. One possibility for this challenge is that reasoning, whether inductive and deductive, is involved in multiple mental processes which dynamically interact with each other, being intrinsic to human high-level cognition [215]. Existing knowledge in inductive reasoning showed its complex interactions with the basic cognitive processes, such as attention, memory, executive functions and symbolic processing [226, 227]. Furthermore, the inductive reasoning also encompasses intricate cognitive subcomponents, such as rule identification and extrapolation [228]. Taken together, a global picture of reasoning from the intra- and inter-perspectives of cognitive function can be given in Figure 4.1.

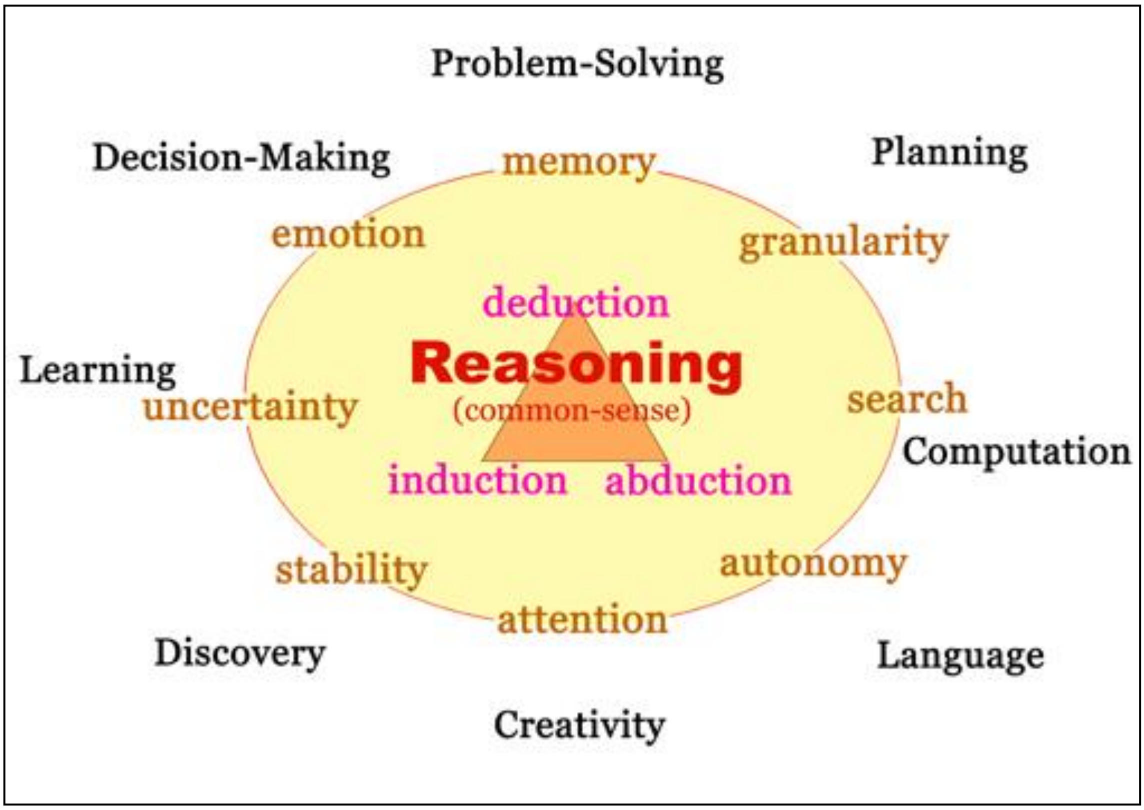


Figure 4.1: The human reasoning-centric constituent elements and its correlation distribution in the complex cognition space.

Furthermore, the complexity of the study to human reasoning is also closely related to the experimental design. For example, several studies were performed to investigate the neural underpinnings of inductive reasoning using different types of tasks, including sentential [229-231], figural [232] and numerical [228] tasks [233]. More specifically, number series completion is a classical task which has been widely used to the study of inductive reasoning. Studies indicate that solving number series problems needs to undergo four stages (including encoding, rule identification, rule application and respond), which involve different cognitive subcomponents of reasoning [87, 234]. As such, a single experiment with limited conditions is difficult to give a full picture of reasoning. It is urgent and necessary to provide the combination and comparison methods about fusion computing of multiple experiments.

4.3 Brain Localization Study Based on the GIM with HITL

For the purpose of presenting the systematic brain computing within the GIM, two sets of experiments are conducted. Our goal is to validate the abilities of systematic experimental design and brain function decoding along with the K-I-D loop. In particular, the evidence combination and fusion computing method is presented to infer the uncertain distribution of mental processes on the voxel-based level and give multi-aspect interpretations. All computing processes and results are illustrated through the implementation of multi-source brain data related to the task-state fMRI. To realize these goals, the knowledge, information and data layers are constructed first.

The knowledge layer is the conceptual Data-Brain that consists of function dimension, experiment dimension, data dimension and analysis dimension, which is illustrated in Figure 3.4. The information layer bridges between the knowledge and data layers, cooperating with the semantic vectors for the data provenance and the analysis provenance. The data layer is the sample library in which each sample is mapped into the standardized Data-Brain space illustrated in Section 3.3.1, including paradigm class, explicit stimuli, conditions, original data and results of studies and so forth. It maintains private data on local servers and builds the channel to communicate with global open sources in the connected SCP spaces. Table 1 in Appendix A shows a fragment of the sample library for several key properties. Hence, the semantic vector in the information layer can systematically integrate multi-angle brain resources to meet each round of the specific computing requirements. Additionally, the data layer achieves sustainable growth along with scientific literature and open resource that is regarded as the primary information source. In this case, the natural language processing techniques and the text mining methods are used to extract formal information and knowledge as external evidence for the needs of systematic brain computing. To illustrate such an issue, some functionality modules related to Neurosynth and BrainMap are integrated into the general intelligence model. It is worth noting that any function similar to these existed platforms can be integrated into the current model, which offers an extensible performance. The raw fMRI data are obtained, followed by a unified preprocessing pipeline that is operated within SPM12 software (the Wellcome Centre for Human Neuroimaging, London, UK, http://www.fil.ion.ucl.ac.uk/spm/software/spm12/). These procedural data, which are intermediate results produced by data preprocessing, are also stored in the data layer for possible pattern and indicator analyses in the future.

4.3.1 Experiments

In this case, the brain localization and its relevant mental processes are studied by using the general intelligence model with human-in-the-loop. To achieve this goal, the general framework is reconstructed to a specialized model towards the human brain mapping study. This model is driven by both KID and DIK inference schemes, by which systematic experimental design, evidence combination and fusion computing-based uncertainty inference are achieved. Suppose an intent is to explore the roles of particular brain regions in mental process related to a dual task of calculation and emotion, using picture stimuli. In this context, an experiment is regarded as the main experiment T_{mae} that is able to induce such effects of calculation and emotion simultaneously. In this case, the main experiment is matched from the sample library. Once the T_{mae} is determined and its corresponding data is obtained, the K-I-D loop will be activated to execute systematic fusion computing and uncertainty inference for which the details are described as follows.

For the KID scheme, the main experiment-centric multiple supplementary experiments are designed based on Algorithm 3.1, followed by sampling the task-state fMRI data and their processed results from the sample library to fill the systematic experimental graph. The contributions of various supplementary experiments are configured to $\lambda_1 = 1, \lambda_2 = 0.7, \lambda_3 = 0.5, \lambda_0 = 0, \lambda_4 = -0.5, \lambda_5 = -0.7, \lambda_6 = -1$, respectively. We expect that all nodes in such a systematic experimental graph are filled with the original fMRI data. Then, the sampled fMRI data can be computed through the integrated multivariate pattern analysis with Searchlight [235] and univariate analysis with GLM [236]. Practically, however, it is hard to fill all nodes with original fMRI data. In this case, the meta-analysis results of scientific literature are regarded as external evidence to fill the node without original fMRI data, for which the meta-analysis interface of Neurosynth is called. Finally, a novel brain mapping, namely uncertainty distribution mapping, is generated to further interpret the brain computing results of the current T_{mae} from univariate and multivariate analyses, for which the systematic experimental design method is implemented by the $T_{next} - Call$ rules defined in Section 3.4.2. For the DIK scheme, the brain computing results of the T_{mae} are regarded as the heuristics to select more experimental tasks, for which the activation coordinate experiment-wise search function of BrainMap is called. In the future, more expanded experimental plans are generated to extend brain computing and interpretations from more perspectives.

4.3.2 Results

Figure 4.2A shows the results during the processes of systematic experimental design and data sampling from the sample library. Since the requirement of exploring the picture task related to both emotion and calculation processes, the T_{mae} such as the emotional arithmetic task is matched on the basis of function dimension and experiment dimension.

Hence, the original data D3 summarized in Table 1 of Appendix A is given from the sample library. In the following, a series of supplementary experiments are designed to fill the template graph of systematic experimental plans, including the T_{spe} such as the mental arithmetic task with the original data D6 as internal evidence, the T_{dee} such as the memory task with the statistical maps E2 as external evidence, the T_{ine} such as the reasoning task with the original data D4 as internal evidence and the T_{mie} such as the language task with the statistical maps E3 as external evidence.

Figure 4.2B gives one of the multi-aspect analyses and inference results for uncertainty, under such a KID process. On the one hand, the first analytical aspect is based on the statistical parametric technique, which is the group-level analysis to examine the brain activation differences in the hypothesized superior frontal gyrus (SFG) subregion between the emotional stimuli and the dual-task stimuli of both emotion and calculation operations. As shown in Figure 4.2B(a), the color bar indicates z-values where $z \geq 1.96$. On the other hand, the Searchlight method is executed to obtain the brain computing results for the hypothesized brain region as shown in Figure 4.2B(b), where the radius is 5 voxels. Such computing processes are applied to all internal evidence. Taken together, the uncertain distribution mapping is shown in Figure 4.2B(c) that fuses the internal (from the univariate and multivariate analyses) and external (from the meta-analysis results with topics of ‘memory’ and ‘language’ in the Neurosynth platform) evidence to extend interpretations of these results from the single-task computing view.

Figure 4.2C gives a new recommended plan under such a DIK process. It can be seen that the tasks of T_{spe} and T_{ine} have been changed to others, such as the emotional pictures task inspired by the external evidence (based on the BrainMap platform) and the emotional face recognition task from the internal evidence (the D2 summarized in Table

1 of Appendix A), respectively. The new experimental plan is used to guide further practice.

4.3.3 Discussions

Although the statistical test and machine learning approaches have proven successful in the selection of brain specificities, it is hard to provide better global understanding of the complex many-to-many structure–function relationships with great uncertainty, particularly facing brain computing results underlying a single experimental task. For instance, the selected regions as shown in Figure 4.2B(a) and (b) are usually regarded as the ROIs with more wealthy information related to a certain mental process through the contrast of multiple conditions in a single task. As it is hard to interpret more characteristics of such ROIs that are extracted based on a single task, this study presented the evidence combination and fusion computing approach during such a KID scheme. Hence, the multi-source evidence with different task characteristics can be modeled and fused systematically to compute the uncertainty distribution mapping. Finally, the uncertainty values are used to interpret multi-aspect brain functions for those given ROIs. For example, the brain region revealed by the analysis of uncertain distribution (see the circled voxels in Figure 4.2B(c)) is localized at the so-called SFG subregion (MNI coordinates of the peak voxel: −21, 30, 42). Besides the brain activation related to the current T_{mae}-related mental process, the SFG is also an important region implicated in a variety of mental processes including working memory, cognitive control, attention, motor control and creativity [237-239]. Lesion studies also showed that impairment in the left SFG could result in a working memory deficit, and the impairment increased with the complexity of the tasks (on domains of verbal, spatial, face) [69]. In this case, since the memory-based evidence is selected and fused into the systematic brain computing process as shown in Figure 4.2A, it can provide deeper insights into the regions surrounded by the circle as shown in Figure 4.2B. The interpretation with respect to uncertain distribution coincides with many of the earlier studies. Furthermore, in order to further interpret regional neural activities, more evidence needs to be obtained by more heuristic experiments. Such computing ability can be provided by such a DIK scheme, as shown in Figure 4.2C, and then a new round of the K-I-D loop is activated.

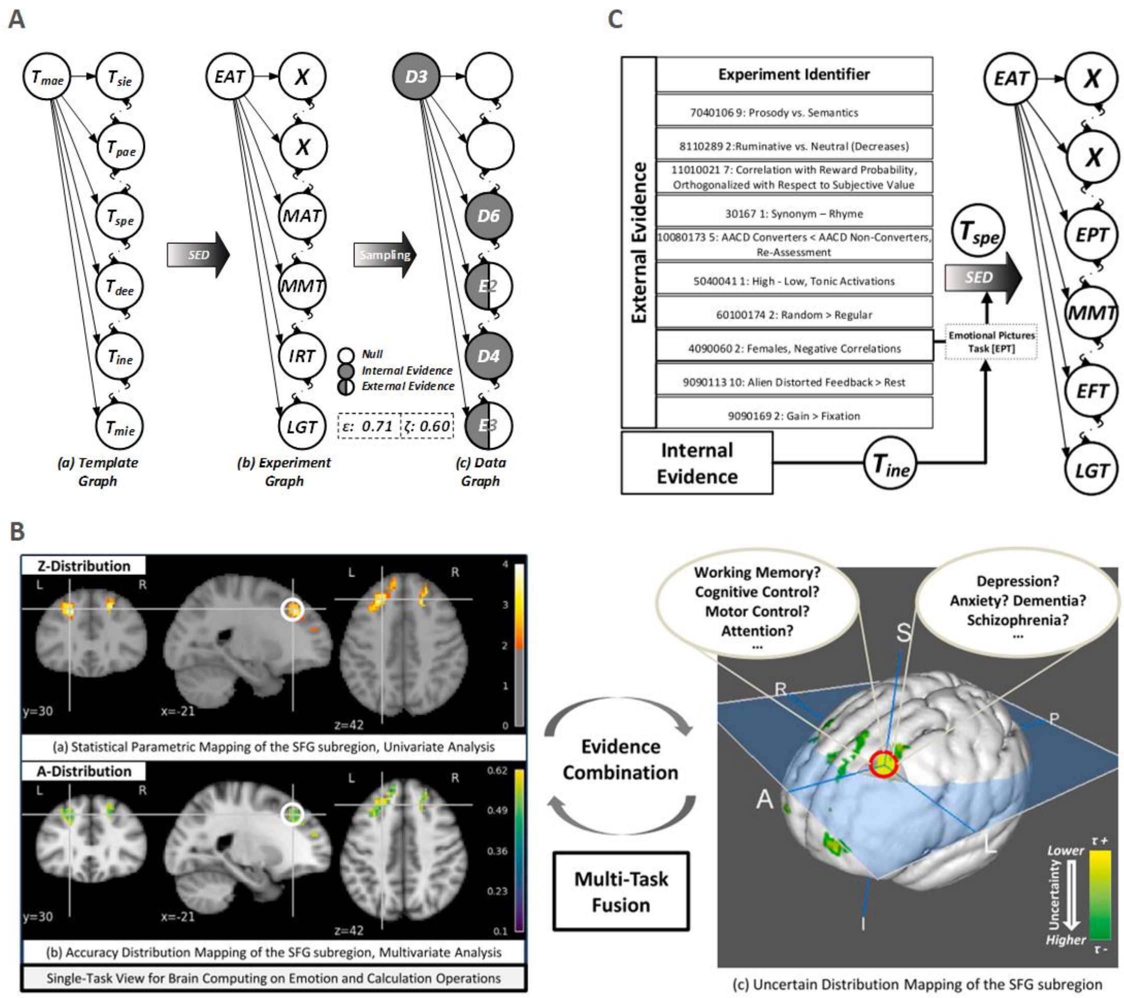


Figure 4.2: The functional specialization-oriented analysis results of the HITL interactive learning and inference in the GIM. A. The results of systematic experimental design (SED) and data sampling during the KID process: First, various tasks are matched from the sample library and then are filled in the experimental template graph; second, the raw data/processed results are extracted by multiple SVs. B. An example of systematic analysis and inference: (a) and (b) show the standard ROI analysis strategies from the single-task view. (c) shows the results of uncertainty analysis and inference based on multi-task evidence combination to provide more interpretations. For instance, the circled voxels, implicated in a variety of tasks such as working memory, cognitive control and attention, are localized at the so-called SFG subregion (MNI coordinates of the peak voxel: −21, 30, 42). Additionally, several mental disorders also show the dysfunction in this region, such as depression, psychiatric and affective disorders. C. The results of data-driven experiment expansion during the DIK process: First, the brain computing results corresponding to the main experiment are given by data sampling; second, new tasks can be from the external evidence and sample library through comparison of the brain computing results between new tasks and the main experiment; third, the previous experimental plans are updated with the new

tasks through the $Tnext - Call$ rules for future practice. Internal evidence: Emotional face recognition task (EFT), Emotional arithmetic task (EAT, D3), Mental arithmetic task (MAT, D6), Inductive reasoning task (IRT, D4). External evidence: Memory task (MMT, E2), Language task (LGT, E3), Emotional pictures task (EPT).

4.4 Brain Localization Study Based on the GIM with HITL-Aided NEL

To obtain an answer A for a specific question Q (such as "which brain regions are involved in the inductive reasoning process?" and "which information related to cognitive functions can be more processed by a specific brain region"), the general intelligence model performs never-ending learning within iterative loops. More specifically, the model interacts with sample library for extracting evidence by inference engine. The single evidence can be computed by univariate and multivariate analyses, followed by preprocessing for fMRI. Increasing with the new evidence, the results will be updated continuously by evidence combination and fusion computing within the model. All of them are presented in Figure 4.3.

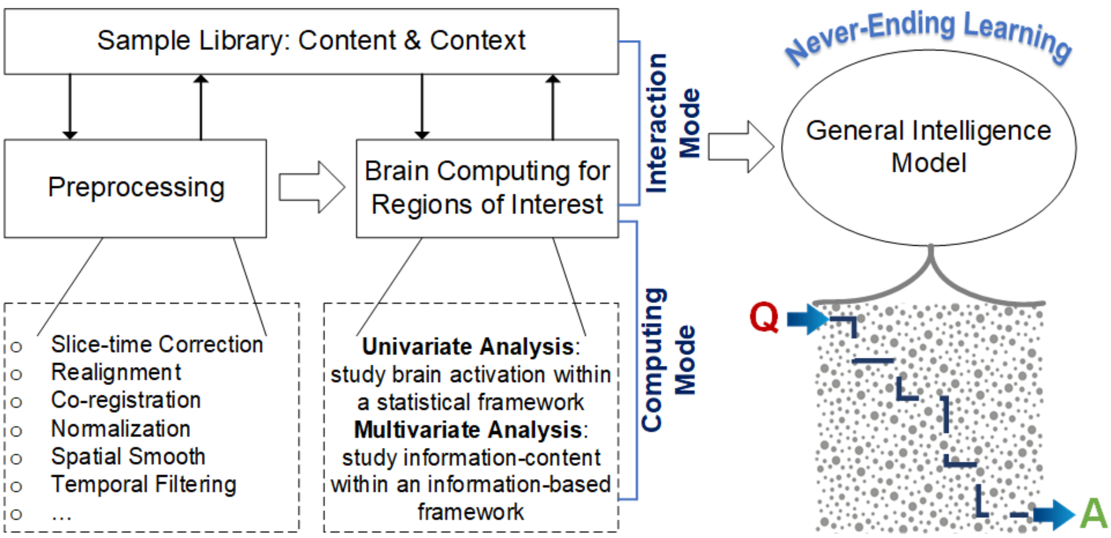


Figure 4.3: The general intelligence model applied to brain research on functional specialization.

On the one hand, we conduct internal evidence learning to realize multi-aspect analyses at brain region scales, then realizing systematic fusion based on experimental and evidential modeling. On the other hand, we conduct external evidence learning to enrich a sample library by combining with meta-analysis methods to realize autonomous learning from brain imaging results across the scientific literature

4.4.1 Experiments

To demonstrate that the approach can systematically model and interpret the human brain function, the human reasoning centric never-ending learning was conducted. A test comes from the analysis of fMRI-related resources. This case study was performed to answer the question about ‘The casual relationships between inductive reasoning and the dorsolateral prefrontal cortex (DLPFC)’. The investigators first set up parameters related to the four dimensions of conceptual Data-Brain, such as functional domain “inductive reasoning”, experimental paradigm “factorial design”, experimental protocol “block design”, explicit stimuli “digits, letters”, data object “fMRI”, analytical method “GLM analysis and Searchlight”, as shown in Figure 4.4. The general intelligence model is driven to select, process, analyze and fuse evidence from the sample library. These parameters are taken as the clue to design main experiment in the first loop, and then provide inspiration to select and compute parameter-matching evidence from the sample library. In line with the design principle of the main experiment, the supplementary experiments are sampled and computed continuously to realize never-ending learning.

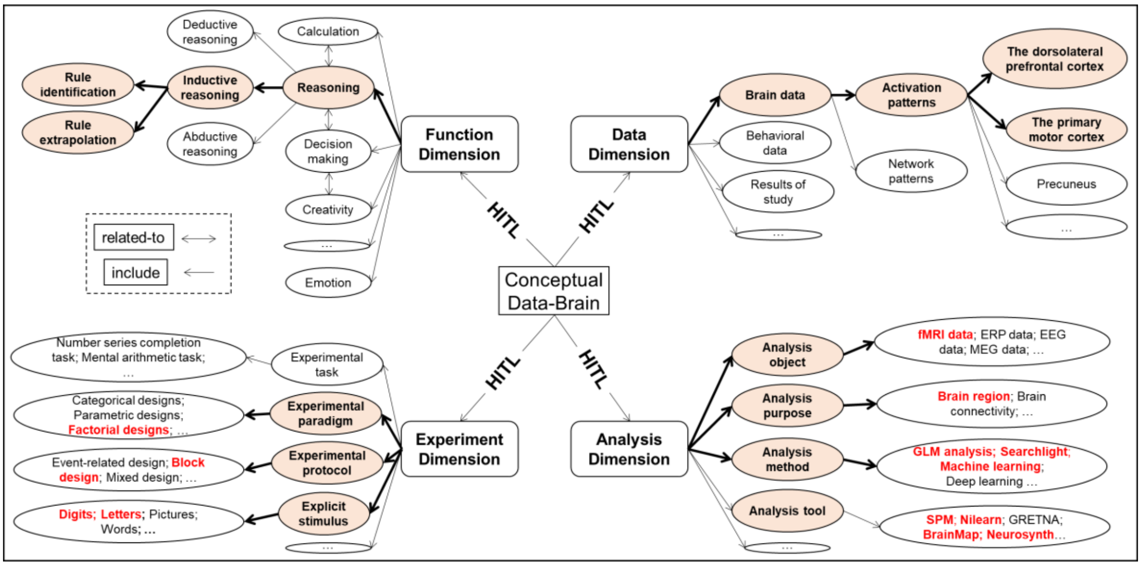


Figure 4.4: Reconstruction of the conceptual Data-Brain for the human reasoning-oriented brain localization study. During the human-in-the-loop (HITL) procedure, the conceptual Data-Brain is specified by users with the parameters of interest. Hence, the internal and external evidence are integrated into the general intelligence model by extracting resources from the sample library drawn from functional neuroimaging studies and associated data.

The internal evidence is mainly involved in the task-state fMRI data, which includes various experimental factors and so forth. For a raw fMRI data, it was processed by a unified pipeline that is operated within SPM12 software and fMRIPrep [240, 241]. These pipelines include most of the preprocessing tools currently available for fMRI investigation: (1) slice-timing correction; (2) estimation of rigid-body motion; (3) co-registration of the anatomical image in the Montreal Neurological Institute (MNI) space; (4) individual co-registration between anatomical and functional images; (5) resampling; (6) spatial smoothing with an isotropic Gaussian kernel; (7) temporal filtering. The procedural data, which are intermediate results produced by data preprocessing, are also stored in the data layer for possible pattern and indicator analyses in the future. Then, the sampled fMRI data are computed through the integrated the multivariate pattern analysis with Searchlight [235] and the univariate analysis with GLM [236].

In the stage of external evidence learning, we collected published neuroimaging papers from the open-access PLOS series of journals and PubMed. Only reasoning related neuroimaging papers were searched by using the keywords "(reasoning) AND (fMRI) OR (reasoning) AND (functional MRI) OR (reasoning) AND (functional magnetic resonance imaging) OR (inductive reasoning) AND (fMRI) OR (inductive reasoning) AND (functional MRI) OR (inductive reasoning) AND (functional magnetic resonance imaging) OR (deductive reasoning) AND (fMRI) OR (deductive reasoning) AND (functional MRI) OR (deductive reasoning) AND (functional magnetic resonance imaging)" in full text. For this study, we searched reasoning-related evidence on this sample library based on the topic words "reasoning". Thirty-two papers are obtained as shown in Table 2 of Appendix A.

4.4.2 Results

While the parameters were set up within the human-in-the-loop, the sample $D81$ in LOOP-1 (a sample for inductive reasoning study using the numerical serial complement task with factorial and block design) with the greatest expectation of experimental characteristic was extracted from the sample library (the details of sample library are listed in Appendix A.). Next, the supplementary experiments from LOOP-2 to LOOP-9 were extracted continuously during the never-ending learning process, as shown in Figure 4.5. Considering the intra- and inter- analyses, these samples were further identified as different evidential types to support evidence combination and fusion computing. In this case, the six samples (including D82, $D1$, $D4$, $D71$, $D51$ and $D52$) were designed as the Type-I, conversely, the other two samples (including $D6$ and $D72$) were designed as the Type-II.

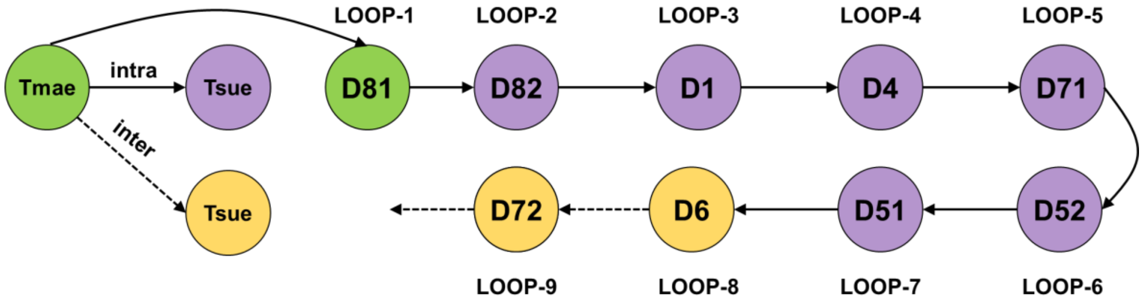


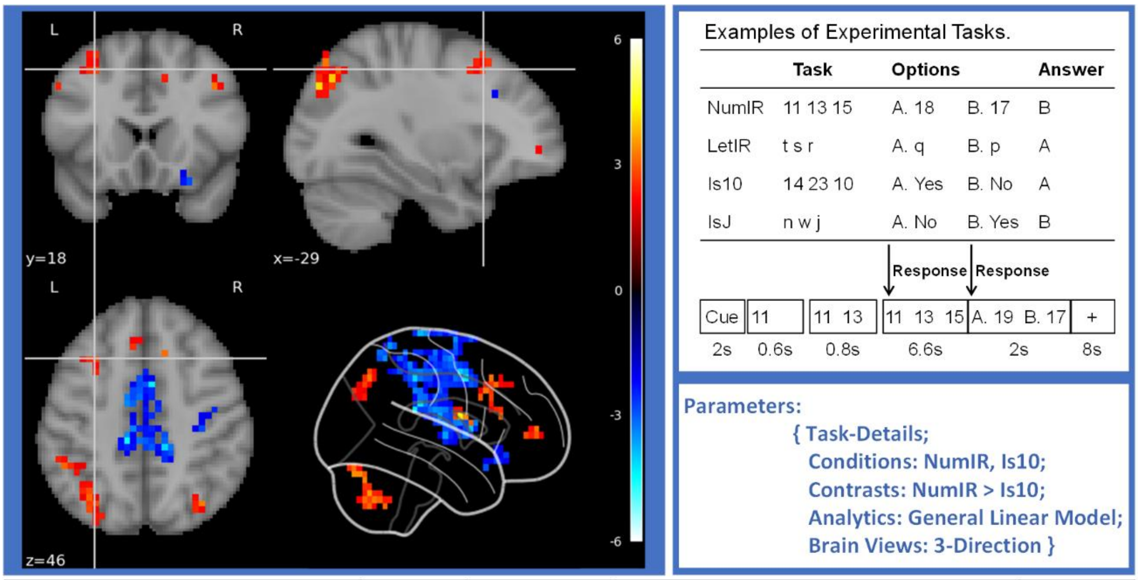
Figure 4.5: The sampled brain data under the never-ending learning process of the brain localization for reasoning.

These extracted samples were further processed by a KID and DIK schemes. On the one hand, the KID schemes were activated to realize hypothesis-based evidence combination and fusion computing. Within each loop, the task-state fMRI data was analyzed to obtain the significant brain regions at group-level by statistical methods ($p < 0.05$, FPR corrected, with a minimum cluster size of $k > 10$ voxels, in MNI space), followed by the contrasts that were created individually based on the GLM framework. As shown in Figure 4.6, the significantly activated brain regions were acquired by analyzing the $D81$ sample in LOOP-1, reveling by the contrasts of 'numerical inductive reasoning > perceptual judgment' within a numerical serial complement task. Regions that showed increased activation during the numerical inductive reasoning were found in the middle frontal gyrus, the superior parietal gyrus, the middle frontal gyrus, the inferior parietal lobules and the middle occipital gyrus, with coordinates of peak (-40, 29, 32), (-29, -80, 37), (-29, 18, 46), (-48, -46, 46) and (35, -69, 46), respectively.

As shown in Figure 4.7, the significantly activated brain regions were acquired by analyzing the $D71$ sample in LOOP-5, reveling by the contrasts of 'numerical inductive reasoning > perceptual judgment' within another numerical serial complement task. Regions that showed increased activation during the numerical inductive reasoning were found in the superior parietal gyrus, the middle occipital gyrus, the inferior parietal lobules, the supplementary motor area and the superior parietal gyrus, with coordinates of peak (-29, -65, 32), (-25, -95, -7), (-48, -46, 51), (5, 21, 46) and (31, -65, 27), respectively.

As shown in Figure 4.8, the significantly activated brain regions were acquired by analyzing the $D72$ sample in LOOP-9, reveling by the contrasts of 'numerical calculation > perceptual judgment' within a mental arithmetic task. Regions that showed increased activation during the calculation process were found in the superior parietal gyrus, the supplementary motor area, the middle occipital gyrus, the inferior frontal gyrus (triangular part) and the superior frontal gyrus (dorsolateral), with coordinates of peak (20, -65, 60), (-7, 10, 51), (-33, -88, -2), (-48, 33, 22) and (35, -5, 61), respectively.

By fusing these brain activation regions we found, the τ distribution was computed to gain a renewed understanding of what has observed brain regions during the KID loop. As shown in Figure 4.9, the τ distribution of peak coordinates changed in the intermediate learning process. From LOOP-1 to LOOP-7, the τ values became bigger according to the accession of Type-I evidence. It suggests that more and more evidences support our hypothesis of the close relations of the selected brain regions and inductive reasoning, not merely the evidence from the main experiment. From LOOP-8 to LOOP-9, the τ values became smaller according to the accession of Type-II evidence. It suggests that such regions broadly participant in various mental process, not merely inductive reasoning from the current goal hypothesis. From LOOP-1 to LOOP-9, some centers of brain regions still experienced fluctuations, such as c2 (-48,30,20) and c4 (-50, 30, 22), but some regions showed more stable trends, such as c1 (46,12,30), c3 (-52,24,26), c5 (-36, -32, 50) and c6 (36, -24,46).



Regions	BA	Cluster size	Coordinate (MNI)			Z-score
			x	y	z	
Lt. Middle Frontal Gyrus	BA9	742.5	-40	29	32	2.70364
Lt. Superior Parietal Gyrus	BA39	4117.5	-29	-80	37	2.64984
Lt. Middle Frontal Gyrus	BA8	877.5	-29	18	46	2.39975
Lt. Inferior Parietal Gyrus	BA40	877.5	-48	-46	46	2.37972
Rt. Middle Occipital Gyrus	BA39	1350.0	35	-69	46	2.32938

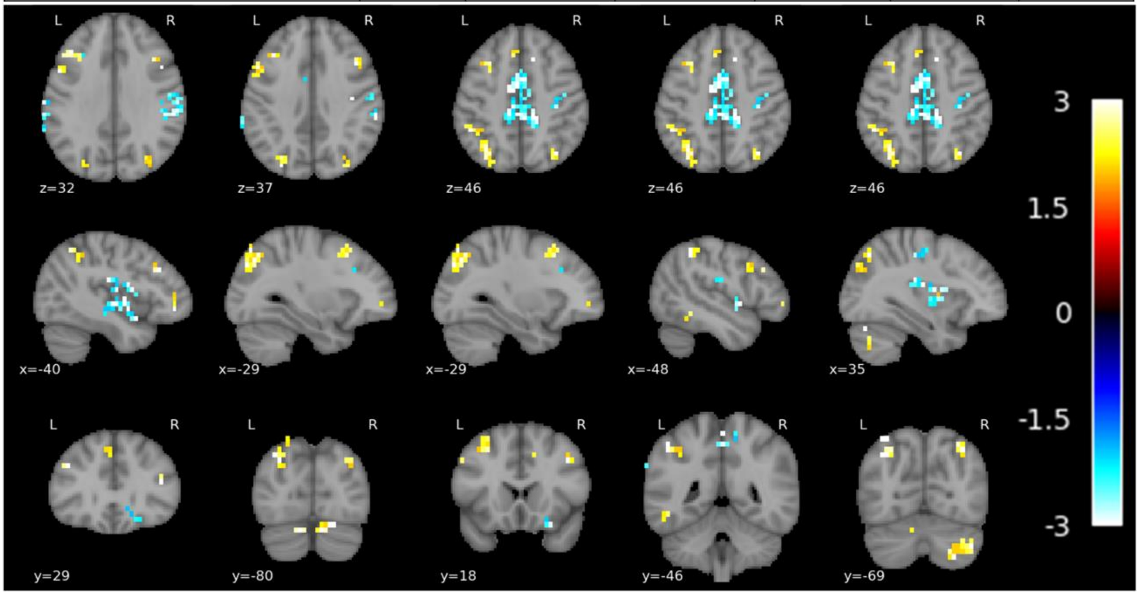
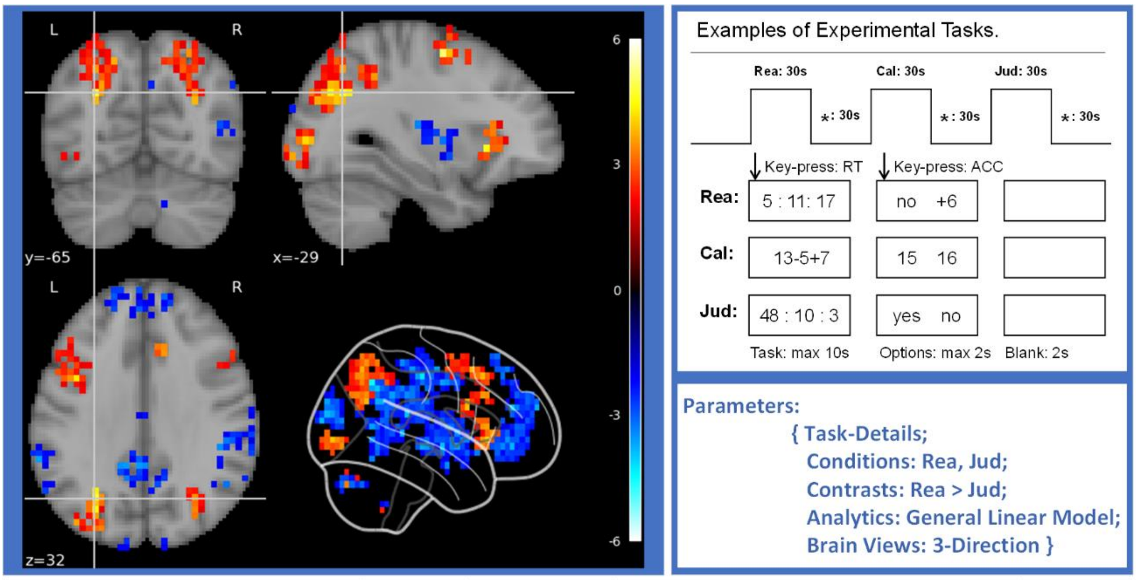


Figure 4.6: The computing results of brain activation patterns for inductive reasoning in LOOP-1.



Regions	BA	Cluster size	Coordinate (MNI)			Z-score
			x	y	z	
Lt. Superior Parietal Gyrus	BA39	10800.0	-29	-65	32	2.71567
Lt. Middle Occipital Gyrus	18	4995.0	-25	-95	-7	2.70650
Lt. Inferior Parietal Gyrus	BA40	2497.5	-48	-46	51	2.66406
Lt. Supplementary Motor Area	BA8	4185.0	5	21	46	2.58988
Rt. Superior Parietal Gyrus	BA39	7155.0	31	-65	27	2.57352

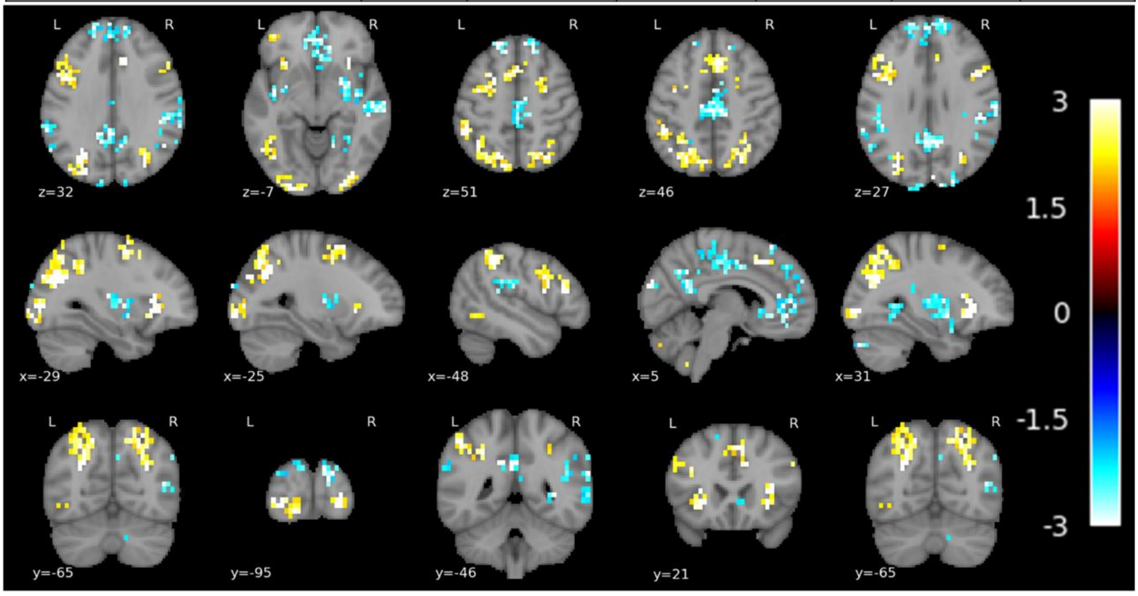
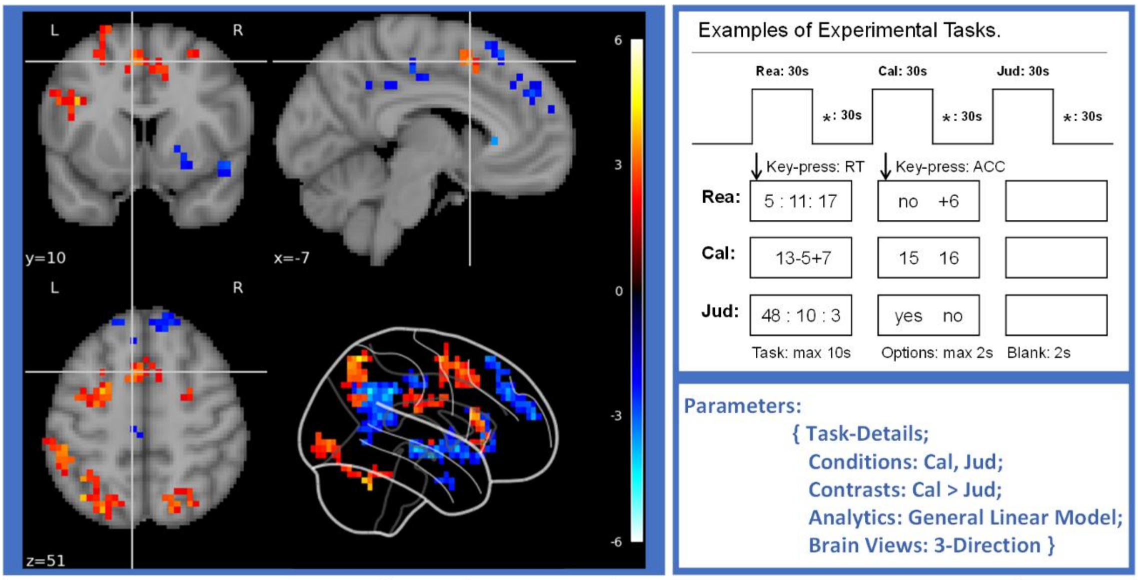


Figure 4.7: The computing results of brain activation patterns for inductive reasoning in LOOP-5.



Regions	BA	Cluster size	Coordinate (MNI)			Z-score
			x	y	z	
Rt. Superior parietal gyrus	BA7	1822.5	20	-65	61	2.82532
Lt. Supplementary motor area	BA6	3645.0	-7	10	51	2.51177
Lt. Middle occipital gyrus	18	2092.5	-33	-88	-2	2.48375
Lt. Inferior frontal gyrus, triangular part	BA46	1417.5	-48	33	22	2.46843
Rt. Superior frontal gyrus	BA6	1890.0	35	-5	61	2.43022

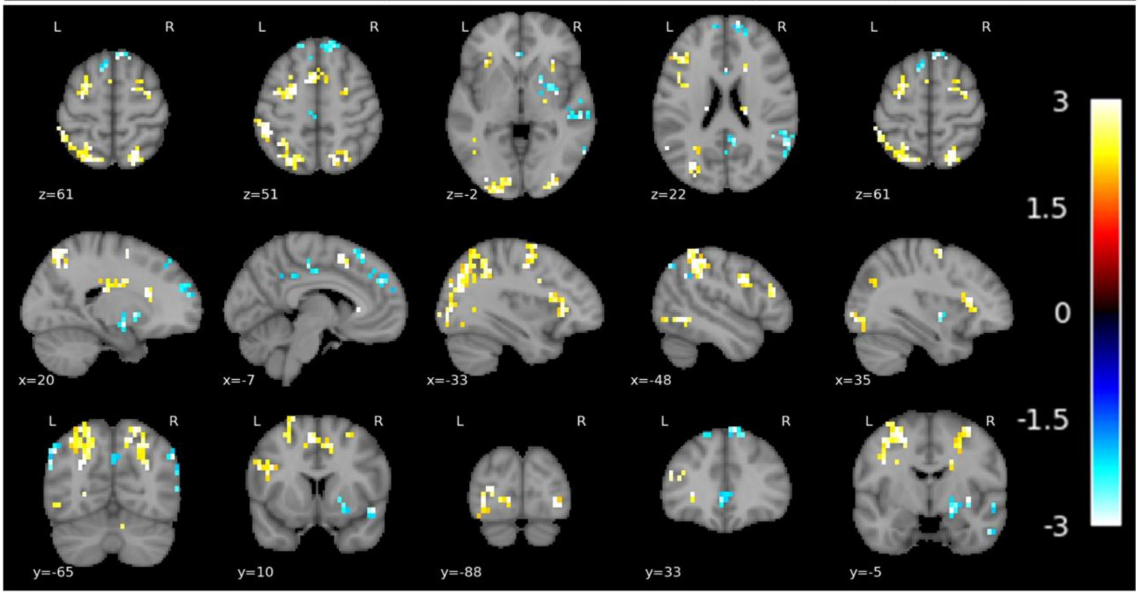
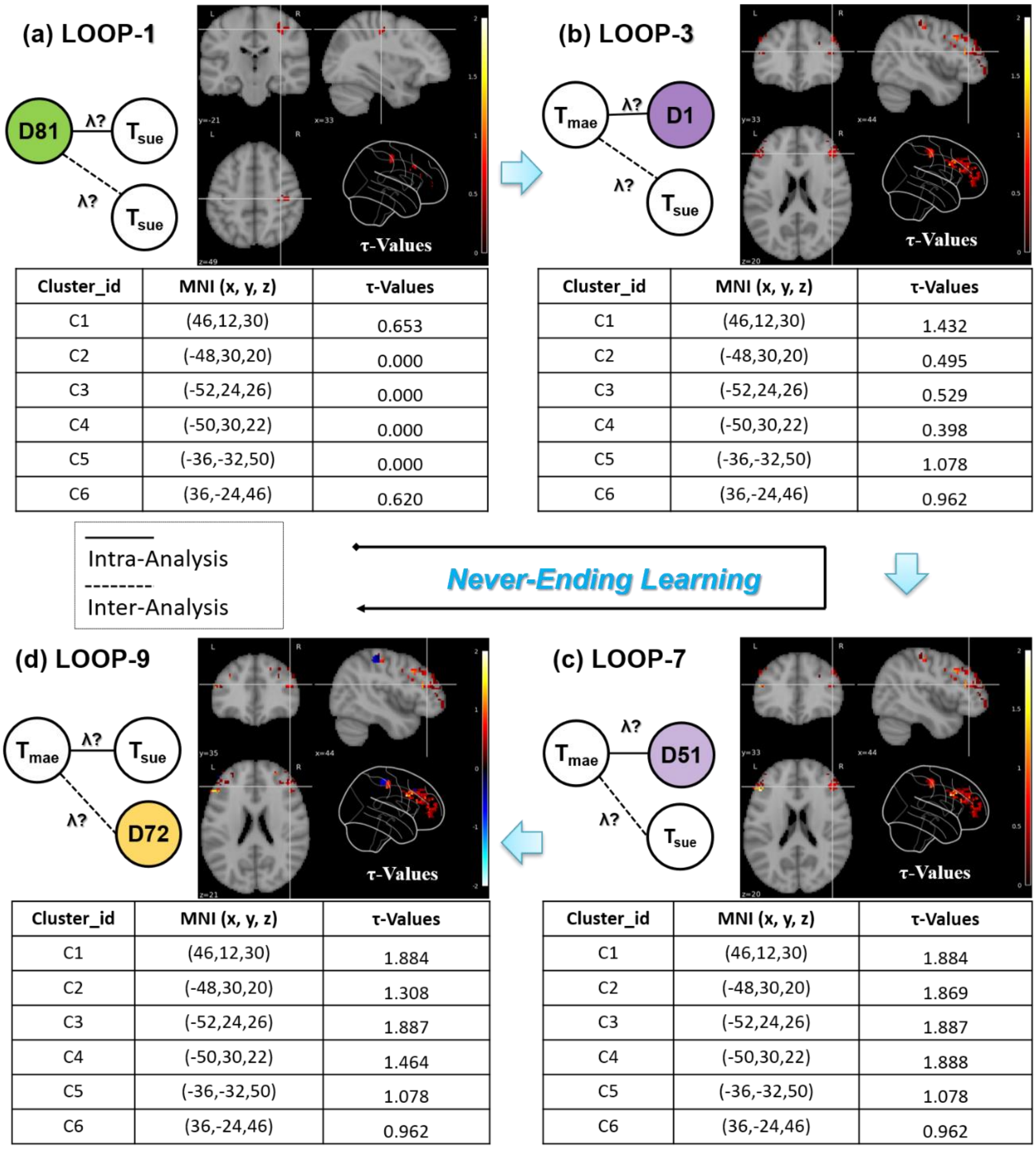


Figure 4.8: The computing results of brain activation patterns under the calculation process in LOOP-9.



(a) LOOP-1

Cluster_id	MNI (x, y, z)	τ-Values
C1	(46,12,30)	0.653
C2	(-48,30,20)	0.000
C3	(-52,24,26)	0.000
C4	(-50,30,22)	0.000
C5	(-36,-32,50)	0.000
C6	(36,-24,46)	0.620

(b) LOOP-3

Cluster_id	MNI (x, y, z)	τ-Values
C1	(46,12,30)	1.432
C2	(-48,30,20)	0.495
C3	(-52,24,26)	0.529
C4	(-50,30,22)	0.398
C5	(-36,-32,50)	1.078
C6	(36,-24,46)	0.962

(d) LOOP-9

Cluster_id	MNI (x, y, z)	τ-Values
C1	(46,12,30)	1.884
C2	(-48,30,20)	1.308
C3	(-52,24,26)	1.887
C4	(-50,30,22)	1.464
C5	(-36,-32,50)	1.078
C6	(36,-24,46)	0.962

(c) LOOP-7

Cluster_id	MNI (x, y, z)	τ-Values
C1	(46,12,30)	1.884
C2	(-48,30,20)	1.869
C3	(-52,24,26)	1.887
C4	(-50,30,22)	1.888
C5	(-36,-32,50)	1.078
C6	(36,-24,46)	0.962

Figure 4.9: The uncertainty distribution of brain activation regions in each loop of the never-ending learning process.

At the same time, the DIK scheme also were executed during the process of never-ending learning. For each newly acceding evidence, the cognitive content of frontal lobe was decoded by the multivariate pattern analysis methods from brain activity. Through fusion computing, the support degree was acquired in reasoning with 1.344, and calculation with 1.387, as shown in Figure 4.10.

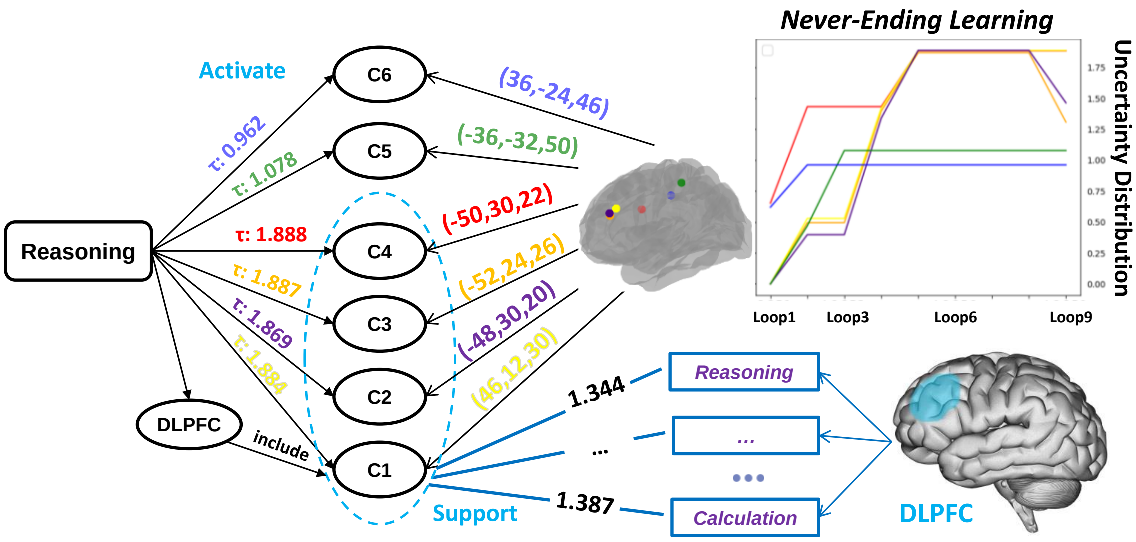


Figure 4.10: The casual inference for interpretations of the goal hypothesis with brain regions and cognitive functions. The left part gives the brain computing results in the task-driven KID inference process, which shows the DLPFC is activated by these inductive reasoning-oriented tasks. Conversely, the right part gives the brain computing results in the data-driven DIK inference process, which shows the DLPFC also plays a core role in inductive reasoning. Hence, integrating results of the KID and DIK inference processes realizes the ability to interpret the casual effects of brain structure and function.

We further examined the extensible capability of Data-Brain driven never-ending learning, which integrates multi-source and multi-level evidence from internal and external sides to realize learning and modeling of larger scale brain data. The learned results to reasoning are shown in Figure 4.11.

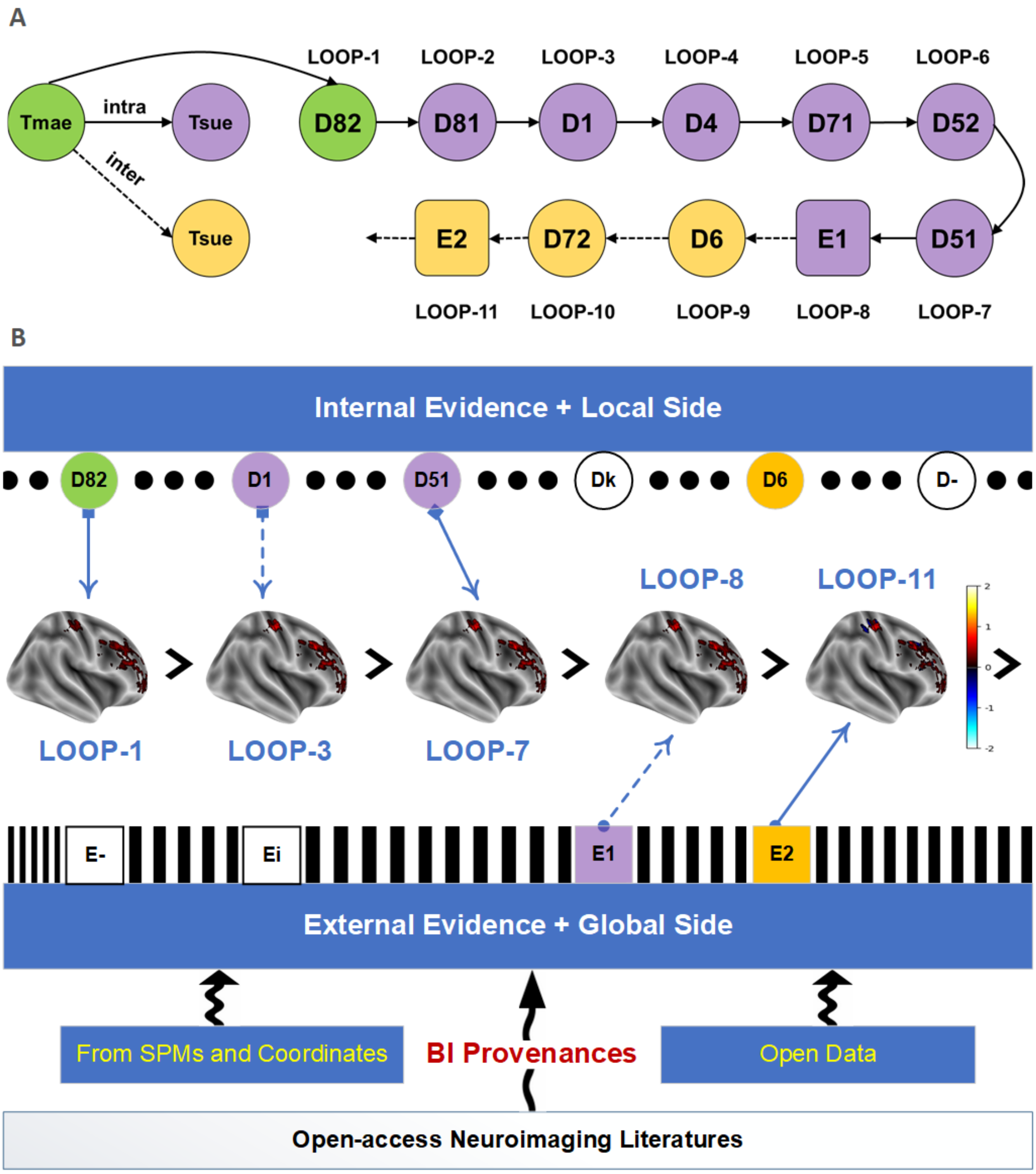


Figure 4.11. Never-ending learning of internal and external evidence for systematic understanding of reasoning. A. The designed experiments from loop 1 to loop 11 based on the combination of internal and external evidence towards never-ending learning of brain region patterns. B. On the basis of internal evidence learning, some finer-grained changes to peak coordinates and uncertainty distribution can be found during the combination of external.

4.4.3 Discussions

Because the brain mechanisms of high-level cognitive function remain vague, we decided to conduct a general intelligence model of never-ending learning to clarify these issues. This is necessary to foster research in the field of cognitive neuroscience because the current neuroimaging studies about a specific cognitive function do not covey a consistent pattern so far. Hence, more insights into the neural and cognitive mechanisms of cognitive functions and their variations concerning task setup and content are necessary. In this case, Data-Brain driven never-ending learning interpreted the specificity of human reasoning within various brain regions. In particular, with respect to inductive reasoning, several regions such as the left inferior frontal gyrus, precentral gyrus, superior frontal gyrus, bilateral middle frontal gyrus, right precuneus, left inferior parietal lobule and left occipital gyrus were identified as the significantly relevant brain regions (see Figure 4.9 for results) [216]. In addition, Data-Brain driven never-ending learning also highlights the important role of some regions such as left middle temporal gyrus, right inferior temporal gyrus, fusiform gyrus, bilateral angular gyrus and right cerebellar lobules-Crus I, which have not been actively reported in previous studies. Together, the integrated experiment from the internal and external evidences demonstrates the reliable and robust performance of Data-Brain driven never-ending learning in elucidating the complex cognitive functions.

As shown in Figure 4.10, the support degrees of reasoning and calculation are similar. One of the reasons is that the current evidence is mainly from the numerical serial complement task, which involves cognitive component of calculation. By using the Bayesian model-based neuroimaging meta-analysis method of the cortical surface, Shin et al. shown a map of common activations during inductive and deductive reasoning, with respect to a pattern of activity extending over a specific set of regions, particularly in the dorsolateral prefrontal cortex (8C and p9-46v), orbital and polar frontal cortex (a47r), insular and frontal opercular cortex (AVI), paracentral lobular and mid cingulate cortex (SCEF), and anterior cingulate and medial prefrontal cortex (8BM) in the left hemisphere [216].

4.5 Conclusion

In this chapter, we empirically study the important problem of learning brain patterns from the functional segregation perspective. We perform the inductive reasoning-centric brain activation pattern analyses based on the general intelligence model. We believe our results take an important step towards understanding human reasoning, and also stimuli future work on the design of cognitive experiments.

Chapter 5

GIM Analysis II: Functional Integration in the Brain

Complementing this effort to decode the complex brain from human brain mapping, the properties of both intra- and inter- regional connectivity provide another view to promote our understanding of the brain as a complex network. In Chapter 5, we apply the general intelligence model to analyze the complex relationships between brain structure and function from the integration perspective.

5.1 Introduction

Up until now, benefitting from the development of noninvasive neuroimaging techniques and graph theory methods, fMRI studies in brain network have reported fruitful results to promote our understanding and re-cognition for functional integration [116, 123, 125, 242]. By calculating the topological properties from spatially distant neural regions, brain patterns in a functional network can be measured at various analysis levels, such node, group and network [243]. At node-level analysis, considering to distinct topological roles for different nodes in the network, the degree and strength of individual nodes are measured to quantify the importance of a node. For example, the highly connected nodes are often called centrality [244] and hubs [54, 82] that strongly affect the brain communication and neural integration. At group-level analysis, the modular community structure is explored to select a subset of highly inter-connected nodes which are relatively sparsely connected to nodes in other modules [80]. At network-level analysis, the brain network is seen as a whole, which is observed by components, density, shortest paths and so forth.

On the basis of the above, numerous functional brain networks with highly test-retest reliability are found and defined [124, 245]. The default mode network is a large-scale brain network primarily composed of the medial prefrontal cortex, posterior cingulate cortex/precuneus and angular gyrus, which more active at rest than during tasks [246, 247]. The control network is further divided into two distinct "fronto-parietal" (to initiate and adjust control) and "cingulo-opercular" (provides stable 'set-maintenance' over entire task epochs) components with different functions [248]. The salience network that is primarily composed of the anterior insula and dorsal anterior cingulate cortex is involved in detecting and filtering salient stimuli, which is theorized to mediate switching between the default mode network and central executive network [249, 250]. The attention network is also divided into two separate sub-systems (the dorsal and ventral attentional system) for the voluntary deployment of attention and the reorientation to unexpected events, respectively [251]. The whole brain network is also parcellated to somatosensory [252, 253] and visual [254] subgraphs.

5.2 Problem Statement

Many functional network properties of the human brain have been identified during rest and task states, yet it remains unclear how the brain processes complex functions by inter-regional coordination and collaboration [255, 256]. By definition, the rest-state fMRI measures the endogenous or spontaneous brain activity as low-frequency fluctuations (< 0.1 Hz) in blood oxygen level-dependent (BOLD) signals [29, 257, 258]. The rest-state functional connectivity is usually used to investigate the "intrinsic" network architecture that is present across multiple brain states, much like structural connectivity [245]. However, just as the world is colorful, it is difficult to specify a unified brain connectivity pattern to represent all conditions. In most cases, the "intrinsic" functional connectivity pattern is interpreted as an architecture that can be related to as many states as possible. Changes in network connectivity modulated by task are another important direction to understand brain integration [119]. The task-state functional network is used to explore specific connections modulated by specific task, measuring task-related coactivation patterns. Prior graph theory work suggests that the functional architecture of the human brain is modulated by age, sex, intelligence, genetic predisposition, working memory, visual stimulation, motor learning, auditory stimulation, emotion processing and brain disorders [259]. These evidences indicate the value, practicality, and broad applicability of this method in neuroimaging research, including potential future applications in translational studies. As such, the increasing demands of task-state functional connectivity push us to rise to the challenge.

Furthermore, the complexity of linking function and structure is also concerned to characterize brain functions for a subnetwork within a specific brain region. This approach parceled brain areas on the basis that each subregion has a unique pattern of connectivity – a "functional fingerprint" [260]. For example, Lucina et al. reviewed six ubiquitous anatomical-named large-scale functional brain networks, including the occipital network (commonly for visual), pericentral network (commonly for somatomotor), dorsal frontoparietal network (commonly for attention), lateral frontoparietal network (commonly for control), midcingulo-insular network (commonly for salience) and medial frontoparietal network (commonly for default) [261]. Yana and colleagues hypothesized that functional connectivity of the DLPFC with other brain regions contributes to different executive functional components, including inhibition, switching, working memory, performance monitoring, selectivity, a verbal component and perseverations with impulsivity, and tested it by using both a neuropsychological assessment and fMRI [262]. Zhang et al. examined the patterns of resting state connectivity in the precuneus, in which the entire precuneus is parceled into three functional subdivisions (the dorsal part with dorsal-anterior and dorsal-posterior subregions, and the ventral part) with connectivity differences [263].

5.3 Brain Connectivity Study Based on the GIM with HITL

Currently, the neuroimaging-based functional integration analysis and mining methods have become an important research direction in the field of cognitive neuroscience. From this, the GIM can be quickly converted and personalized in different computing strategies according to requirements and customizations of experts and users. In this case, we focus on the application of the GIM in the field of brain network, especially for the extensible mining and analysis of the hidden correlation between complex cognitive functions and brain network systems. At this time, brain, cognition, network patterns and indicators become several important concepts involved in the current model. One of its main aims is to explore network topology with unique cognitive and functional characteristics from the perspective of large-scale brain networks. Another aim is to measure brain network characteristics and information-processing mechanisms by computing various performance indicators. Therefore, a realistic use case combining multiple fMRI datasets and network analysis methods is performed to evaluate the effectiveness of this model. In order to realize the GIM-based brain network understanding and analysis, the acquisition processing and organization strategies of the resources are firstly defined in the experimental stage surrounding the $KnowL$, $InfoL$ and $DataL$.

5.3.1 Experiments

a. Conceptual Definition in the $KnowL$

Human cognition is summarized as some complex mental activities such as human reasoning [264], problem-solving [265] and decision-making [266] that typically rely on the combination and interaction of elementary processes such as perception, learning, memory, emotion [267, 268], and so forth. In this study, these cognitive functions or mental processes are represented as concepts, which are organized into hierarchical ontology structures. And the hierarchical relations of cognitive elements in the conceptual Data-Brain are constructed by reference to the existed cognitive model such as Cognitive Atlas [95]. The cognitive function-related graph in the $KnowL$ is shown in Figure 5.1A.

b. Information Organization in the *InfoL*

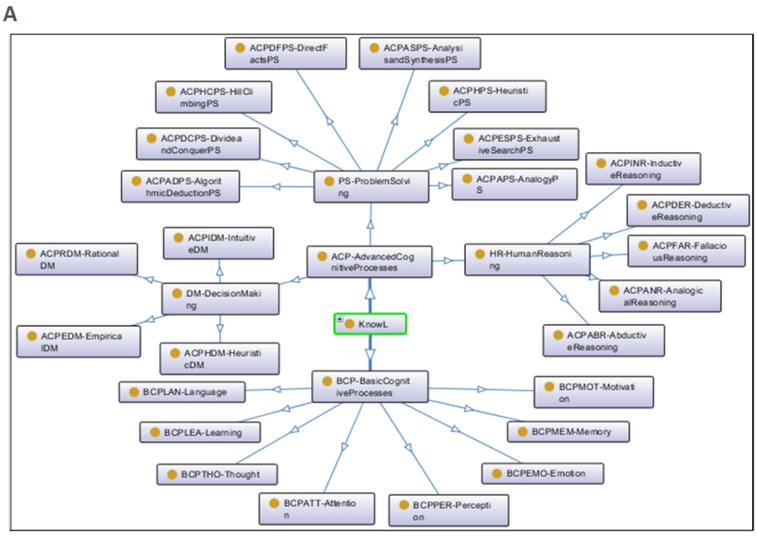
The $InfoL$ consists of two parts: the definition of patterns (PID) and the computing methods of indicators (PIM). In current work, multiple representative brain networks are discussed, such as the Default (Mode) Network (DN), the Attention Network (AN), the Salience Network (SN) and the Control Network (CN) [124]. In addition, we also define an emotionally related network, the core affect architecture (CAA) [269]. Here, various brain network structure information is represented, and these networks corresponding to functional meanings or cognitive processes were stored in the PID of the *InfoL*. For example, existing research showed that the DN (including the core DN subsystem DN_{CORE}, the medial temporal lobe-centred DN subsystem DN_{MTL} and the third DN subsystem DN_{SUB3}) has a greater correlation with spontaneous cognition, mental and emotional processes; the AN (including the dorsal attention network DAN and the ventral attention network 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 brain functional networks, on the one hand, can be used as the reference to test the rationality of hypotheses, and on the other hand, encourage us to discover new information and knowledge on the basis of these existing patterns. Furthermore, some methods such as statistics, machine learning, and network topology analysis are defined in the PIM of the *InfoL*. In this case, three commonly used index calculation methods are focused, including the Clustering Coefficients Index (CCI), the Local Efficiency Coefficients (LEC) and the Global Efficiency Coefficients (GEC). These indicators will be computed in the $DataL$ of the GIM.

c. Data Processing in the $DataL$

From the description in Section 3.4.5, at least two Thinking-Entities are required to achieve comparison, interaction and inference in the GIM within human-in-the-loop. In current work, three task-state fMRI datasets were acquired by implementing various cognitive experimental tasks, including the emotional face recognition (EFR) task, the number series completion (NSC) task and the number placement puzzles (NPP) task, which are primarily related to emotion, reasoning and problem-solving processes, respectively. These three datasets are mapped to three Thinking-Entities in the GIM, as the minimum computing unit to verify its effectiveness. 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.

5.3.2 Results

The goal of learning is to measure the level of difference between Thinking-Entities. Through the interactive learning processes defined in Section 3.4.5, we can get the results of the $Sdif$ and $Kdif$. First, we constructed $DTEKs$ of ERF, NSC, and NPP entities from the definition of the $KnowL$, as shown in Figure 5.1B. Then, the semantic distance between Thinking-Entities, $Sdif$, was calculated by the hamming distance evaluation method, as shown in Figure 5.1C. In order to calculate $Kdif$, two parameters need to be preset, that is the P−Value and max_{iter}. 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 cognitive weights and their differences between Thinking-Entities were measured, as shown in Figure 5.1D.

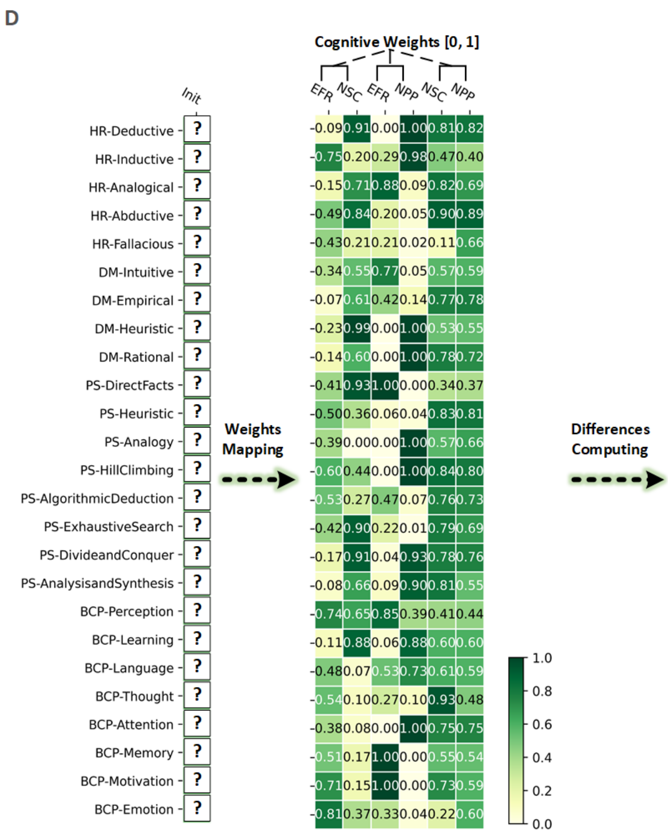


B

Cognitive Functions \ Thinking-Entities	EFR	NSC	NPP
ACPDER	0.00	1.00	1.00
ACPINR	0.00	1.00	0.00
ACPANR	1.00	0.00	0.00
ACPABR	0.00	1.00	0.00
ACPFAR	0.00	1.00	1.00
ACPIDM	0.00	0.00	0.00
ACPEDM	0.00	1.00	1.00
ACPHDM	0.00	1.00	1.00
ACPRDM	1.00	1.00	1.00
ACPDFPS	1.00	1.00	1.00
ACPHPS	0.00	1.00	1.00
ACPAPS	1.00	0.00	0.00
ACPHCPS	0.00	0.00	1.00
ACPADPS	0.00	1.00	1.00
ACPESPS	1.00	1.00	1.00
ACPDCPS	0.00	1.00	1.00
ACPASPS	0.00	1.00	1.00
BCPPER	1.00	0.00	0.00
BCPLEA	0.00	0.00	0.00
BCPLAN	0.00	0.00	0.00
BCPTHO	0.00	1.00	0.00
BCPATT	1.00	1.00	1.00
BCPMEM	0.00	0.00	0.00
BCPMOT	1.00	1.00	1.00
BCPEMO	1.00	0.00	0.00

C

	EFR-NSC	EFR-NPP	NSC-NPP
Sdif	15.00	13.00	4.00



Differences Computing

The *Kdif* Differences Among EFR, NSC and NPP

EFR-NSC	EFR-NPP	NSC-NPP
0.82	1.00	0.01
0.55	0.69	0.07
0.56	0.79	0.13
0.35	0.15	0.01
0.22	0.19	0.55
0.21	0.72	0.02
0.54	0.28	0.01
0.76	1.00	0.02
0.46	1.00	0.06
0.52	1.00	0.03
0.14	0.02	0.02
0.39	1.00	0.09
0.16	1.00	0.04
0.26	0.40	0.03
0.48	0.21	0.10
0.74	0.89	0.02
0.58	0.81	0.26
0.09	0.46	0.03
0.77	0.82	0.00
0.41	0.20	0.02
0.44	0.17	0.45
0.30	1.00	0.00
0.34	1.00	0.01
0.56	1.00	0.14
0.44	0.29	0.38

Figure 5.1: The functional connectivity-oriented analysis results of the HITL interactive learning and inference in the GIM. A. The definition of cognitive concepts in the *KnowL* of the conceptual Data-Brain. B. The weight distribution of data-to-cognitive concept mapping for EFR, NSC and NPP entities, respectively. C. The semantic differences are given by measuring among various Thinking-Entities. D. The results of interactive learning during the DIK loop.

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 on the basis of the related ROIs defined in the $InfoL$. Further, the indicators (including, CCI, LEC and GEC) of the subnet at 1-100 sparsity were calculated separately. Finally, we used the analysis of 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 case, 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 5.1.

Table 5.1: The comparison of differences between Thinking-Entities in the $DataL$.

Brain Functional Networks \ Differences \ Network Metrics	The Clustering Coefficients Index (CCI)			The Local Efficiency Coefficients (LEC)			The Global Efficiency Coefficients (GEC)		
	EFR | NSC	EFR | NPP	NSC | NPP	EFR | NSC	EFR | NPP	NSC | NPP	EFR | NSC	EFR | NPP	NSC | NPP
DN_{CORE}	3.00	1.00	0.00	0.00	1.00	1.00	8.00	11.00	1.00
DN_{SUB3}	7.00	0.00	1.00	8.00	1.00	1.00	10.00	2.00	2.00
DN_{MTL}	1.00	4.00	5.00	2.00	4.00	5.00	4.00	8.00	4.00
DAN	15.00	29.00	3.00	8.00	22.00	1.00	7.00	7.00	8.00
VAN	8.00	0.00	0.00	11.00	1.00	0.00	11.00	14.00	4.00
SN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	10.00	10.00
FPCN	1.00	10.00	0.00	1.00	11.00	3.00	0.00	5.00	6.00
COCN	0.00	0.00	2.00	0.00	0.00	2.00	2.00	2.00	6.00
CAA	61.00	23.00	12.00	39.00	14.00	9.00	11.00	1.00	6.00

According to the two types of knowledge inference rules defined in Section 3, we have obtained some interesting results. From the KID inference scheme, we can select some $\langle PID, PIM \rangle$ 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 DIK 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 $\langle\langle \mathrm{CAA}, \mathrm{CCI}\rangle, \mathrm{Emotion} \rangle$ and so on. The complete inference results from a one-time run of one expert are shown in Table 5.2.

Table 5.2: The results obtained by the GIM with HITL from the brain connectivity perspective.

Network Metrics / Cognitive Functions / Brain Functional Networks	The Clustering Coefficients Index (CCI)	The Local Efficiency Coefficients (LEC)	The Global Efficiency Coefficients (GEC)
DN_{CORE}	Heuristic problem solving; Emotion	Analysis and synthesis problem solving; Motivation	Deductive reasoning; Inductive reasoning; Analogical reasoning; Intuitive decision-making; Empirical decision-making; Heuristic decision-making; Rational decision-making; Hill climbing problem solving; Algorithmic deduction problem solving; Divide and conquer problem solving; Learning; Language; Memory
DN_{SUB3}	Heuristic problem solving; Emotion	Heuristic problem solving; Emotion	Heuristic problem solving; Emotion
DN_{MTL}	Analysis and synthesis problem solving; Motivation	Analysis and synthesis problem solving; Motivation	Direct facts problem solving; Perception; Attention
DAN	Direct facts problem solving; Perception; Attention	Direct facts problem solving; Perception; Attention	——
VAN	Heuristic problem solving; Emotion	Heuristic problem solving; Emotion	Deductive reasoning; Inductive reasoning; Analogical reasoning; Intuitive decision-making; Empirical decision-making; Heuristic decision-making; Rational decision-making; Hill climbing problem solving; Algorithmic deduction problem solving; Divide and conquer problem solving; Learning; Language; Memory
SN	Abductive reasoning; Exhaustive search problem solving	Abductive reasoning; Exhaustive search problem solving	Analogy problem solving
FPCN	Direct facts problem solving; Perception; Attention	Direct facts problem solving; Perception; Attention	Analogy problem solving
COCN	——	——	——
CAA	Heuristic problem solving; Emotion	Heuristic problem solving; Emotion	Fallacious reasoning; Thought

5.3.3 Discussions

In this case, the GIM is presented to implement the KID and DIK 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.

For the KID 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 be obtained the semantic distance between different Thinking-Entities. From Figure 5.1C, 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 [270]. On the other hand, emotion is seen as an independent factor that is perceived and studied for its impact on advanced cognition [271]. 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 Figure 5.1E, 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 [269]. 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 [272, 273]. 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 Figure 5.1E, which complements the Pan's results in [274]. For the DIK loop, Figure 5.1F shows the subnet-related cognitive processes, which are the inference results based on Figure 5.1D and Figure 5.1E. 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 [275]. The fMRI studies have previously implicated both the FPCN and COCN, which play dissociable roles in control, but their respective contributions are unclear [248, 276]. From the results in Figure 5.1F, 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 [277, 278]. However, the COCN is more related to word and language tasks [279]. 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 KID and DIK schemes in the GIM constitute a supervisory loop, which can achieve mutual verification of decision rationality. Towards never-ending learning workflow interacting within the GIM, more novel results will be discovered.

5.4 Brain Connectivity Study Based on the GIM with HITL-Aided NEL

To obtain an answer A for a specific question Q (such as "which brain nodes in a network are involved in the inductive reasoning process?" and "which information related to cognitive functions can be more processed by a specific brain network"), the general intelligence model performs never-ending learning within iterative loops. More specifically, the model interacts with sample library for extracting evidence by inference engine. The single evidence can be computed by univariate and multivariate analyses, followed by preprocessing for fMRI. Increasing with the new evidence, the results will be updated continuously by evidence combination and fusion computing within the model. All of them are presented in Figure 5.2.

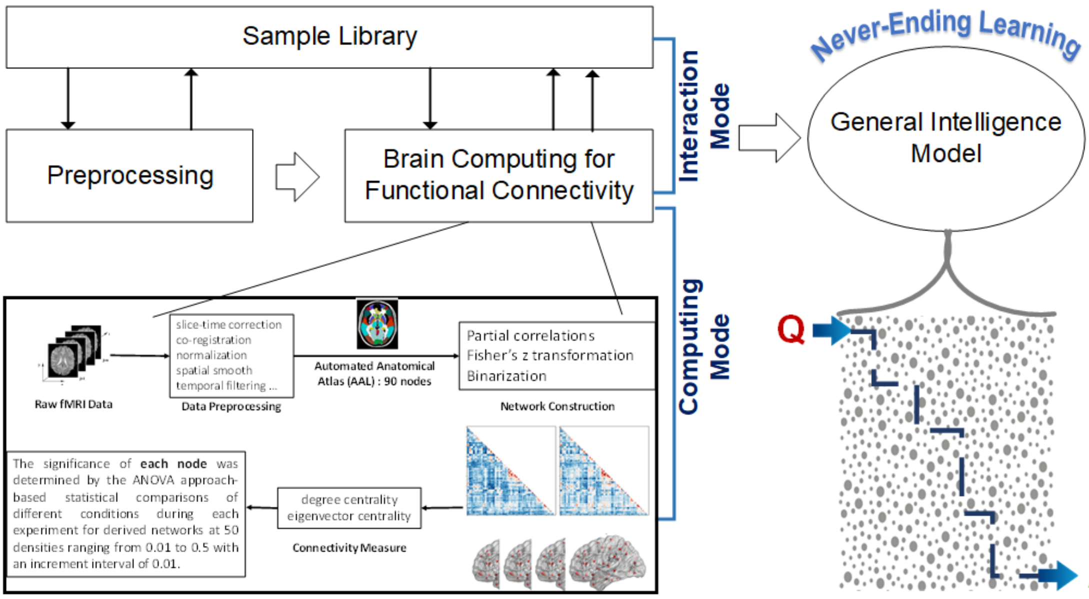


Figure 5.2: The general intelligence model used for the functional connectivity-oriented never-ending learning.

5.4.1 Experiments

In this case, the general intelligence model was evaluated from the human brain connectome perspective. The functional connectivity analysis was performed to interpret the casual relationships between inductive reasoning and a specific brain region by processing task-state fMRI data. The investigators first set up parameters related to the four dimensions of conceptual Data-Brain, such as functional domain “inductive reasoning”, experimental paradigm “categorical design”, experimental protocol “block design”, explicit stimuli “digits, letters”, data object “fMRI”, analytical method “degree centrality, machine learning and ANOVA”, as shown in Figure 5.3. The details of network construction and connectivity measure are illustrated as follows, followed by preprocessed operations.

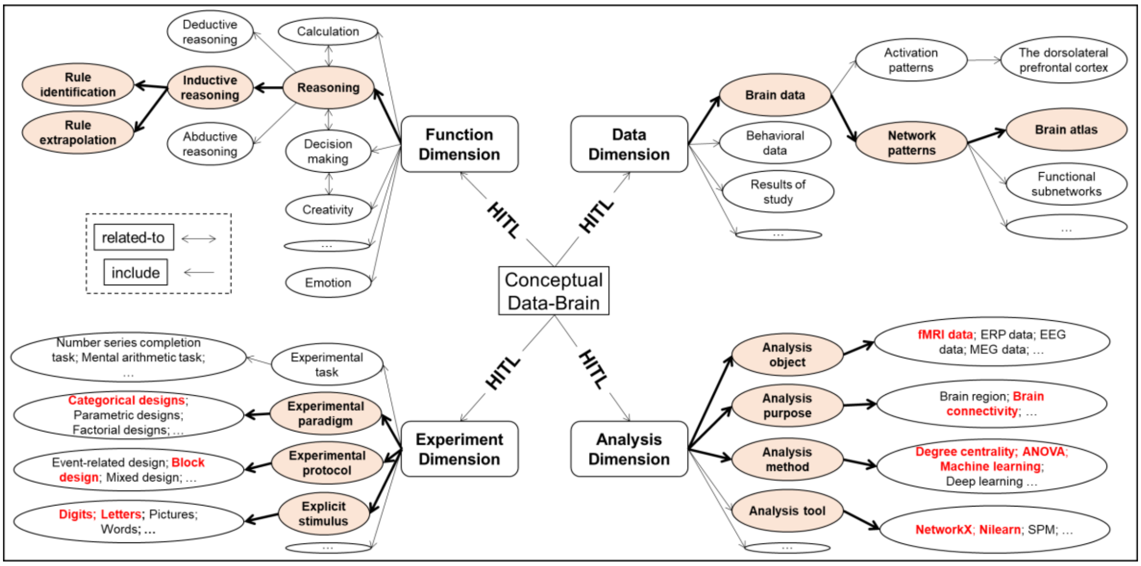


Figure 5.3: Reconstruction of conceptual Data-Brain for the human reasoning-oriented brain connectivity study. During the human-in-the-loop (HITL) procedure, the conceptual Data-Brain is specified by users with the parameters of interest. Hence, the evidence is sampled and integrated to realize systematic brain computing with never-ending learning.

Network construction. The CC400 atlas was used to parcellate the gray matter into 392 cortical and subcortical brain regions [280]. The time series from the processed data for each node were extracted to build a 392×392 pairwise correlation matrix for each scan during each experiment using partial correlations. The derived correlation coefficients were normalized to Fisher's z score and the positive values were considered. Afterwards, these matrices were transformed to binary networks based on the various densities, where edges with value "1" were defined to the connections with coefficients higher than the given threshold.

Connectivity measure. We quantified nodal contribution within the whole-brain functional network by two centrality measures, including: degree centrality. For more details, these graph theoretical measures were described in [Network Centrality in the Human Functional Connectome]. All measures were calculated by using the NetworkX package (https://networkx.org).

5.4.2 Results

While the parameters were set up within the human-in-the-loop, the sample $D71$ in LOOP-1 (a sample for inductive reasoning study using the numerical serial complement task with categorical and block design) with the greatest expectation of experimental characteristic was extracted from the sample library (the details of sample library are listed in Table 1 of Appendix A.). Next, as shown in Figure 5.4, the supplementary experiments from LOOP-2 to LOOP-9 were extracted continuously during the never-ending learning process, following the order listed by $D81$, $D52$, $D51$, $D82$, $D1$, $D4$, $D2$, D6 and D72. Considering the intra- and inter- analyses, the six samples (including $D1$, $D4$, $D51$, $D52$, $D81$ and $D82$) were designed as the Type-I, conversely, the other three samples (including $D6$ and $D72$) were designed as the Type-II.

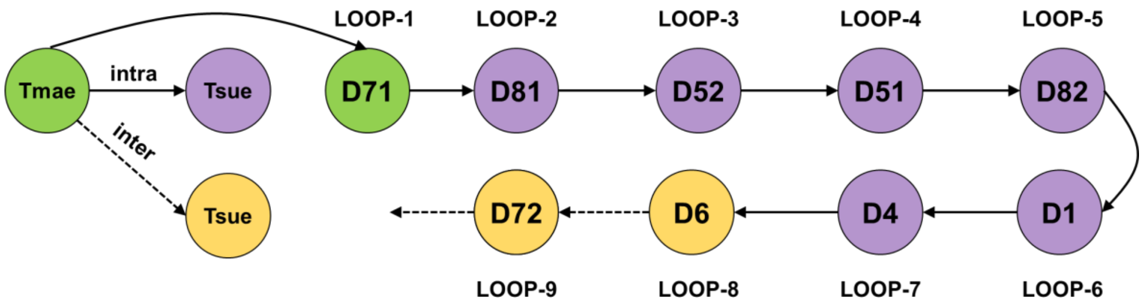


Figure 5.4: The sampled brain data under the never-ending learning process of the brain connectivity for reasoning.

In the same way as a functional segregation study, these extracted samples were further processed by a KID and DIK schemes. On the one hand, the KID schemes were performed by evidence combination and fusion computing. The significance to each node in brain atlas was determined by the ANOVA approach-based statistical comparisons of different conditions in each sample for derived networks at 50 densities ranging from 0.01 to 0.5 with an increment interval of 0.01. After determination, the summation of the significant nodes was counted across all densities for each experiment and normalized to gain the uncertainty weights of a single evidence. As shown in Figure 5.5, the significant nodes were acquired by analyzing the $D71$ sample in LOOP-1, reveling by the contrasts of 'numerical inductive reasoning > perceptual judgment' within the numerical serial complement task. Nodes that showed the positive effects during the inductive reasoning process were found in amygdala, the percental gyrus, the inferior frontal gyrus (orbital part), the postcentral gyrus, the supplementary motor area, the middle frontal gyrus, cerebellum, thalamus, cuneus, insula and the middle temporal gyrus.

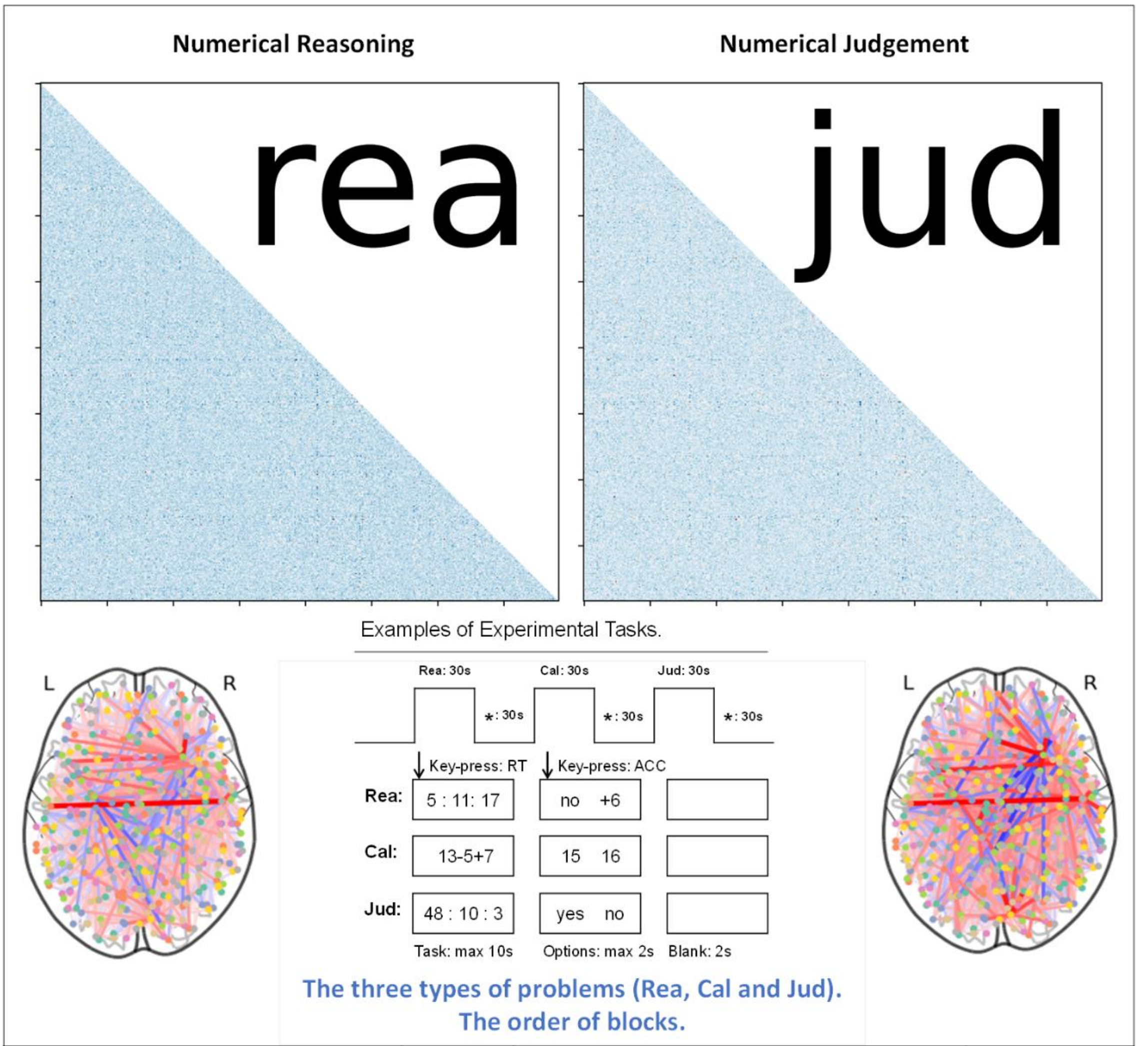
As shown in Figure 5.6, the significant nodes were acquired by analyzing the $D81$ sample in LOOP-2, reveling by the contrasts of 'numerical inductive reasoning >

perceptual judgment' within the numerical serial complement task. Nodes that showed the positive effects during the inductive reasoning process were found in insula, the anterior cingulate and paracingulate gyri, the caudate nucleus, the supplementary motor area and hippocampus.

As shown in Figure 5.7, the significant nodes were acquired by analyzing the $D72$ sample in LOOP-9, reveling by the contrasts of 'numerical calculation > perceptual judgment' within the mental arithmetic task. Nodes that showed the positive effects during the calculation process were found in the middle occipital gyrus, the postcentral gyrus, the supplementary motor area, the middle frontal gyrus, the inferior temporal gyrus, the superior frontal gyrus, the middle temporal gyrus and thalamus.

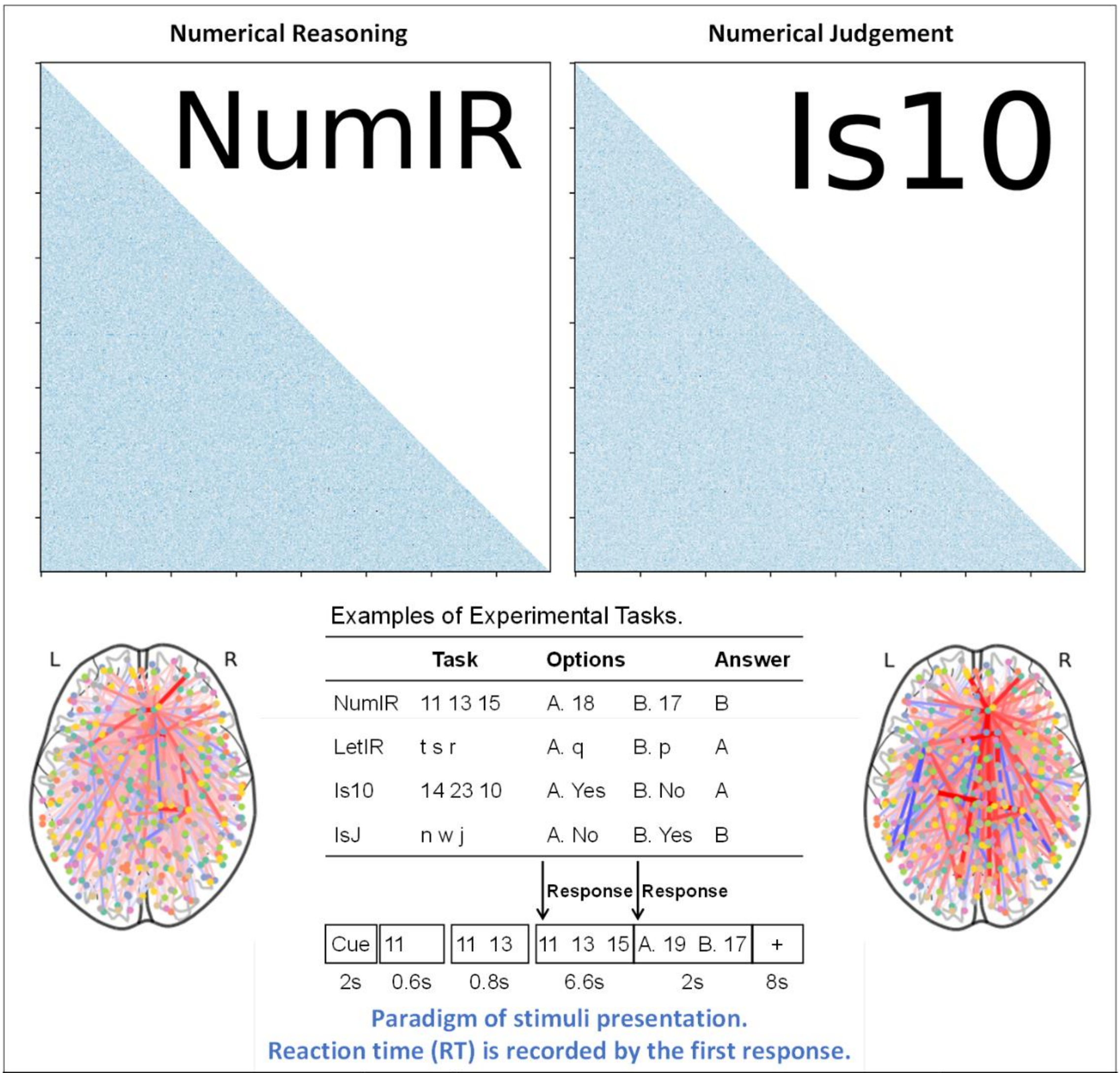
By fusing these nodes that are sensitive to various experiments, the uncertainty was computed to gain a renewed understanding of the inductive reasoning during the KID loop. As shown in Figure 5.8, the weights of nodes at uncertainty changed in the intermediate learning process. From LOOP-1 to LOOP-9, the uncertainty weights of node change from small to big, which indicates more than one evidence can support the importance of nodes of what have greater relevance for the inductive reasoning.

Along with the KID scheme, the DIK scheme were performed during the process of never-ending learning in general intelligence model. For each newly acceding evidence, the cognitive contents of nodes in the frontal lobe were decoded by the multivariate pattern analysis methods from brain activity. Through fusion computing, the support degree was acquired in inductive reasoning with 0.563 and calculation with 0.533, as shown in Figure 5.9.



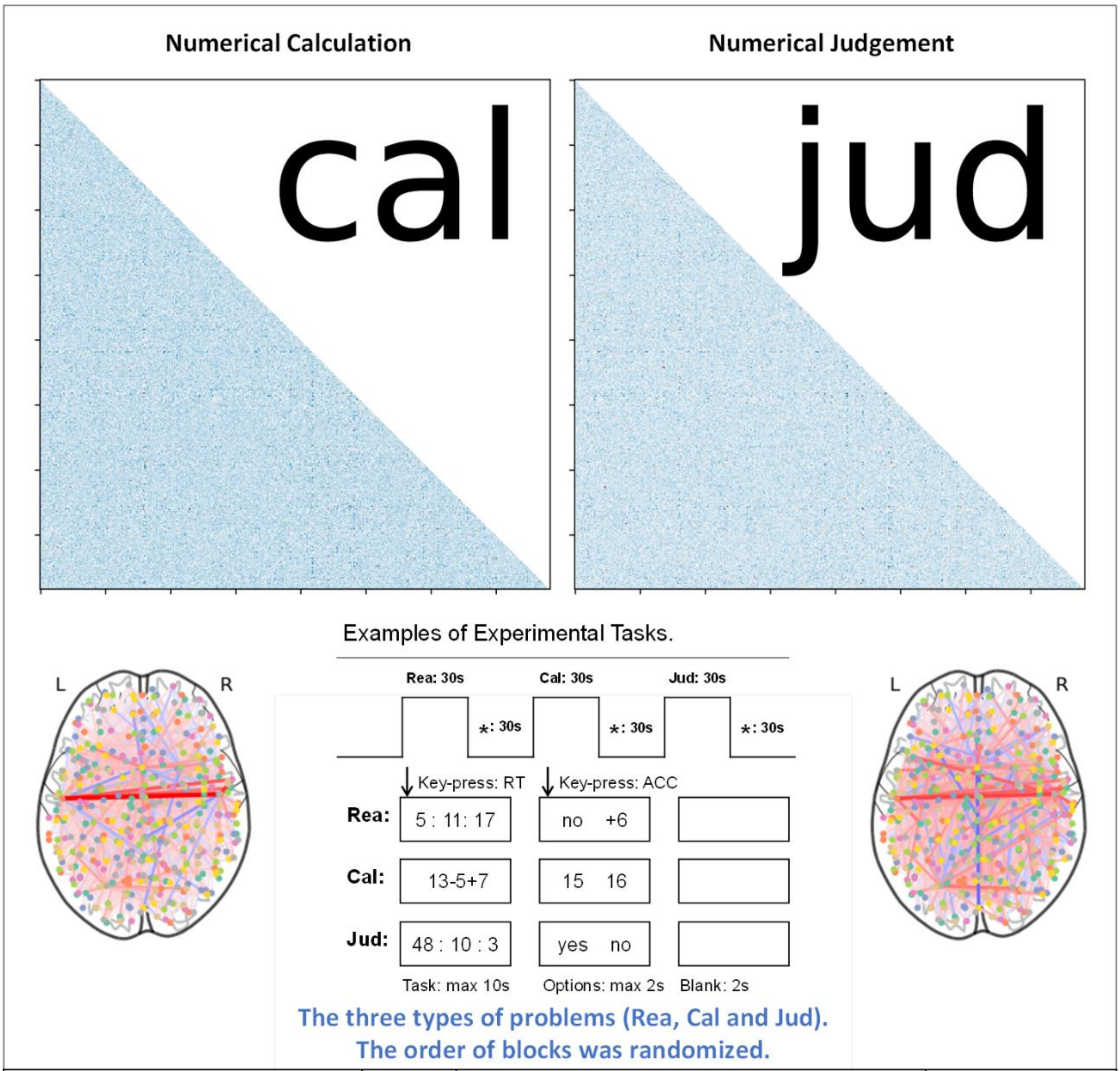
Regions	BA	Coordinate (Nodes in cc400)			Nodal Weights
		x	y	z	
Lt. Amygdala	49	-27	-6	-9	1.000000
Lt. Precental Gyrus	BA6	-26	-13	65	0.740741
Rt. Inferior Frontal Gyrus, Orbital Part	BA47	28	19	-18	0.074074
Rt. Precental Gyrus	BA6	53	-9	39	0.037037
Rt. Supplementary Motor Area	BA6	15	19	61	0.037037
Rt. Middle Frontal Gyrus	BA9	35	30	42	0.037037
Lt. Thalamus	50	-12	-24	13	0.037037
Rt. Cuneus	18	8	-83	28	0.037037
Rt. Insula	BA44	38	14	7	0.037037
Lt. Middle Temporal Gyrus	BA21	-57	-16	-21	0.037037

Figure 5.5: The computing results of brain functional connectivity patterns for inductive reasoning in LOOP-1.



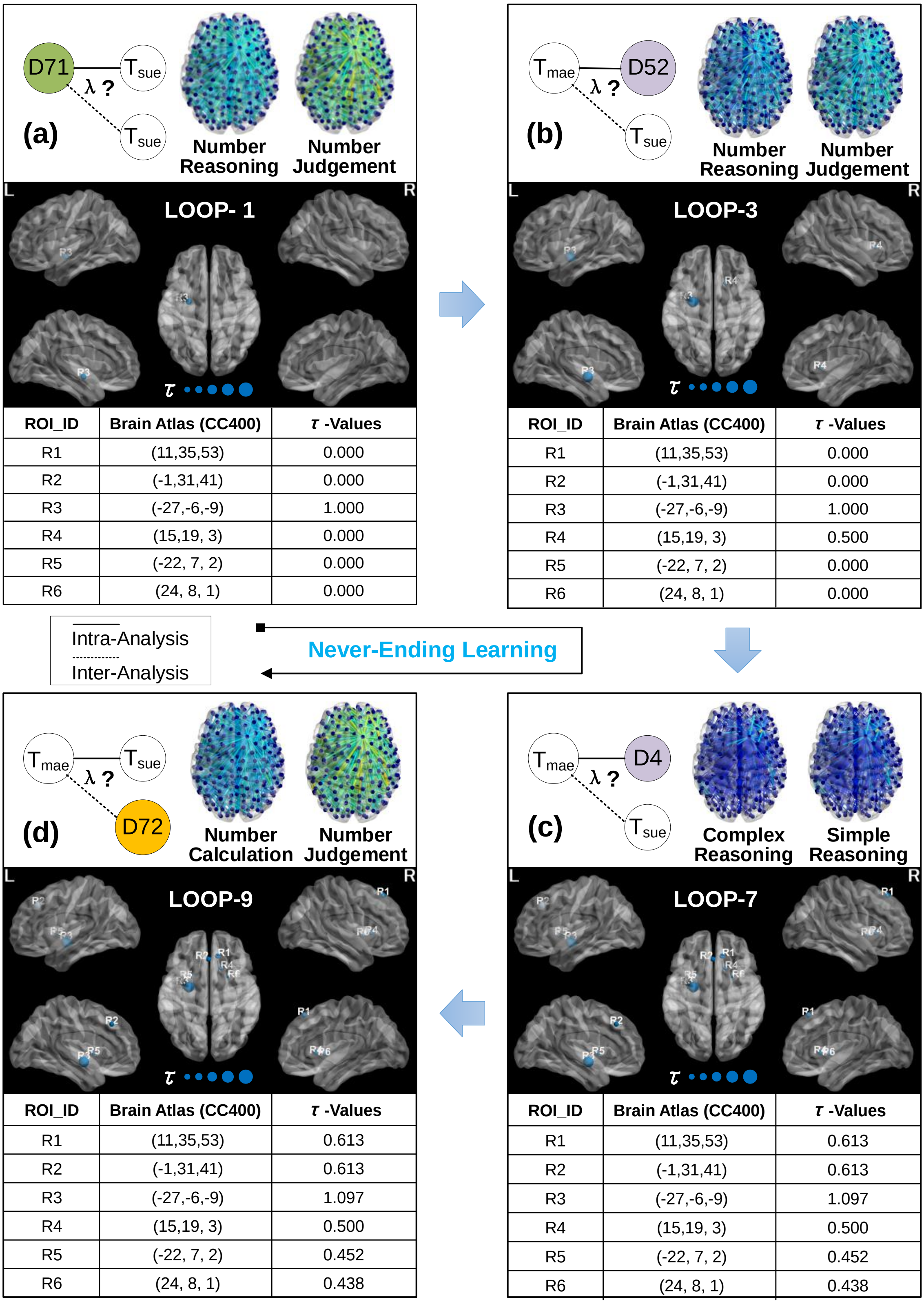
Regions	BA	Coordinate (Nodes in cc400)			Nodal Weights
		x	y	z	
Lt. Insula	13	-32	11	-7	1.000000
Rt. Anterior Cingulate and Paracingulate Gyri	BA8	8	33	28	0.500000
Rt. Caudate	48	15	19	3	0.500000
Rt. Supplementary Motor Area	BA6	15	19	61	0.500000
Rt. Hippocampus	54	30	-31	-9	0.500000

Figure 5.6: The computing results of brain functional connectivity patterns for inductive reasoning in LOOP-2.



Regions	BA	Coordinate (Nodes in cc400)			Nodal Weights
		x	y	z	
Lt. Middle Occipital Gyrus	BA7	-25	-71	35	1.000000
Lt. Postcentral Gyrus	4	-54	-12	38	0.600000
Lt. Supplementary Motor Area	BA6	0	9	55	0.150000
Lt. Middle Frontal Gyrus	BA6	-35	4	57	0.100000
Lt. Middle Frontal Gyrus	BA8	-29	24	46	0.100000
Rt. Inferior Temporal Gyrus	BA38	52	3	-30	0.050000
Rt. Postcentral Gyrus	BA6	53	-9	39	0.050000
Rt. Superior Frontal Gyrus	BA6	26	9	58	0.050000
Rt. Middle Temporal Gyrus	BA22	52	-9	-13	0.050000
Rt. Thalamus	50	12	-14	11	0.050000

Figure 5.7: The computing results of brain functional connectivity patterns for calculation in LOOP-9.



(a) LOOP-1

ROI_ID	Brain Atlas (CC400)	τ -Values
R1	(11,35,53)	0.000
R2	(-1,31,41)	0.000
R3	(-27,-6,-9)	1.000
R4	(15,19, 3)	0.000
R5	(-22, 7, 2)	0.000
R6	(24, 8, 1)	0.000

(b) LOOP-3

ROI_ID	Brain Atlas (CC400)	τ -Values
R1	(11,35,53)	0.000
R2	(-1,31,41)	0.000
R3	(-27,-6,-9)	1.000
R4	(15,19, 3)	0.500
R5	(-22, 7, 2)	0.000
R6	(24, 8, 1)	0.000

(d) LOOP-9

ROI_ID	Brain Atlas (CC400)	τ -Values
R1	(11,35,53)	0.613
R2	(-1,31,41)	0.613
R3	(-27,-6,-9)	1.097
R4	(15,19, 3)	0.500
R5	(-22, 7, 2)	0.452
R6	(24, 8, 1)	0.438

(c) LOOP-7

ROI_ID	Brain Atlas (CC400)	τ -Values
R1	(11,35,53)	0.613
R2	(-1,31,41)	0.613
R3	(-27,-6,-9)	1.097
R4	(15,19, 3)	0.500
R5	(-22, 7, 2)	0.452
R6	(24, 8, 1)	0.438

Figure 5.8: Uncertainty results for each loop within the never-ending learning of brain functional connectivity patterns.

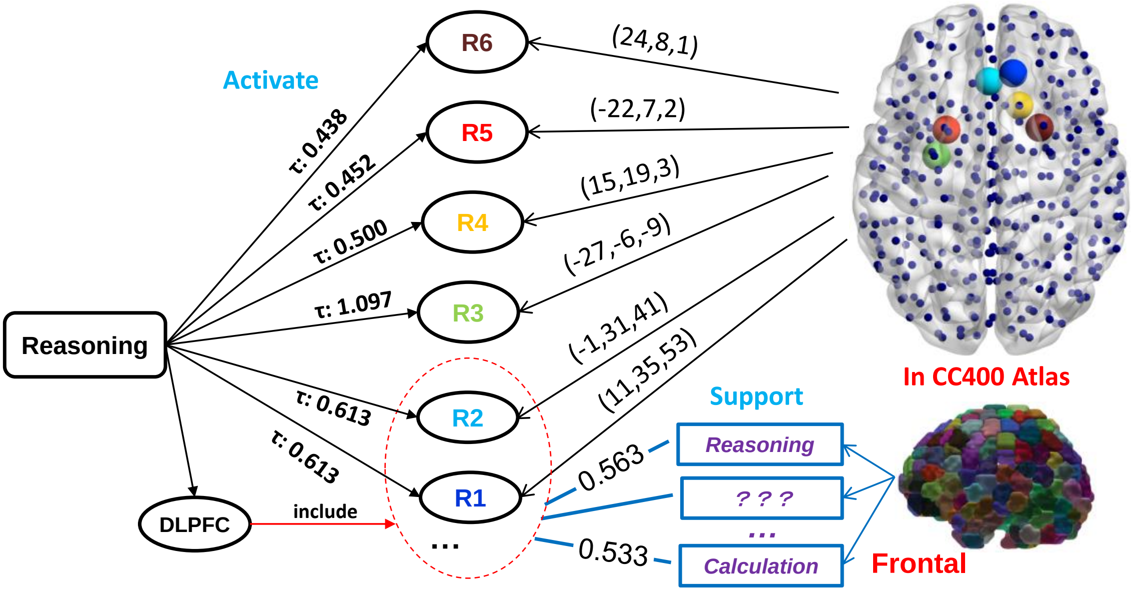


Figure 5.9: The casual inference for interpretations of the goal hypothesis with cognitive functions and crucial nodes within brain atlas. The brain functional connectivity-centric forward results show the prefrontal cortex and striatum are required to participant in the human reasoning process. Meanwhile, the reverse inference results show the prefrontal cortex exhibits the specific support for reasoning, comparing with calculation.

5.4.3 Discussions

From functional integration theory, the separated brain regions interact with each other to maintain the basic activities in body, and serve as the high-level cognitive functions as a whole. The study in human brain connectome is another important view to provide insight into how the brain mechanisms of functional connectivity are interpreted at various cognitive functions. In this case, the functional connectivity mechanisms of human reasoning are investigated. For deductive reasoning, Goel et al. observed a large brain network covered by bilateral occipital, parietal, temporal, and frontal lobes; basal ganglia; and cerebellar regions [281]. During deductive problems, activation was located in the bilateral frontoparietal network, whereas for inductive problems, we found activation in the further left-sided PFC, the parieto-occipital junction, and the BG, suggesting additional cognitive demand [281]. Prado et al. reported activations in specific regions of a left fronto-prietal network, as well as in the left BG for deductive reasoning, by using a quantitative meta-analysis of 28 neuroimaging studies [224]. Monti et al. isolated the neural correlates of deductive reasoning and addressed the role of language in deduction [282]. They revealed a network of activations disjoint from the "core" regions (including the left rostral and bilateral medial prefrontal cortex) which perform deductive operations and the "support" regions (including the left frontal and parietal cortices) which maintain the formal structure of arguments. Furthermore, Hampshire et al. found the right lateralized network (including the dorsolateral prefrontal cortex and superior parietal cortex) seems to take part in the process of induction, specifically when the cognitive loads increase with respect to reasoning [283]. For both deductive and inductive reasoning, the frontoparietal network is the most consistently activated brain network (the bilateral DLPFC (BA 9) and the SMA (BA 6), as well as in the left PPC (BA 7, BA 40)) [284, 285]. For example, Jia et al. (2011) showed that the particular involvement of the frontoparietal network in relation inference processes [228]. Moreover, Liang et al. found the striatal–thalamic network plays an important role in figural inductive reasoning [286]. In a lesion study, Schmidt et al. (2012) differentiated between associative and categorical analogies and showed that the former relies on a left-lateral language network whereas the latter one recruit's areas from both hemispheres [287]. During general reasoning, that is, syllogistic, as well as conditional reasoning, Wertheim et al. found a wide-spread activation network encompassing the frontal, parietal, sublobar, limbic, posterior lobes [288]. Blackwood and Rao et al. found the coactivation of the cerebellum with the SMA, IPL and occipital cortex to mediate decision-making under uncertainty [289] and the active during conceptual reasoning [290]. It was suggested that the cerebellum plays a key role in the construction of a mental working model of the world under uncertainty [289, 291, 292]. Furthermore, it is assumed that the cerebellar–thalamic–DLPFC network serves as a mechanism for integrating and gating of structured thought [293, 294]. This is especially the case, Wertheim et al. found activation in the parietal and frontotemporal networks in content and abstract tasks, respectively [288]. Porcaro et al. found a contradictory reasoning network (corresponding to the right middle frontal gyrus, the right inferior frontal gyrus, the right medial frontal gyrus and the anterior cingulate cortex) by an EEG and fMRI study [295]. Shokri-Kojori et al. revealed the brain-wide connectivity between primary visual and parietal regions, and their influenced activity in frontal lobes [296]. They found a caudal-rostral flow of process within prefrontal cortex (PFC) in reasoning tasks with minimal top-down deductive requirements.

5.5 Conclusion

In this chapter, we empirically study the important problem of learning brain patterns from the functional integration perspective. We perform the inductive reasoning-centric brain connectivity pattern analyses based on the general intelligence model.

Chapter 6

Translational Study Learned by GIM Analyses

The previous two chapters carried out in the GIM, and generated uncertainty distribution to promote understanding the higher-level cognitive functions. Such basic cognitive neuroscience-oriented results are further considered to transfer from one site to multiple sites. This chapter applies the research results from the GIM analyses to the translational applications.

6.1 Problem Statement

Mental health is the foundation for the well-being and effective functioning of individuals. Good mental health enables individuals to think, to work, to learn, to engage with other people, and to participate in society. Conversely, mental disorders increase lifetime risk and cause significant suffering for individuals, their families and society as a whole. Currently, more than 970 million people are affected by mental health disorders in the world, which is slightly more than one in ten people globally. A high disease burden of mental disorders has been noted worldwide, including Japan. It is important to monitor mental disorder prevalence trends and the use of mental health services over time using epidemiological data, and to plan appropriate policies and measures that consider mental health in each country [296]. There is a commonly accepted notion in mental disorders that are often defined as disorders of the brain, involving complex patterns of disturbances of cognition, affect and emotion, somatic functioning and behavior. Hence, decoding the relations between brain functions and mental disorders is a particularly important avenue for providing better mental health service and reducing the burden of mental disorders, laying the foundation for a shift in clinical practice [297].

On the one hand, the regional abnormalities in the brain may lead to various types of mental disorders. Phillips reviewed the existing findings about biomarker of bipolar disorder, regrading functional abnormalities in neural systems underlying emotion processing (amygdala centered), working memory and attention (dorsolateral prefrontal cortex centered) that are bipolar specific rather than common to unipolar depression [298]. Lim et al. given evidence about the neuroprogressive loss of gray matter volume in prefrontal and anterior cingulate cortex and the subgenual region, as well as the changed activation patterns involving fronto-limbic circuitry in bipolar disorder from reported studies of longitudinal brain structural/functional magnetic resonance imaging [299]. Meta-analysis of case-control differences in task-fMRI activation revealed the relatively overrepresented regions with meaningful diagnosis-specific effects across psychiatric disorders, such as the dorsal and ventral striatum, the amygdala and hippocampus and cortical regions within the frontal operculum/anterior insula, the posterior parahippocampal gyrus and the paracingulate gyrus [300]. Mental disorders also are the important reason for suicide, which can pose a nearly 80% increased risk of suicide compared with individuals without a mental disorder [301]. Neuroimaging studies mainly showed the involvement of the ventrolateral orbital, dorsomedial and dorsolateral prefrontal cortices, the anterior cingulate gyrus, and to a lesser extent, the amygdala [302].

On the other hand, network organization fundamentally influences the brain diseases, and a connectomic approach grounded in network science is integral to understanding neuropathology [51, 303, 304]. Cui et al. found the abnormal global-brain functional connectivity in major depressive disorder, including the increased global-brain functional connectivity (specifically for the bilateral insula, the right inferior parietal lobule (IPL), and the right supramarginal gyrus/IPL) and the decreased global-brain functional connectivity (specifically for the bilateral posterior cingulate cortex/precuneus and the left calcarine cortex) compared with healthy controls [305]. Studies showed the strength of functional connectivity was significantly decreased in people with schizophrenia, whereas diversity of functional connections was increased [306, 307]. The abnormality in brain connectivity of social network (mainly including the anterior cingulate cortex, amygdala, the dorsomedial prefrontal cortex, the fusiform face area, insula, the inferior occipital gyrus, the intraparietal sulcus, the mirror neuron system, the posterior cingulate cortex, the premotor cortex, the posterior superior temporal sulcus, the temporoparietal junction and the ventromedial prefrontal cortex) has impact on autism spectrum disorders [308]. Wolf et al. found both the regional brain activation deficits and the functional connectivity changes (including the abnormal functional connectivity between the left ventrolateral prefrontal cortex and the cerebellum, and the abnormal functional connectivity between the anterior cingulate and the parietal cortex) in the attention deficit hyperactivity disorder (ADHD) adults during working memory processing [309]. Bani-Fatemi et al. reviewed 78 functional and structural neuroimaging studies to conclude that suicidal brain across psychiatric diagnoses seems to heavily involve dysfunction of the fronto-temporal network, primarily involving reductions of gray and white matter volumes in the prefrontal cortex (PFC), the anterior cingulate and the superior temporal gyrus [310].

Cognitive dysfunction is a primary symptom in mental disorders, which primarily affects cognitive abilities including learning, memory, perception, and problem solving [311]. Systematic consideration of the relations between cognitive dysfunctions and mental disorders can contribute to precision medicine and personal therapy, as shown in Figure 6.1. Historically, the unidimensional idea is concerned, that is exploring the same risk factors and biomarkers shared across multiple disorders, and often responding to the same therapy [312]. Furthermore, similar to the understanding of the complex relations between brain structure and function, differently activated regions are often ascribed disorder-specific functions in an attempt to link disease expression and brain function [300].

Neuroimaging has developed into central to the quest for a biological and/or functional psychiatric diagnosis [313, 314]. By meeting neuroimaging and computational science, artificial intelligence algorithms have been widely used to different purposes from the diagnosis, treatment, intra-operative and postoperative assessment of brain diseases and mental disorders [147, 315]. For example, the machine learning and pattern recognition methods are applied to diagnosis, classification and predication of obsessive-compulsive disorder [316], attention-deficit/hyperactivity disorder [317], addiction [318] and dementia [319]. A serious problem in psychiatric practice is the lack of the specific and objective biomarker-based assessments to guide diagnosis and treatment. The use of such biomarkers could assist clinicians in establishing differential diagnosis, which may improve the specific individualized treatment [320, 321]. In this context, the systems-level neuroscience such as fusion computing can help towards advancing the translational studies in neuropsychiatric disorders [322, 323].

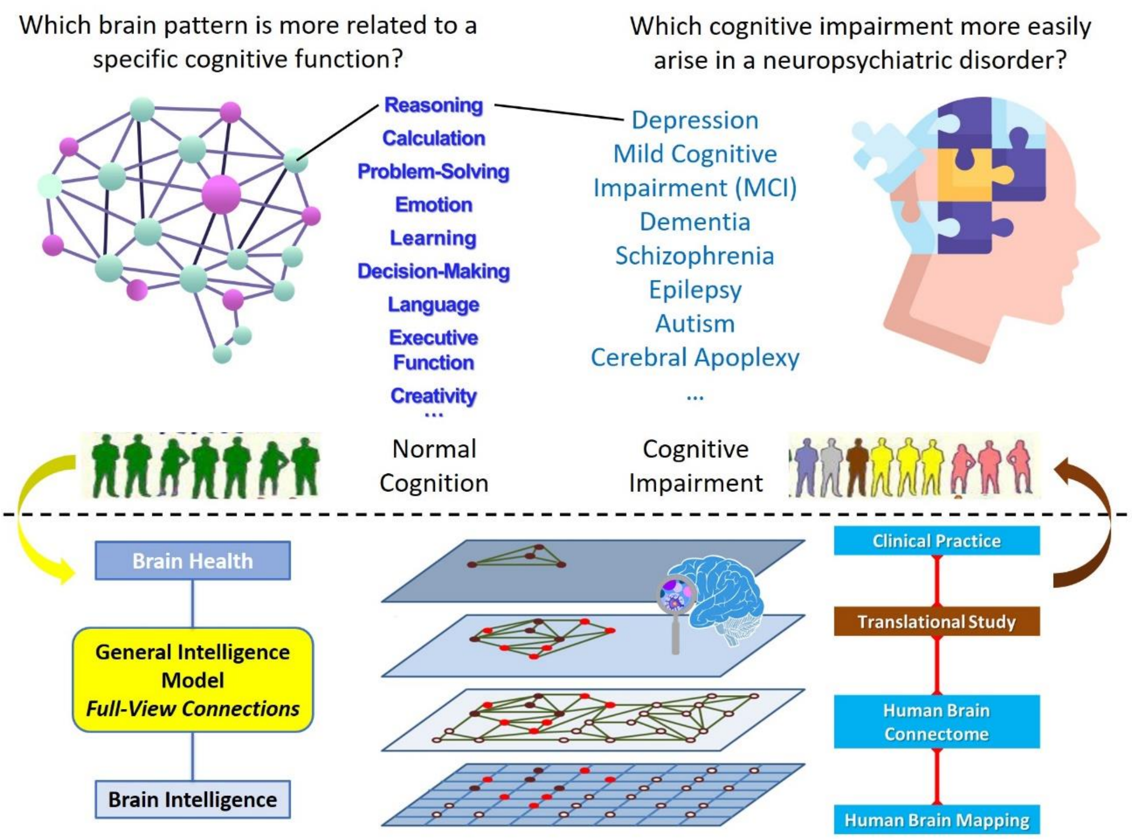


Figure 6.1: Systems neuroscience with translational research towards smart health.

6.2 Datasets

In this case, the translational research is focused around the recognizing scenario of major depressive disorder. To meet the requirement, the training and testing samples were extracted within *D*3 from the sample library (see Appendix A Table 1). Diagnostic assessments for all participants (including 19 MDD patients and 19 matched healthy control) were performed, using the Mini International Neuropsychiatric Interview 6.0 (MINI 6.0) based on the fourth edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM). Additionally, both resting-state and task-state fMRI data were acquired with a 3.0 Tesla MRI scanner (Siemens Trio Tim, Siemens Medical System, Erlanger, Germany). Details of the experimental task are described as shown in Figure 6.2.

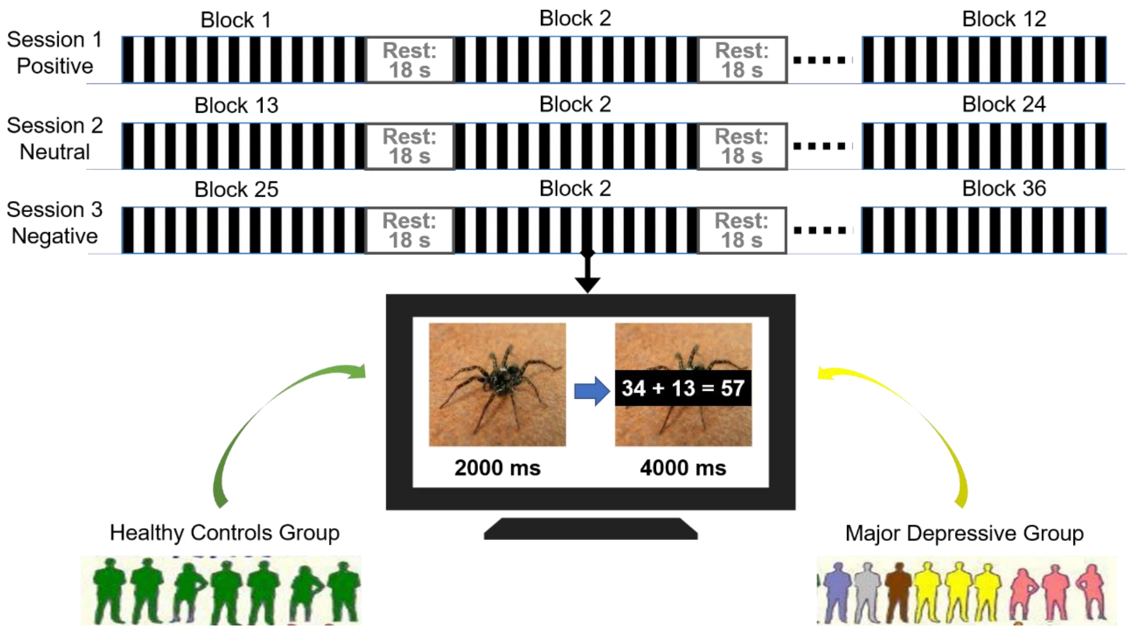


Figure 6.2: Details of experimental data in translational research. Subjects were shown pictures and then required to solve mental arithmetic problems presented as overlays on the pictures. Three types of pictures corresponding to each task condition were applied, with positive (e.g., joyful, exciting), neutral, and negative (e.g., aversive) valences, respectively. As distractors, 2-digit simple mental addition and subtraction problems without carrying and borrowing were employed.

In this dataset, each trial consisted of an emotion induction phase and a distraction phase. During the induction phase (2000 ms), a picture with a specific valence was displayed. Subjects passively viewed the picture to elicit an initial emotional response. During the distraction phase (4000 ms), subjects needed to shift attention from the picture to an arithmetic problem, and then decide whether the displayed solution was correct or incorrect by pressing two response keys using the left and right thumbs. Twelve successive trials with same task condition constituted a task block. Blocks of three conditions were mixed and counterbalanced, and every two task blocks were separated by a rest block. Data were acquired in three functional runs with a total of 36 trials for each type of task. The task design modifies and combines previous paradigms of distraction task to study attention control of MDD patients [324, 325]. Three task conditions were included and presented in a block-designed pattern. Affective pictures were selected from the International Affective Picture System (IAPS) which is based on normative ratings in valence and arousal [326].

6.3 The GIM in Brain and Mental Health

Figure 6.3 shows the overview of the general intelligence model-aided diagnosis framework that consisted of pattern learning, feature extraction and predictive model. The uncertainty weights of initial patterns are learned to guide feature extraction, and then affect the training of predictive models. Details of the different components in the general intelligence model-aided diagnosis framework are described as follows:

- Pattern Learning: The general intelligence model is performed to learn the brain patterns with the uncertainty weights from the perspectives of brain region, node and connectivity, including the hypothesis tests of regions of interest, the exploratory analysis of the whole-brain activation pattern, the full-scale network topology analysis of the nodal pattern, and the connectivity analysis of the functional subnetwork pattern.
- Feature Extraction: Features at different levels of uncertainty weights are extracted from the whole-brain pattern to various smaller subsets with different characteristics. In this case, the features corresponding to the patterns with the higher uncertainty weights ($\tau > 0$) are identified as the high specificity, whereas the feature patterns with the lower uncertainty weights ($\tau < 0$) are identified as the high robustness.
- Predictive Model: The uncertainty level-specific neuroimaging features are divided into the training and testing samples, which are input into the machine learning methods to realize the mental health recognition. In this case, the constructed model is used to discriminate the samples between the patients with major depressive disorder and the healthy controls.

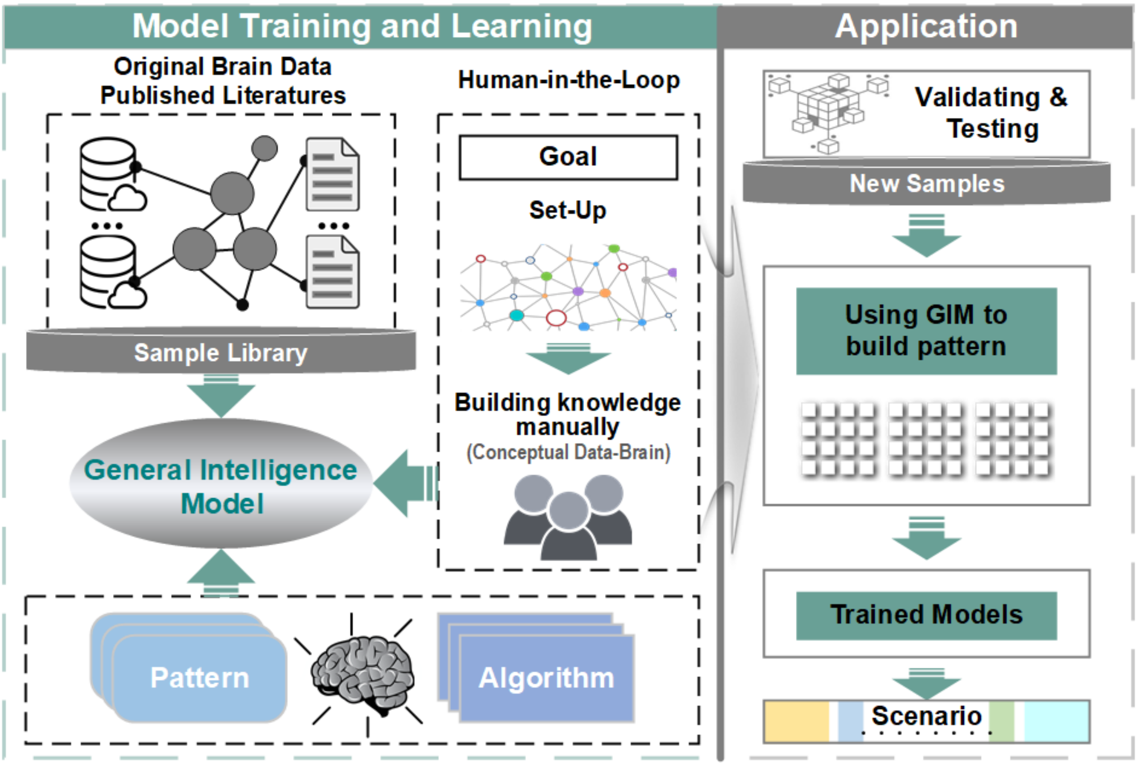


Figure 6.3: Flowchart of the general intelligence model-based diagnostic classification. Brain imaging data are obtained from two or more diagnostic groups and relevant features extracted, as in standard univariate analysis. Because data reduction is crucial to the success of this procedure, the general intelligence model-aided feature selection can be performed, including brain regions, functional connectivity and subnetworks. The preselected data are then fed into a classifier algorithm, which finds the optimal boundary between the two groups (e.g., the data points from the "healthy controls" and "mental disorder" groups). The performance of the trained classifier then has to be tested in independent data.

6.4 Experiments and Results

The experiments combined the machine learning methods and the information-processing mechanisms, testing the brain patterns selected by the general intelligence model from the two views of brain localization and connectivity: (a) investigating the brain patterns with the specificity and robustness at different levels of uncertainty, and (b) estimating the predictable capability of brain patterns to help differentiate between the group of healthy controls and the group with major depressive disorder.

From the first view, the regions of interest in $\tau > 0$, DLPFC (including the superior frontal gyrus and the middle frontal gyrus) and $\tau < 0$ were selected as three brain patterns. The brain activities with respect to these three types of brain patterns were extracted from the fMRI data, respectively, and then were input to the classifiers to distinguish between healthy controls and the group with major depressive disorder. More specifically, ten nodes were select to construct these three patterns, where the nodes in $\tau = 0$ were random. From the second view, thirty nodes in $\tau > 0$, $\tau = 0$ and $\tau < 0$ were selected by the general intelligence model respectively, which were further constructed as three types of brain networks by estimating the partial correlation coefficient. In order to facilitate comparison, ten brain functional networks were constructed on the basis of a widely adopted consensus, including the default mode network, the fronto-parietal network, the sensorimotor network and the cerebellum network from the Dosenbach-160 atlas [327], the visual network, the salience network, the subcortical network, the ventral attention and the dorsal attention networks from the Power-264 atlas [245], and the limbic-lode network from the brainnetome atlas [328]. Such computed partial correlation coefficients from different brain networks were taken as features, which could be learned by classifiers to distinguish between healthy controls and the group with major depressive disorder. The current disease recognition model is constructed on the basis of XGBoost, which is a scalable end-to-end tree boosting system [329]. The 10-fold cross validation was applied to all classification tasks, corresponding to different cognitive experiment scenarios.

6.4.1 Translational Brain Localization

In this case study, the functional segregation-oriented uncertainty distribution was learned by running the general intelligence model as stated in Chapter 4, particularly in relation to inductive reasoning. Then, the samples were extracted from the dataset D3 (see

Appendix A Table 1), including the MDD and healthy groups that experienced tasks under different states of the rest state, the emotional picture-induced state and the state induced by emotional picture with arithmetic task. Finally, the features extracted from the different groups were recognized by the XGBoost library. Figure 6.4 shows the classification results of two groups of MDD and healthy for brain region and node patterns, respectively. On the one hand, for regions of interest-based classification results in Figure 6.4 (a), (c) and (e), we can find that the accuracies do not appear to differ significantly, but the number of boosting iterations to these three conditions has differences. Considering to the number of boosting iterations patterns in Figure 6.4 (a) and (c), it was found that the classification model with the uncertainty-guided brain patterns carried out less iterations than that of DLPFC-based brain. However, from Figure 6.4 (e), it was found that the classification model with the brain patterns of the uncertainty distribution at $\tau > 0$ carried out more iterations than those of other patterns. On the other hand, for nodes of interest-based classification results in Figure 6.4 (b), (d) and (f), we can find that the accuracies appear to differ relatively, and the number of boosting iterations to these three conditions has differences significantly. Considering to the number of boosting iterations in Figure 6.4 (b) and (d), the classification model with the random 10 nodes-based brain patterns carried out less iterations than that of the uncertainty distribution-guided brain patterns. However, the classification model with the brain patterns of the uncertainty distribution at $\tau > 0$ carries out less iterations than those of other patterns in Figure 6.4 (f). In addition, whether from the regional perspective or from the nodal perspective, the classification model could achieve recognition results exceeding ninety-five percent.

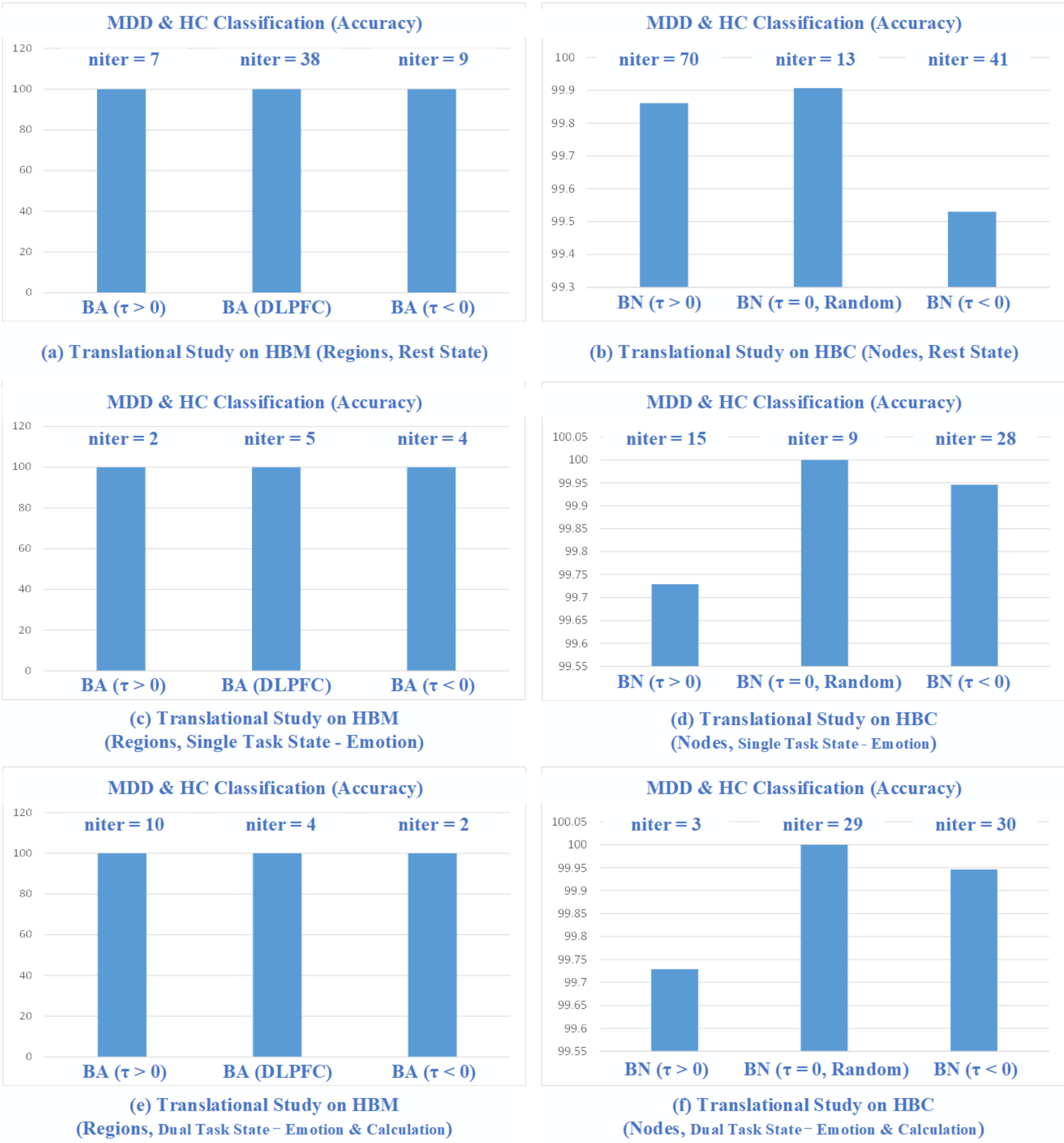


Figure 6.4: The classification results of the MDD group and healthy controls under different task states, corresponding to three types of brain region and node patterns. (a), (c) and (e) are the classification results corresponding to the brain region patterns, while (b), (d) and (f) are involved to the nodal patterns from the brain connectivity measurements. niter: number of boosting iterations; BA: Brain Area; BN: Brain Network; DLPFC is the dorsolateral prefrontal cortex involving the superior and middle frontal gyri; MDD: Major Depressive Disorder; HC: Healthy Control; HBM: Human brain Mapping; HBC: Human brain connectome. Ten nodes at different τ-distribution levels were extracted as feature patterns for the HBC-based classification tasks.

6.4.2 Translational Brain Connectivity

The inductive reasoning-oriented uncertainty distribution was first learned by running the general intelligence model from the functional integration perspective, on the basic of task-state fMRI data from the sample library (see details in Table 1 of Appendix A). The learned uncertainty distribution guided the connectivity-based feature extraction for the prediction of the MDD samples, on the basic of the rest-state fMRI data. Figure 6.5 (top) shows that the predictive accuracies based on the constructed brain network patterns could achieve approximate 70%, 75% and 77%, respectively, corresponding to the $\tau > 0$, $\tau = 0$ and $\tau < 0$ related nodes. In this case, all nodes are from the CC400 atlas. Furthermore, the same predictive task was performed to achieve the accuracies of 78.631%, 73.631%, 74.354%, 77.446%, 67.732%, 63.077%, 66.477%, 56.538%, 68.846% and 66.523%, respectively, corresponding to the network patterns of default, fronto-parietal, sensorimotor, visual, salience, subcortical, limbic lobe, ventral attention, dorsal attention, and cerebellum, as shown in Figure 6.5 (bottom). It was found that the predictive results based on the patterns at these brain networks of salience, limbic lobe, ventral attention, dorsal attention, subcortical and cerebellum exhibited the similar level of recognition accuracy, aligned with the brain patterns at $\tau > 0$. Meanwhile, the predictive results based on the patterns at these brain networks of default, fronto-parietal, sensorimotor and visual exhibit the similar level of recognition accuracy, aligned with the brain patterns at $\tau < 0$.

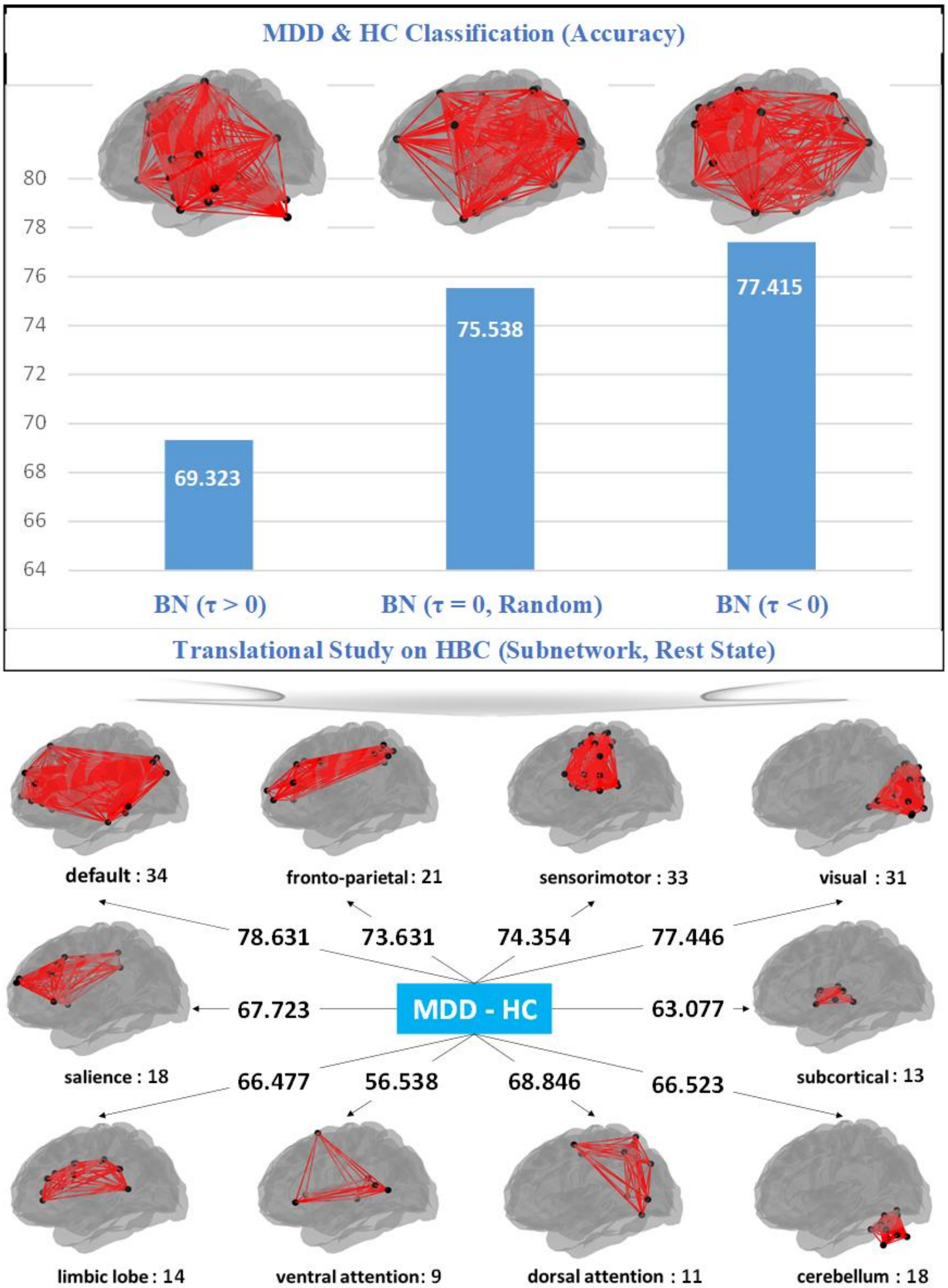


Figure 6.5: The classification results of MDD group and healthy group under rest-state task, corresponding to different functional subnetwork patterns. Thirty nodes were constructed as a subnetwork for classification tasks, respectively corresponding to three levels of uncertainty distribution. ten brain functional networks were constructed on the basis of a widely adopted consensus, including the default mode network, the fronto-parietal network, the sensorimotor network and the cerebellum network from the Dosenbach-160 atlas [327], the visual network, the salience network, the subcortical network, the ventral attention and the dorsal attention networks from the Power-264 atlas [245], and the limbic-lode network from the brainnetome atlas [328].

6.5 Discussions

While the combination of neuroimaging and machine learning has encountered great success, it is still difficult to select a satisfactory brain pattern that is easy to interpret towards translational research. In this case, the brain patterns from two views of functional segregation and integration were selected by the uncertainty distribution, where the brain patterns corresponding to the higher uncertainty distribution indicate the higher functional specificity, the brain patterns corresponding to the near-zero uncertainty distribution indicate the high functional randomness, and the brain patterns corresponding to the smaller uncertainty distribution indicate the higher functional robustness. Therefore, the features could be extracted by those learned brain patterns. Furthermore, the functional networks from various brain atlases that have been widely recognized in the world are investigated, as the comparison to predicate the MDD samples. From Figure 6.4 (a), (c) and (e), it was found that the selected brain region patterns at $\tau > 0$ and $\tau < 0$ can relatively accelerate the convergence of classifiers under all task conditions, in contrast to the control of the random patterns in DLPFC. However, it was found that only the selected brain node patterns at $\tau > 0$ can significantly accelerate the convergence of classifiers under the dual-task state, as shown in Figure 6.4 (f). Figure 6.5 (top) shows that the network-based brain patterns constructed by the $\tau > 0$ related nodes could achieve the significantly higher accuracy than that of brain patterns at the $\tau < 0$ and the relatively higher accuracy than that of brain patterns at the $\tau = 0$. It seems to suggest that the impairment of the reasoning function is not obvious in the current MDD group. Furthermore, it was found that the selected brain network patterns at the $\tau > 0$ indicate the similar sensitivity aligned to functional networks of salience, subcortical, limbic lobe, ventral attention, dorsal attention and cerebellum, while the selected brain network patterns at the $\tau < 0$ indicate the similar sensitivity aligned to functional networks of default, fronto-parietal, sensorimotor and visual, as shown in Figure 6.5.

6.6 Conclusion

In this chapter, we empirically study the important problem of translational research coupled with the intelligence model. We evaluate the uncertainty distribution-guided brain patterns on performance of classifiers and their applications in the recognition of samples with mental disorders.

Chapter 7

Epilogue

In this chapter, we conclude the thesis and envision some future directions to work on Data-Brain driven general intelligence model.

7.1 Contributions and Discussion

In this thesis, we concern intelligent nature, intelligent development and smart health by the systematic brain computing with big data science. The general intelligence model is studied to explore brain information processing mechanisms from functional segregation and integration to extensible applications towards translational goal. More specifically, four points are highlighted as follows:

1. Brain big data integration. Multi-source brain big data from local and global sites are modeled in a hierarchical knowledge (K)-information (I)-Data (D) architecture, namely K-I-D architecture. For this, the conceptual Data-Brain in the knowledge layer is developed to systematically model the whole life-cycle process of brain investigation, directed by the Brain Informatics methodology. The sematic vector in the information layer is developed to read requests of investigators, and at the same time, coordinate resources from the knowledge layer to the data layer. The sample

library in data layer is developed to map diffused brain resources into a standard space, constructing a resource network in the connected world.

2. Systematic brain computing. A Data-Brain driven General Intelligence Model (GIM) is proposed as a novel brain-inspired computing approach, thinking like a human with capabilities on reasoning, learning, computing and decision making. It performs systematic experimental design, evidence combination and fusion computing within a K-I-D loop, driving never-ending learning of brain intelligence and health. Human-in-the-loop is given to this model to realize interactive learning between both human and machine.
3. Human intelligence understanding. The GIM is applied to realize systematic brain computing from perspectives of human brain mapping and human brain connectome. We performed reasoning and calculation-centric systematic investigations of higher cognitive functions. One the one hand, the association mining among brain functions, experiments, feature patterns and computing methods was executed by systematic experimental design and human-in-the-loop learning. On the other hand, never-ending learning is executed to verify the effect of incremental learning in the brain big data era.
4. Brain wisdom services. Brain is the important window to understand mental health. The GIM is applied to realize systematic brain computing from basic cognitive neuroscience studies to translational study for smart health. In this study, a classification model was constructed to realize the recognition of samples with major depressive disorders from healthy control, coupled with the brain localization and connectivity results from the GIM.

A study on Data-Brain driven general intelligence model will attract more and more widespread attention because of its ability to leverage the advantages of both human-in-the-loop and never-ending learning of data, information and knowledge, which is expect to acquire more novel and solid results. Faced with this emerging field, a conceptual model that takes into account the power of systematic fusion has been proposed, namely Data-Brain. It inspires us to perform systematic brain investigation in the process of knowledge discovery. Furthermore, the collective wisdom is expressed as two interactive learning processes: one is from the external evidence learning, such as the published results; another is personal wisdom through dynamic human-machine interaction, which provides a feasible solution for systematic brain research.

A series of representative case studies were executed to verify and illustrate the proposed Data-Brain driven general intelligence model. The main results for human intelligence are about the understanding of casual relationship between the dorsolateral prefrontal cortex and inductive reasoning. We can find that the dorsolateral prefrontal cortex is highly related to and has a strongly support to inductive reasoning in the processes of both the task-driven KID inference and the data-driven DIK inference. It should be mentioned that the proposed model also makes it possible to generate new hypotheses. With respect to inductive reasoning, several regions such as left middle temporal gyrus, right inferior temporal gyrus, fusiform gyrus and bilateral angular gyrus, were identified in the whole-brain exploratory analysis as the relevant brain regions, which were not reported in previous studies. Additionally, several functional circuits such as the fronto-striatal circuits, in which the involved key brain regions (including the prefrontal cortex, caudate, putamen) were detected by functional connectivity analysis, were also not ever reported. These results may act as new potential hypothesis, and inspire us to design and run new experiment to test them. The main results for smart health are about the validation of feature patterns and the performance of classification accuracy. On the one hand, the learned feature patterns can accelerate the convergence of classification model and show robust to fit various task states. In particular, the brain localization-based feature patterns improve classification performance. On the other hand, the learned feature patterns from the GIM show the cognitive specificity, with the similar characteristics to the functional brain systems, such as the default network and the fronto-parietal network. Although various case studies have been proposed to demonstrate the current model in the field of brain cognitive science, its other directions are worthy of attention.

7.2 Future Work

By meeting brain informatics and web intelligence, the general intelligence model is asked for mastering more abilities to dock with rapid development of brain science in the connected social-cyber-physical world. Along with never-ending learning, the thinking-supported general intelligence model decodes brain information processing mechanisms to promote understanding of brain intelligence and brain health. At the same time, the human thinking ability inspired by brain intelligence is developed and integrated to the general intelligence model that performs like human. The complementary effects will promote continuous growth of the model for further adaptation to a wider range of scenarios, which interacts closely with each other within brain network.

7.2.1 Brain Intelligence

The Wisdom Web of Things (W2T) developed recently provides a SCP space for all human communications and activities, in which big data are used as a bridge to connect relevant aspects of humans, computers and things [153, 167]. It is a trend to integrate brain big data and human behavior big data with knowledge graphs in the SCP space for realizing the harmonious symbiosis of humans, computers and things. In the relation between the cognitive neuroscience and big data, there are several interactions: brain function/structure measurements generate big data in multimodal and multi-scale, which could be used as open sources and interconnected by information networks and knowledge graph; social-media and sensor networks generate human behavior data in multi-modal and multi-media, which is also big data. Both types of data offer the stimulus sets for brain and AI researches. For neuroscience and cognitive science, thus, utilization of the big data as the stimulus sets has now provided new ways to better understanding of brain intelligence mechanisms in multi-scale. In order to realize these goals that depend on holistic intelligence research, the following challenges need to be dealt with:

- How to understand brain from neural microcircuits to macroscale intelligence systems, supported by connecting network and brain with big data;
- How to realize human-level collective intelligence as a big data sharing mind on the W2T by developing brain inspired intelligent technologies to provide wisdom services.

On the one hand, hundreds of millions of neurons connect and interact with each other to form an intricate and vast network that is running orderly and at high speed all the time. Hence, the brain's high-efficiency and high-rate properties can be cloned to optimize mathematical models and intelligent agents by simulating the neuron's morphological structure, tissue connection and information transmission mechanisms [177, 330]. The realization of this achievement will greatly promote the breakthrough in the field of computational science. On the other hand, as a creature with the ability to learn and think, every action of human beings is affected and regulated by brain intelligence [331, 332].

For instance, it is interesting to note that even though there is a huge difference in physical functions between two people, they are still able to perform certain intellectual tasks at a highly consistent skill level. It shows that human beings can make full use of the advantages of individual intelligence to make up for the deficiency of physical functions, so as to maintain stable operation of this complex system. Such a personalized adjustment mechanism is worthy of an in-depth study [333-335]. In addition, the reward mechanism is another important mechanism related to the human brain, which drives our behavior towards pleasure and drives us away from painful ones [336-338]. The reinforcement learning algorithm that learns through rewards has been applied to various domains [339] and given us a chance to understand how our brain does.3 Especially, a new theory has been proposed from recent studies about the reward mechanisms within our brains by optimizing reinforcement learning, namely the dopamine-based reinforcement learning [175]. Hence, it is indispensable to develop advanced brain-inspired intelligent algorithms by analyzing and imitating brain intelligence for realizing human-level general intelligence.

As a novel brain computing platform, Data-Brain driven general intelligence model provides the powerful means to investigate the human brain as an information-processing system with big data helping us understand its capacities and limitations. Brain big data collected in the SCP space and integrated with human behavior big data and worldwide knowledge bases could help us realize human-level collective intelligence. The proposed Data-Brain model builds bridges between biological brain and intelligence systems.

7.2.2 Brain Health

As the most important information processing and control center in the human body, the brain is closely related to cognitive, emotional, psychological and behavioral functions. The individual with good brain health can realize his/her own abilities and optimize his/her functions to cope with life situations, which reflects the enormous potential of brain intelligence. In such a case, the healthy brain big data can be systematically collected, managed, analyzed and simulated to power future progress for building human-level intelligence systems and applications. Conversely, abnormal brain may lead to the loss of certain feelings and cognitive functions that are associated with a wide range of specific brain function diseases. For instance, dementia, which is a group of disorders caused by abnormal brain changes, can trigger the declines in memory, language, problem-solving, decision-making and other cognitive abilities [129, 340]. Mental disorders can also cause significant distress or impairment of personal functioning [341]. Such diseases give us more challenges on the combined investigations in cognition, emotion, pathology and their interactions from brain function and structure perspectives. In order to realize these goals that depend on systematic investigations, the following challenges need to be considered:

- How to understand brain intelligence in depth, supported by the investigations of healthy and abnormal brains;
- How to explore neural mechanisms of cognition, emotion and pathology, as well as their biomarkers;
- How to investigate the disease progression across the whole cycle with respect to the prevention, diagnosis, evaluation, treatment, prognosis and rehabilitation.

Based on the systematic Brain Informatics methodology, Data-Brain driven general intelligence model supports the combined investigations on various constituent elements of cognition, emotion and pathology within both healthy and abnormal brains, as well as novel services for brain and mental health.

7.2.3 Brain Internet

Developing brain internet can be regarded as a tangible goal to implement brain-machine intelligence and provide new solutions for brain health services in the connected world. Although the social network can be regarded as the most common form of brain internet, it is only a superficial connection, that is, ideas and thoughts (results of reprocessing) from the brain are transmitted and shared through the Internet, and the essence is not the direct interaction between brain and brain. Currently, direct brain-to-brain interfaces and communication modes have received widespread attention, which combine multiple non-invasive technologies to extract and deliver information between brains, allowing direct brain-to-brain communication [208, 342, 343]. Moreover, the deep brain stimulation (DBS) [344] and intracranial electrophysiology [345, 346] technologies have also been applied to the study of neuropsychological and neuropsychiatric issues, which represent a window of opportunity for shaping the brain internet on the daily modes. The development of brain-machine intelligence with various neuromodulation technologies is bringing closer the vision of future Internet, where the brain and machine functions seamlessly blend into the background and the personalized capabilities are made possible through access of specific information sources. In order to implement a smooth, flexible and highly robust brain internet, the following suggested issues need to be considered:

- How do we achieve brain-to-brain interactions of thoughts, perceptions and feelings based on neuroelectric recording and computational tools;
- How do we advance brain-machine interfaces, powered by understanding neural mechanisms of cognition, emotion and pathology in depth;

- How do we provide innovative services and collective solutions for brain health, supported by future brain internet.

As a bi-directional decoder between the inner brain information and the outer brain information, Data-Brain driven general intelligence model provides opportunities and new solutions for improvement by helping us understand and apply neural mechanisms of cognition, emotion and pathology, as well as helping us develop brain internet based new services for brain health.

Appendix A

Appendix A Table 1: A fragment of the sample library from multiple sources.

ID	HIP	EPM	EPL	ESI	Contrast	Subjects (※)
D71[347]	Reasoning	Categorical	Block	Digits	Numerical Induction, Perceptual Judgment	Healthy (15)
D72 [347]	Calculation	Categorical	Block	Digits	Numerical Calculation, Perceptual Judgment	Healthy (15)
D4 [87]	Reasoning	Factorial	Event-related	Digits	Complex Rule, Simple Rule	Healthy (15)
D1 [348]	Reasoning	Factorial	Event-related	Digits, Symbols	Numeric, Symbols	Healthy (13)
D51 [228]	Reasoning	Categorical	Event-related	Digits	Rule Induction, Perceptual Judgment	Healthy (20)
D52 [228]	Reasoning	Categorical	Event-related	Digits	Rule Application, Perceptual Judgment	Healthy (20)
D81 [233]	Reasoning	Factorial	Block	Digits	Numerical Induction, Perceptual Judgment	Healthy (23)
D82[233]	Reasoning	Factorial	Block	Letters	Letter Induction, Perceptual Judgment	Healthy (23)
D3 [349]	Emotion, Calculation	Categorical	Block	Pictures	Emotional Calculation, Emotion	Healthy (13), MDD (13)
D6 [350]	Calculation	Categorical	Block	Digits, Symbols	Addition, Subtraction	Healthy (22)
D2 [160]	Emotion	Factorial	Event-related	Faces, Shapes	Fear Face, Happy Face	Healthy (30)
E1 [34]	Reasoning	Full	Full	Full	Mate-analysis	--
E2 [32]	Memory	Full	Full	Full	Mate-analysis	--
E3 [32]	Language	Full	Full	Full	Mate-analysis	--
				…		

Note: MDD, major depressive disorder; MCI, mild cognitive impairment; ※, The number of subjects; HIP, human intelligence problem; EPM, experimental paradigm; EPL, experimental protocol; ESI, explicit stimulus.

Appendix A Table 2: Reasoning related external evidence from PubMed and PLOS series. They were searched from the sample library based on topic matching.

NO	Title	Publication Year	Subject Number	Source
1	Dissociation of mechanisms underlying syllogistic reasoning	2000	11	NeuroImage
2	Functional neuroanatomy of three-term relational reasoning	2001	14	Neuropsychologia
3	The neural substrate of analogical reasoning: an fMRI study	2003	36	Cognitive Brain Research
4	Reasoning and working memory: common and distinct neuronal processes	2003	12	Neuropsychologia
5	Differential involvement of left prefrontal cortexin inductive and deductive reasoning	2004	15	Cognition
6	The cerebellum and decision making under uncertainty. Brain research	2004	8	Cognitive Brain Research
7	The effect of social content on deductive reasoning: An fMRI study	2005	55	Human Brain Mapping
8	fMRI evidence for a three-stage model of deductive reasoning	2006	12	Cognitive Neuroscience
9	Neural correlates of superior intelligence: Stronger recruitment of posterior parietal cortex	2006	36	NeuroImage
10	Frontopolar cortex mediates abstract integration in analogy	2006	27	Brain Research
11	An fMRI investigation of the role of the basal ganglia in reasoning	2007	22	Brain Research
12	Neural basis of generation of conclusions in elementary deduction.	2007	14	NeuroImage
13	Distinct neural substrates for deductive and mathematical processing	2008	16	Brain Research
14	Developmental shifts in fMRI activations during visuospatial relational reasoning	2009	16	Brain and Cognition
15	Differential patterns of cortical activation as a function of fluid reasoning complexity	2009	20	Human Brain Mapping
16	Prefrontal and medial temporal contributions to episodic memory-based reasoning	2008	17	Neuroscience Research
17	The dynamics of deductive reasoning: An fMRI investigation	2009	12	Neuropsychologia
18	Emotional and cognitive stimuli differentially engage the default network during inductive reasoning	2011	20	Social Cognitive and Affective Neuroscience

19	Long-range functional interactions of anterior insula and medial frontal cortex are differently modulated by visuospatial and inductive reasoning tasks	2013	22	NeuroImage
20	Contradictory reasoning network: A study.	2014	13	PLOS series
22	Common and dissociable neural correlates associated with component processes of inductive reasoning	2011	20	NeuroImage
23	Relational complexity modulates activity in the prefrontal cortex during numerical inductive reasoning: An fMRI study	2014	20	Biological Psychology
24	Neural efficiency as a function of task demands.	2014	58	Intelligence
25	Modafinil Alters Intrinsic Functional Connectivity of the Right Posterior Insula: A Pharmacological Resting State fMRI Study	2014	26	PLOS series
26	Tracking Functional Brain Changes in Patients with Depression under Psychodynamic Psychotherapy Using Individualized Stimuli	2014	35	PLOS series
27	Decreased Peripheral and Central Responses to Acupuncture Stimulation following Modification of Body Ownership	2014	17	PLOS series
28	Task and Resting-State fMRI Task and Resting-State fMRI Reveal Altered Salience Responses to Positive Stimuli in Patients with Major Depressive Disorder	2016	38	PLOS series
29	Activity in the fronto-parietal network indicates numerical inductive reasoning beyond calculation: An fMRI study combined with a cognitive model.	2016	15	Scientific Reports
30	Neuroscientific insights into the development of analogical reasoning	2018	138	Developmental Science
31	Decoding rule search domain in the left inferior frontal gyrus.	2018	13	PLOS series
32	The neural bases of argumentative reasoning	2020	52	Brain and Language

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Publications

Research Interests

脳情報学、ウェブインテリジェンス、脳ビッグデータコンピューティング、

汎用知能、認知神経科学、橋渡し研究

(Brain Informatics, Web Intelligence, Brain Computing, General Intelligence,

Cognitive Neuroscience, and Translational Research)

The Title of the Ph.D. Thesis

「データブレインドリブン汎用知能モデル及び知能健康への応用」

(Data-Brain Driven General Intelligence Model with Smart Health Applications)

Publications in the Ph.D. Program

Scientific International Journals

1. **Hongzhi Kuai**, Ning Zhong, Jianhui Chen, Yang Yang, Xiaofei Zhang, Peipeng Liang, Kazuyuki Imamura, Lianfang Ma and Haiyuan Wang, Multi-Source Brain Computing with Systematic Fusion for Smart Health, Information Fusion, an International Journal, 75: 150–167, 2021. Elsevier, ISSN: 1566–2535
2. **Hongzhi Kuai** and Ning Zhong, The Extensible Data-Brain Model: Architecture, Applications and Directions, Journal of Computational Science 101103, 2020. Elsevier, ISSN: 1877–7503
3. **Hongzhi Kuai***, Xiaofei Zhang*, Yang Yang*, Jianhui Chen, Bin Shi and Ning Zhong, THINKING-LOOP: The Semantic Vector Driven Closed-Loop Model for Brain Computing, IEEE Access, a Multidisciplinary, Open Access Journal of the IEEE, 8: 4273-4288, 2020. ISSN: 2169–3536 (* contributed equally to this work)

4. **Hongzhi Kuai***, Xiaohui Tao* and Ning Zhong, Web Intelligence Meets Brain Informatics: Towards the Future of Artificial Intelligence in the Connected World, World Wide Web: Internet and Web Information Systems (WWW), an International Journal, 2022. Springer, ISSN: 1573-1413 (* contributed equally to this work)

Proceedings of International Conferences

1. **Hongzhi Kuai**, Jianhui Chen, Xiaohui Tao, Kazuyuki Imamura, Peipeng Liang and Ning Zhong, Exploring the Brain Information Processing Mechanisms from Functional Connectivity to Translational Applications, The 14th International Conference on Brain Informatics (BI 2021), Lecture Notes in Artificial Intelligence, vol 12960. Springer
2. **Hongzhi Kuai**, Yang Yang, Jianhui Chen, Xiaofei Zhang, Jianzhuo Yan and Ning Zhong, Specificity Analysis of Picture-Induced Emotional EEG for Discrimination Between Schizophrenic and Control Participants, The 12th International Conference on Brain Informatics (BI 2019), Lecture Notes in Artificial Intelligence, vol 11976. Springer

Conference Presentations

Invited Talk

Hongzhi Kuai, Data-Brain Driven General Intelligence Model with Smart Health Applications. The 20th IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology, Workshop on Web Intelligence meets Brain Informatics, WImBI'21, Virtual, 2021.

Oral Presentations

Hongzhi Kuai, Exploring the Brain Information Processing Mechanisms from Functional Connectivity to Translational Applications. The 14th International Conference on Brain Informatics (BI2021), Virtual, 2021.

Hongzhi Kuai, Specificity Analysis of Picture-Induced Emotional EEG for Discrimination Between Schizophrenic and Control Participants, The 12th International Conference on Brain Informatics (BI2019), Hainan, China, 2019.

Other Publications

1. Jianzhuo Yan, **Hongzhi Kuai**, Jianhui Chen and Ning Zhong, Analyzing Emotional Oscillatory Brain Network for Valence and Arousal-Based Emotion Recognition Using EEG Data, International Journal of Information Technology & Decision Making, 18(4): 1359–1378, 2019. World Scientific Publishing, ISSN: 0219-6220 (IF: 2.22)
2. **Hongzhi Kuai**, Hongxia Xu and Jianzhuo Yan, Emotion Recognition from EEG Using Rhythm Synchronization Patterns with Joint Time-Frequency-Space Correlation, The 10th International Conference on Brain Informatics (BI 2017), Lecture Notes in Artificial Intelligence, vol 10654. Springer
3. **Hongzhi Kuai**, Jianzhuo Yan, Jianhui Chen, Yongchuan Yu, Haiyuan Wang and Ning Zhong, A Knowledge-Driven Approach for Personalized Literature Recommendation Based on Deep Semantic Discrimination, Proceedings of the IEEE/WIC/ACM International Conference on Web Intelligence (WI' 17), Leipzig, Germany, 1253–1259, 2017. ACM Press

Award

Best Student Paper Award in the 14th International Conference on Brain Informatics (BI2021), Online, 17-19 September 2021