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Web Intelligence meets Brain Informatics: Towards the future of artificial intelligence in the connected world

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Abstract
Understanding human intelligence, especially brain intelligence, is the cornerstone of reaching the ultimate AI. In this paper, we briefly review the historical interactions between AI and brain science, and look towards the future vision of AI in the connected world. In particular, we introduce two rapidly developing fields in Web Intelligence (WI, AI in the Connected World) and Brain Informatics (BI, the brain/mind-centric study and the application of brain-machine intelligence), and combine them to accelerate the arrival of a human–level AI society. Furthermore, combining these two fields by connecting AI and brain science with big data, creates a new vision from the systematic brain-machine intelligence research to new AI industry chain in the connected social-cyber-physical-thinking spaces.

Keywords Web Intelligence · Brain Informatics · Human-level AI · Brain computing · General intelligence model

1 Introduction

From its conception, artificial intelligence (AI) has experienced several key milestones, each of which had its own topics that inspired new development trends enriching scientific and technological progress. More specifically, the perception capability was focused

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in the early period. Subsequently, the inference-centric study led AI to developing the first-generation robotic and intelligent software. For instance, the structure learning and inductive learning systems were developed as the main viewpoint, at that time. In this period of knowledge, the expert system was studied as the mainstream. Meanwhile, neural networks also achieved a breakthrough, especially for multilayer perceptron and backpropagation. In the third period to now, machine learning and deep learning have become the mainstream, achieving remarkable gains in many fields such as pattern recognition, neural language processing and control [52, 83]. In this period, scientists focus on how to make machines own the higher-level learning capability, that is, human intelligence and the cognitive capability. In this context, many supercomputers, intelligent robots and online applications were developed in academia and industry, such as Deep Blue [76], the NAO humanoid robots [82] and Alpha Go[89]. When it comes to developing the intelligence techniques, brain decoding is widely regarded as its fundamental and essential roads. By understanding biological characteristics and brain information-processing mechanisms, the intelligence capability is developed, modeled, simulated and assigned into machines, empowering them to become more humane. It is a long history to develop the brain-inspired intelligence applications, especially from the bottom-up perspective. However, owing to the limit of decoding brain, its support for AI seems rather slow. In recent years, with the development of new technologies and methodologies, the brain intelligence study has become a hot topic again. We argue that this topic will keep leading trends of AI study. For this, the core issue is how to narrow the gap between brain science and artificial intelligence towards achieving the human-level AI society.

In this paper, we view the interaction of brain science and artificial intelligence in the big data era, as an opportunity to close the ultimate goal of human-level AI. More specifically, we propose a way of *Web Intelligence meets Brain Informatics* towards accelerating the progress of human-AI society, as shown in Figure 1. We look forward to having a general intelligence model with the joint power of brain intelligence and artificial intelligence. Here, we use the term "brain intelligence" in the widest possible sense, from human thinking to behaviors that reflect everything within intelligence. Meanwhile, the term "AI" is also used in the widest possible sense, including the works related to statistics, machine learning and AI research that aims to build intelligent machines [60]. For this, the intelligence mechanisms in the brain are studied by the Brain Informatics methodology to support the development of the intelligence technology. Conversely, the Web Intelligence technology is developed to promote brain intelligence research, empowering machines with intelligence capability. As a general intelligence model, it should systematically integrate these capabilities such as reasoning, learning, computing, planning, decision-making and creativity, as well as the capability to process interconnected big data in various scenarios. We argue that such an intelligence model within the thinking space can more easily interact with: (1) the social space, in which the model supports the human-human interaction; (2) the cyber space, in which the model supports the human-machine interaction; and (3) the physical space, in which the model supports the machine-machine interaction. Hence, it can perform action and response, meeting or exceeding the human capability, when meeting complex environmental stimuli and external requests.

In the rest of this paper, we first introduce the five core topics and relevant works in the Web Intelligence field. Second, we give a new perspective of Web Intelligence research from the viewpoint of Brain Informatics, in which we emphasize the bi-directional support between both Web Intelligence and Brain Informatics. Next, we provide a practical version towards meeting the targets of "Web Intelligence meets Brain Informatics", that is the Data-Brain driven general intelligence model as the engine of intelligence technology

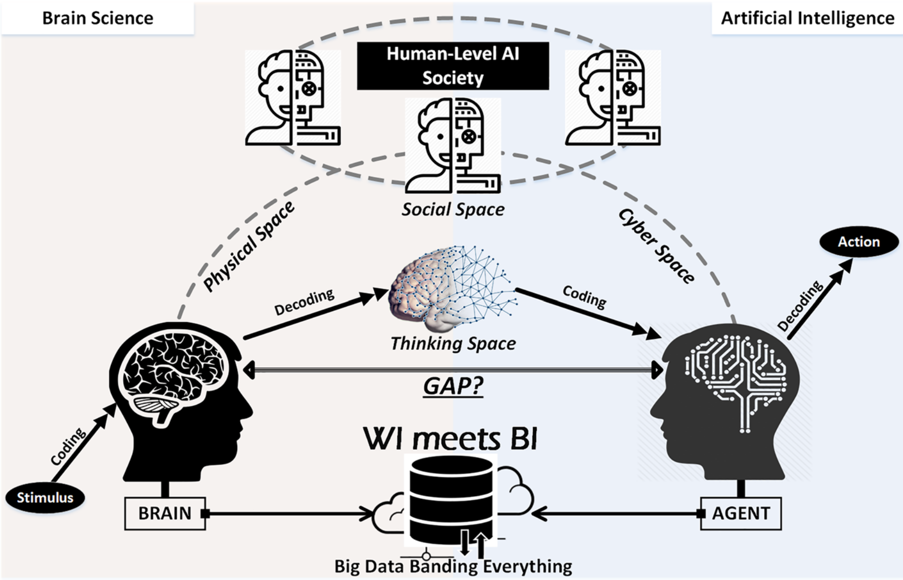

Fig. 1 The synergy of Web Intelligence (WI) and Brain Informatics (BI) in the social-cyber-physical-thinking spaces towards human-level AI society. Web Intelligence embraces various AI fields in the connected world, which can provide the advanced technology and methodology to promote the progress of brain investigation. Meanwhile, Brain Informatics contributes to the study of human information-processing mechanisms in the big data era, which can promote our systematic understanding of human intelligence surrounding the brain. By integrating Web Intelligence and Brain Informatics, the brain-inspired intelligence technology is developed and the wisdom service is provided to build human-level AI society

and the smart portal as the provider of wisdom services. Finally, we give our concluding remarks.

2 WI = AI in the connected world

Web Intelligence is now a cutting-edge research field exploring fundamental roles and practical impacts of artificial intelligence (AI) and advanced information technology (IT) on the Web, and the next generation of Web-empowered wisdom services [115]. The term "Web Intelligence" was first introduced in 2000 [116], and promoted in several papers and books during the early stages [68, 101, 114, 116]. Web Intelligence aims to achieve a multi-disciplinary balance among research advances in theories, methods and applications usually associated with collective intelligence, data science, human-centric computing, knowledge management and network sciences. Furthermore, Web Intelligence is considered an enhancement or extension of AI and IT, and focuses on answering the core question about how to study intelligence on the Web and intelligence for the Web. Currently, Web Intelligence research is not limited to Internet/Web but extends to any network patterns, and especially highlights the power of both connection and intelligence in the social-cyber-physical-thinking (SCPT) spaces of Internet of Everything. With an eye on the future, Web Intelligence begins a new chapter around the theme of

"Web Intelligence = AI in the Connected World".

The core of this theme is to both deepen the understanding of computational, logical, cognitive, physical and social foundations of the future human-level AI society, and enable the development and application of intelligent technologies. More specifically, these five 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.

Over the past twenty years, there are many results have been published to enrich the theme of Web Intelligence and advance the possibilities. Here, we review various endeavors that study Web Intelligence and potential applications from these five topics: Web of People, the Web of Data, the Web of Things, the Web of Trust and the Web of Agents, with each encompassing several subtopics.

- Web of People: This topic focuses on the people-oriented research in the connected world, in which humans (as individuals and in societies) are understood and human-oriented services are provided. Related subtopics include human-centric computing [37, 43], user behavior modeling techniques [47], crowdsourcing [24, 99], information diffusion [35, 63], knowledge community support [30], recommendation engines [103], social network analysis [10, 13], social media [53], social groups [26, 87], social network dynamics [9], sentiment analysis [32] and opinion mining [7], and so forth.
- Web of Data: This topic focuses on the methods, techniques and standards related to storage, management, queries, processing, mining, computing, analysis, visualization and application, as well as other issues concerning data in the connected world. Related subtopics includes graph database [1], information search and retrieval [92], knowledge graph and semantic networks [11, 44], linked data management and analytics [71], data integration and provenance [38, 50, 94], big data analytics [46, 95], machine learning and data science [21, 45], graph theory and analytics [59], as well as data-driven services and applications [36, 70], and so forth.
- Web of Things: This topic focuses on the interactions between the Web and physical objects to realize the organic amalgamation and harmonious symbiosis among humans, computers and things in the connected world. Related subtopics include Internet of Things (IoT) [4], sensor networks [104], distributed systems and devices [91], web infrastructures and devices [100], industrial multi-domain web [90], location and time awareness [62], transparent computing [86], mobile edge computing [75], fog computing [74], cloud computing [2], ubiquitous computing [34], and so forth. Furthermore, in order to realize a goal of making “network” wisdom, an emerging direction, namely Wisdom Web of Things, has gained increased attention in recent years to develop techniques and applications around a cycle of “from things to data, information, knowledge, wisdom, services, humans, and then back to things” [118–120].
- Web of Trust: This topic focuses on methods, techniques, applications and services related to the assessment, prediction, management, computation and analysis of trust, as well as other issues concerning trust in the connect world. Related subtopics include web cryptography [22], web safety and openness [8], blockchain analytics and technologies [106], fake content and fraud detection [93], hidden web analytics [64], monetization services and applications [31], and so forth.
- Web of Agents: This topic focuses on the development of virtual and physical entities in the connected world, where an entity can perform perceiving, reasoning, adapting, learning, cooperating and delegating in a dynamic environment. Related subtopics include behavior modeling in agent [72], behavioral interactions [20], knowledge information agents [6, 85], autonomous agents [67], self-driving vehicles [5], self-adaptive

evolutionary systems [73], self-organizing systems [23], trust models for agents [81, 102], virtual services [78], multi-agent systems [69], agent networks [39], and so forth.

To accelerate AI in the connected world, brain science plays a vital role in developing intelligent technologies with the thinking-power and perception abilities. It provides a window to explore biological intelligence in the human brain, and at the same time, provides a rich source of inspiration for and validation of AI techniques. Although the interactions between AI and brain science have a long history, there are still major challenges that provide a smooth transition from the brain intelligence studies to the intelligence technology applications. Brain Informatics is a cutting-edge field that focuses on the full-scale human brain study by cooperatively using experimental, computational, cognitive neuroscience and advanced Web Intelligence centric information technology [108]. More specifically, it provides a unique framework to address human brain related issues from the computational, cognitive, physiological, biological, physical, ecological, social and informatics perspectives, as well as its applications in brain-machine intelligence, brain-inspired intelligent systems, mental health and brain disorders, etc. We argue that the human-level AI society may be achieved by the "Web Intelligence meets Brin Informatics" research [55–57, 109].

3 WI meets BI: Trends and challenges

3.1 WI meets BI

We provided a brief overview of the five topics about Web Intelligence and some potential research directions in the last section. Although the development of Web Intelligence-centric research has surpassed expectations, the road ahead remains very long in building a truly human-level AI society. We believe that the urgent need is to understand the nature of intelligence or the source of thinking to develop general intelligence models, rather than merely developing next-generation AI technology towards the application of a specific scenario. The brain investigation, as a source of inspiration for Web Intelligence research, plays a vital role in this process. With this background information, Brain Informatics is proposed to study the human brain from the viewpoint of informatics (i.e., human brain is an information processing system) and uses informatics (i.e., Web Intelligence-centric information technology) to support brain science study [117]. Meanwhile, Brain Informatics-centric research results are committed to driving continued progress in the Web Intelligence field. Here, we first discuss the bi-directional support between Web Intelligence and Brain Informatics (i.e., "WI for BI" and "BI for WI"), and then give the future vision of AI in the connected world from the "Web Intelligence meets Brain Informatics" perspective.

- WI for BI: The WI-centric technologies (e.g., AI, big data, computational science, the wisdom Web, Wisdom Web of Things, and information and communication technology) provide a powerful platform for brain science, which have penetrated into all aspects of brain investigations, including collection, storage, archives, curation, management, sharing, analysis and visualization. For instance, big data, cloud computing and high performance computing approaches have improved our ability to respond to large-scale brain data [12, 15, 48, 66]. The computational approaches are used to investigate the human representational spaces [17], such as machine learning [61] and deep learning [42]. New equipment and techniques give us opportunities to investigate brain structure, function and dynamics from the fusion perspectives of multi-modal (e.g., functional magnetic resonance imaging, positron emission tomography, deep brain stimulation, transcranial direct/alternate current stimulation, transcranial magnetic stimulation and optogenetics) and multiple macro-meso-micro scales (e.g., molecular, cellular, circuit/pathway, brain regions, systems, cognitive/behavioral and social scales) [105]. The brain cloud/ machine interface technologies are designed to enable the real-time interactions among the brains, machines and things in the social-cyber-physical spaces [77, 98]. The brain investigations related tools and software are already in broad use, such as TeraVR [97]. In particular, the community-driven tools and platforms provide support to meet requirements of big open brain science in a collaborative era [14]. By using the WI technologies, some multi-database mining grid architecture based agents on the wisdom Web were proposed to build a brain informatics portal [107, 112, 113].

- BI for WI: New understanding and discovery of the intelligence and behavior related brain science (e.g., cognitive science, neuroscience, and BI), at the same time, accelerate the development of WI research towards a more intelligent view. One path that was taken is to attempt to closely mimic or directly reverse engineer the brain from the bottom-up perspective, such as the blue brain project [76] and neuromorphic computing [27]. Further, neural computation is investigated to construct artificial neural network or deep learning methods [58]. Apart from constructing the deep nets, the reward mechanism is considered to stimulate the emergence of reinforcement learning [19]. AI research has also drawn inspiration from various brain function mechanisms, such as attention [79], memory [40, 89] and continual learning [49], by integrating these mechanisms into algorithms or architectures at the system level. In addition, the neural mechanisms of the brain function provide access to build intelligent machines in silico [28]. These paradigms such as semantic and cognitive computing shape human experience into machines to provide the personalized data processing capability [88]. The cognitive theory is studied by Brain Informatics to push forward general artificial intelligence [51, 65]. The behaviors from working brains are taken as a guide for machine learning algorithms to leverage the benefits of both human and machine within a human-in-the-loop [33, 41]. Brain investigations also help us realize the validation of AI theories and techniques, and improve the explainability of AI methods [3, 96].

3.2 Connected challenges

As described previously, there are many theoretical foundations and practical demands to promote communication and collaboration between WI and BI. On the one hand, WI research makes requests to understand intelligence in depth and develop intelligent systems that integrate all the human-level capabilities [110]. The WI centric technologies can help us meet various demands intelligently in such a social-cyber-physical space. On the other hand, BI investigates the essential functions of the brain and their mechanisms underlying the human information processing system, ranging from perception to thinking, which provides the support in such a thinking space [111]. Combining these two fields opens a new perspective to construct such SCPT spaces, and hence realizes the harmonious symbiosis of humans, computers and things within different dimensional networks. More specifically, it is a trend to integrate brain big data and human behavior big data with the extensible representation to model all human communications and activities, in which big data are used as a bridge to connect various aspects of humans, computers and things. For this, the study of "WI meets BI" raises important conceptual and theoretical problems, including:

- How do we understand brain from neural microcircuits to macroscale intelligence systems, supported by connecting network and brain with big data?
- How do we realize human-level collective intelligence as a big data sharing mind by developing brain inspired intelligent technologies?
- How do we drive never-ending learning and generalize knowledge to provide multi-dimensional wisdom services in the connected world?

4 WI and BI: Putting it all together

More and more investigators have paid attention to the connected power of WI and BI, and made efforts to contribute to this research direction. Here, we propose the Data-Brain driven general intelligence model to implement representative case studies [56]. We emphasize the advantages of integrating brain science and informatics technology: combining the research results of the brain mechanisms with systematically collected brain big data related to the human thinking and perception activities; make full use of the advantage of WI to develop brain big data-based wisdom service platforms and applications; and formalize an innovative ecological chain from the brain intelligence research to the application of the brain-inspired intelligence technology.

4.1 Data-Brain oriented research

Data-Brain is a general intelligence model designed by the hierarchical knowledge (K)–information (I)–data (D) architecture (that is KID architecture) [55–57, 112], which realizes the brain-centric big data processing, analyzing and computing. More specifically, the knowledge layer corresponding to the conceptual Data-Brain includes multiple knowledge graphs to represent the systematic brain investigation process related to function domains, experimental design, data details and analysis methods; the information layer corresponding to the data and analysis provenances bridges across the knowledge and data layers, in which the properties of inner (such as brain information processing mechanisms) and outer (such as environmental stimuli) brain are organized systematically; and the data layer covers the multi-type data such as raw data, processed data and results of study from local and global sources. As a novel brain computing platform, the Data-Brain driven general intelligence model has some representative characteristics, which are summarized as follows:

- Systematic methodology. The general intelligence model follows the top-down priority principle aligned with the systematic Brain Informatics methodology, including: systematic investigations of complex brain science problems, systematic design of cognitive experiments, systematic brain data collection and management, and systematic brain data analysis and simulation. It models a whole process of systematically investigating human intelligence, towards a holistic view at a long-term and a global vision to understand the principles and mechanisms of the human information processing system, including, but not limited to, human reasoning, computation, attention, emotion, language, multiperception, memory, heuristic search, planning, decision making, problem solving, learning, discovery and creativity, etc.

- Big data approaches. The general intelligence model integrates big data related to all major aspects and capabilities of human information processing mechanism from local and global sources by means of modern informatics such as knowledge graph technique, towards systematic analytics, curation, management and provenance of brain and health big data. On this basis, the evidence combination and fusion computing-based data processing pipeline is developed to realize modeling and computing of the multimodal and multi-scale brain big data for brain–centric understanding and translational applications.
- Never-ending learning. The never-ending learning in the general intelligence model is to learn multiple sources of data, information and knowledge cumulatively, the continuously over long spans of time, and to provide greater explanation, new findings and innovative services over time. It integrates the reasoning capability within the thinking space and the human intervention mechanism into such a human-in-the-loop learning paradigm, together with some autonomous modes such as self-supervision, self-evaluation and self-reflection. The never-ending learning drives the continuous iteration and evolution of the model to meet increased service requirements.
- Generalizability and transferability. The root node of the general intelligence model processes the commonsense knowledge about facts and truths gained through big data mining, at the same time, integrates the brain-inspired generalized mechanisms into problem-solving solutions, which are applicable to smaller areas and personalized scenarios. Furthermore, the general intelligence model builds the capabilities of context-aware and transfer learning to jointly address diverse issues in ever-dynamic real-world scenarios, such as the transformation of research findings between healthy and abnormal brains.

By integrating brain big data as the extensional representation of the human information processing system, the 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 [56].

4.2 Brain-inspired wisdom service

The interconnections of humans, machines and things in the SCPT spaces form a super network, in which the voluminous contents of big data are continuously generated to enrich and enhance the world. How we maximize the potential of the network and realize the harmonious symbiosis of everything is a critical issue. Investigators have recognized the importance of collective wisdom, enhancing the global effectiveness of the information technology and high-performance computing. Here, the "wisdom" means that the machine can be aware of the real intent of each request (such as the system-oriented request and content-oriented request from itself or other objects in the social-cyber-physical spaces) to provide the right service for the right object at the right time and context. In this context, the machine needs not only the revolutionizing of information processing technology and methodology, that is wisdom-oriented information processing, but also the dynamic reconstruction of its component and content to improve the general capability. For this, the Data-Brain driven general intelligence model is proposed to encourage the integration of multiple applications, the transfer learning among various domains, the translational study for smart health, and so on. More specifically, the general intelligence model-centric wisdom service ecosystem is given, in which various applications are integrated into a smart portal to process multi-dimensional demands at various abstract levels, as shown in Figure 2.

The details of wisdom services and smart portals are described as follows:

- The multi-layered wisdom services are inspired by the Data-Brain driven general intelligence model, as shown in the left part of Figure 2. The wisdom service follows the hierarchical architecture surrounding data, information, knowledge, thinking and robot, relying on sequential and parallel operations. More specifically, the multi-layered wisdom services [56] includes Robot as a Service (RaaS), Thinking as a Service (TaaS), Knowledge as a Service (KaaS), Information as a Service (IaaS) and Data as a Service (DaaS):

– Robot as a Service trains various agents in the form of both physical and virtual environments, enhancing customized service and user experiences through the interactive interface of bridging inter and outer agents;

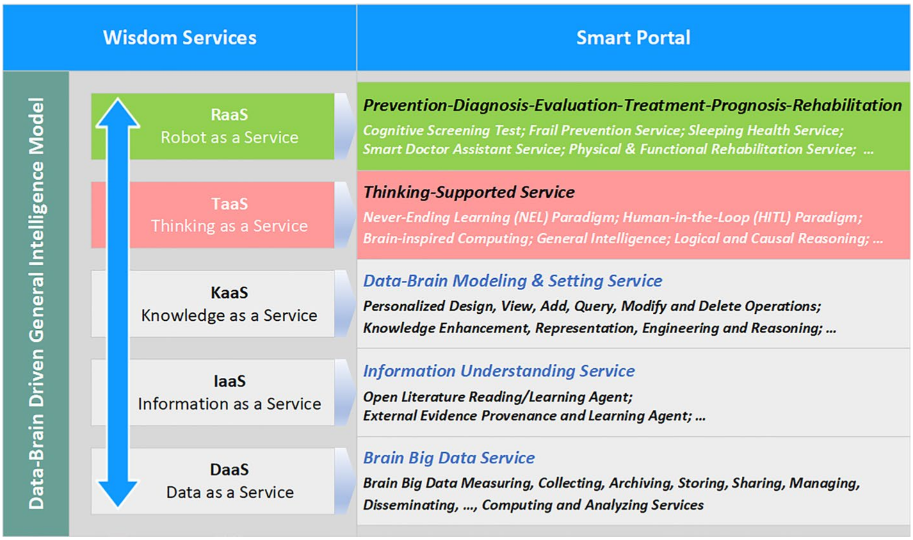

Fig. 2 The general intelligence model-centric wisdom service ecosystem. In the left part of the figure, the wisdom service-generated chain of "data-information-knowledge-thinking-robot-thinking-knowledge-information-data" derives from the hierarchical architecture, including Robot as a Service (RaaS), Thinking as a Service (TaaS), Knowledge as a Service (KaaS), Information as a Service (IaaS) and Data as a Service (DaaS). In the centralized mode, the model is required to achieve the broader objective of supporting the resource learning and the service scheduling. In the decentralized mode, the model is configurable to serve a personalized requirement from users, which contributes to the ability to work and learn collabratively in networks as well as independently. For example, in the right part of the figure, the applications could be developed separately at different layers for a specific scenario. Meanwhile, these potential applications in different scenarios could be integrated to strengthen the full system-wide response for a common development vision

- Thinking as a Service models human intelligence-related activities such as the creative and logical function, making correct judgments from the stimuli, performing reasoning in agents, and developing the rational response;
- Knowledge as a Service processes facts/principles spanning different domains, in which the connectivity is taken as the basic and core mode, simulating commonsense to improve the problem-solving ability surrounding transfer and generalization;
- Information as a Service extracts properties, parameters and features from data entity to give the finer interpretation, at the same time, providing provenance of the data object for meeting requirements of the systematic computing;
- Data as a Service produces flexible data models, data schemes and data clusters, supporting systematic data management, organization, linkage, integration, computing, dissemination, and visualization.

On that basis, these services can offer sequential operations, driving the wisdom generated chain from bottom to top and the wisdom application chain from top to down. Meanwhile, the parallel operations increase independence between different service levels, enabling it to scale up its flexibility and personalization.

- The broader applications from the multi-domain smart portal are interpreted in the right part of Figure 2. Under the wisdom service architecture, various applications within the smart portal can be reconstructed to create more integrated services, such as translational research for the 'P4 (Personalized, Predictive, Preventive and Participatory approaches)' medicine. For example, studies show that depression not only causes emotional and physical symptoms, but also occupational and functional disability (such as memory, thinking and cognition), which has become a common illness worldwide [80]. In response to this, the multi-aspect services are provided by developing applications throughout the whole process of prevention, diagnosis, evaluation, treatment, prognosis and rehabilitation. More specifically, the RaaS layer provides interfaces, such as the cognitive screening test and the frail prevention service, which are applied to measure the physical and mental state at an early stage. The smart doctor assistant service is applied to participate in decision-making in the middle stage. Moreover, the physical and functional rehabilitation services produce planning and provide support at the later stage. Such the interface-based interactive services receive the support from other layers simultaneously. In the TaaS layer, the smart portal produces methods, strategies and solutions for meeting the multi-aspect analytical requirements such as depression, advancing systematic brain computing-centric never-ending learning of knowledge, information and data. In the KaaS layer, the multi-domain knowledge is organized into the interconnected graph, together with various computing operations, enhancing public awareness and the development of knowledge-driven methods. In the IaaS layer, the information is read and learned from the internal and external evidence, especially from the open literature. Meanwhile, it also provides the provenance service to help track entities and assist computing in the complex environment. In the DaaS layer, the brain big data from the local and global sources is managed to meet various requirements such as data sharing and data computing, at the same time, enhancing the development of data-driven methods.

The smart portal relies on large-scale converging of the intelligent information technology to meet the seven factors of the infrastructure, platform, software (developing and scheduling abilities), data, information, knowledge and wisdom. More specifically, some areas have received special attention, such as artificial general intelligence, the end-edge-cloud orchestrated network paradigms with high-performance computing, the network and information communication technology, and the organization and management of big data using knowledge graph and graph database techniques, and so forth.

4.3 Systematic brain computing

Systematic brain computing inspires us to investigate the brain from multiple dimensions, such as the basic neuroscience study with brain-inspired multi-aspect applications. One of its representatives is brain-related translational research. In this context, the Data-Brain driven general intelligence model [56, 57], as core of the smart portal, is a wisdom provider in the thinking space to realize wisdom-oriented information processing, such as human-in-the-loop and never-ending learning. Considering the importance of advancing translational research, the systematic brain computing and its case study are further interpreted, as shown in Figure 3.

From Figure 3A, people interacts with the conceptual Data-Brain to set the goal-related factors and parameters [56], during the human-in-the-loop and never-ending learning processes. Such a goal could be an exploratory study that explores the possible brain patterns of a specific cognitive function. Based on these pre-defined factors, the general intelligence model integrates the experience/facts from the knowledge layer, the contextual information from the information layer, and the samples from the data layer, depending on the KID architecture. Activated model carries out the systematic brain computing [57], including systematic experimental plan, evidential type inference, evidential weight evaluation, together with evidence combination and fusion computing. In the training stage, the model receives the planned samples continuously to learn the significant patterns from the brain, using various methods. Then, these learned patterns and models enable the trial of further scenarios.

Initial tests were implemented to explore the brain network patterns related to human reasoning, using the task-state and resting-state fMRI data from the sample library [54, 57]. The intent is to select the brain activity pattern with specificity for a cognitive function of interest. For this, the τ values can be measured using our previously proposed approach [54, 57], which is the evaluation indicator of the brain functional characteristics by fusing multiple task-related functional neuroimaging data during never-ending learning. In this process, various datasets are integrated and computed throughout a task sequence, which are planned by the general intelligence model. Correspondingly, the higher τ values could be used to evaluate specificity of the brain activity patterns for a specific cognitive function, while the lower τ values could be used to evaluate robustness of the brain activity patterns for multiple cognitive functions. Figure 3B shows a recommended plan of experimental samples with priority from highest to lowest ranking. For each sample, the connectome-wide networks for different tasks were constructed by measuring the partial coefficients between various nodes defined in the CC400 atlas [18]. Then, the network centrality coefficient [121] was calculated at sparsity from 0.01 to 0.5, followed by the nodal significance was evaluated by using a one-way analysis of variance (ANOVA) model with the experimental condition as random factors. The significant nodes were counted in each contrast and their weights were nominalized to give τ values. These computed τ values based on the single sample will be fused continuously, throughout the never-ending learning process. Furthermore, the nodes selected by the size of the τ values can be connected to various brain network patterns.

Figure 3C shows three types of brain network patterns constructed by different nodal sets, including the specific brain network where it has the first 30 nodes with the highest τ values,

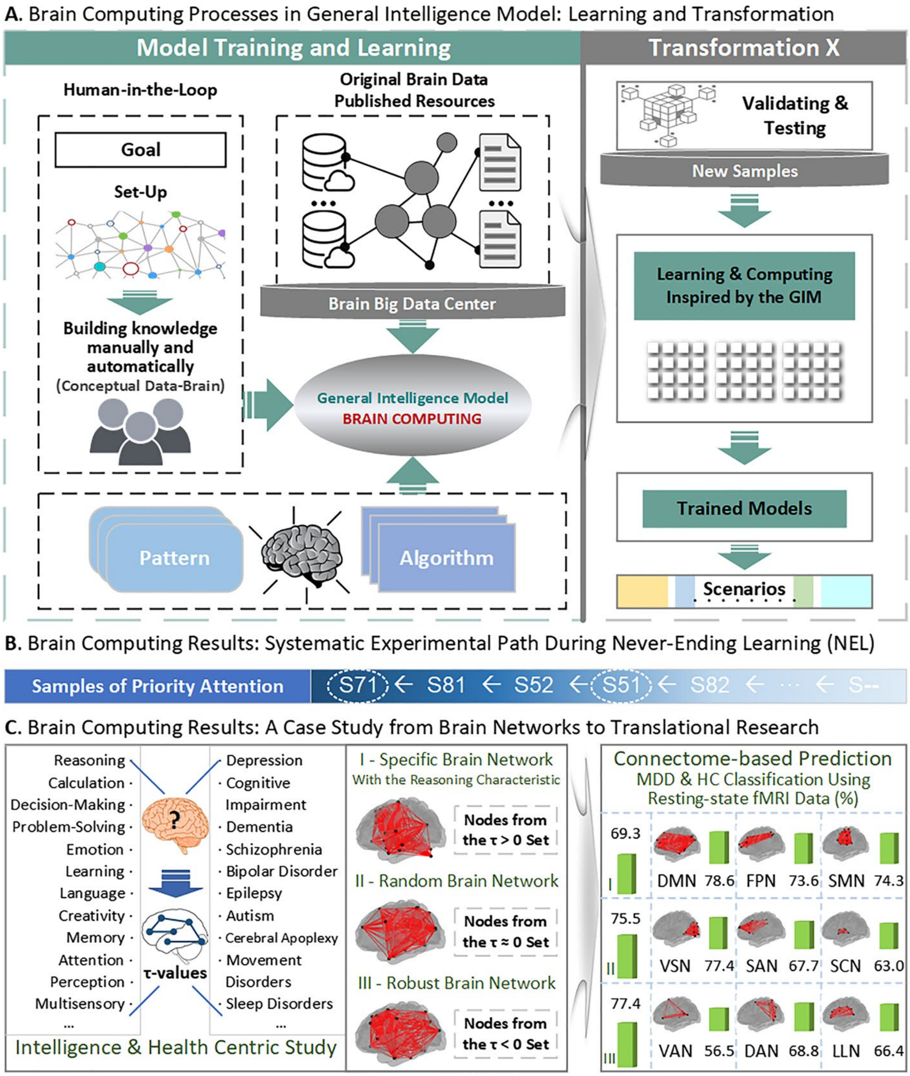

Fig. 3 The Data-Brain driven general intelligence model for systematic brain computing. **A.** The model is trained to contribute to various scenarios, together with human-in-the-loop and never-ending learning. **B.** The experimental plan recommended by the model is given to integrate brain data systematically. **C.** The τ values are computed to interpret the characteristics of brain patterns and their extended applications in translational research. GIM: Data-Brain driven general intelligence model; MDD: Major Depressive Disorder; HC: Healthy Control; the nine functional subnetworks, including the default mode network (DMN), the fronto-parietal network (FPN) and the sensorimotor network (SMN) from the Dosenbach-160 atlas [25], the visual network (VSN), the salience network (SAN), the subcortical network (SCN), the ventral attention (VAN) and the dorsal attention networks (DAN) from the Power-264 atlas [84], and the limbic-lode network (LLN) from the brainnetome atlas [29]

the random brain network where it is taken as the control with the 30 random nodes of $\tau = 0$, the robust brain network where it has the last 30 nodes with the lowest τ values, respectively. According to various strict levels, the size of nodal sets is adjustable. On the basis of these network patterns, the features are extracted and entered in the predictive model, aiming at the scenario of translational research. In this case, the features extracted by the three selected brain networks and other nine functional subnetworks were used to classify the samples with major depressive disorders and healthy controls, using the resting-state fMRI data and the XGBoost algorithm [16]. The nine functional subnetworks include the default mode network (DMN), the fronto-parietal network (FPN) and the sensorimotor network (SMN) from the Dosenbach-160 atlas [25], the visual network (VSN), the salience network (SAN), the subcortical network (SCN), the ventral attention (VAN) and the dorsal attention networks (DAN) from the Power-264 atlas [84], and the limbic-lode network (LLN) from the brainnetome atlas [29]. It was found that the specific brain network shares the similar recognizing scale with SAN, SCN, VAN, DAN and LLN, while the robust brain network shares the similar recognizing scale with DMN, FPN, SMN and VAN. Additionally, the accuracy based on the robust brain network is higher than that of the specific brain network with the reasoning characteristic. It is an intriguing attempt to inspire us to enhance our efforts in the relational analysis among the complex brain, higher-order cognition and diseases. Details on data processing and network construction were described previously [54, 57].

In this study, the Data-Brain driven general intelligence model was introduced by exploring the different types of brain network patterns and their possible extended applications in the field of translational research. From results, three types of brain network patterns are obtained to interpret specificity, randomness and robustness, respectively. In the stage of translational research, these brain network patterns are used to detect the potential functional abnormality from the MDD groups. By comparing the classification results as shown in the right of Figure 3C, it was found that the accuracy corresponding to the specific brain network is relatively smaller than that of the robust brain network, which inspires us to rethink the broader cognitive difference between the MDD and HC groups, in addition to reasoning. In the future, it will be important to extend the study of more cognitive functions and functional disorders in the brain, enhancing their global interpretation on brain intelligence, brain health and their complex interactions.

5 Concluding remarks

Having undergone twenty years of development from 2000 to now, Web Intelligence has grown into one of the most popular research fields. As an enhancement or an extension of AI and IT, its initial goal was to develop wisdom Web centric products, systems, services and applications to meet the requirements of the rise of knowledge economies. For the next twenty years, Web Intelligence will be on an ever-greater role in the connected world towards the organic amalgamation and harmonious symbiosis among humans, computers and things. In this paper, we have presented the systematic review of Web Intelligence-related topics with respect to people, data, things, trust and agents, respectively. Furthermore, the role of “brain intelligence” and “intelligence technology” is discussed to promote the development of Web Intelligence, specifically from the viewpoint of “Web Intelligence meets Brain Informatics”. Finally, we highlight two representative directions that are Data-Brain oriented research and brain-inspired wisdom service to accelerate the practice of Web Intelligence and Brain Informatics. More and more investigators will contribute their knowledge and experience in areas concerning the new paradigm of “Web Intelligence meets Brain Informatics”, which will produce new efficiencies and provide a strong catalyst towards achieving the ultimate goal of a human-level AI society.

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Declarations

Conflicts of interest The authors declare that they have no conflict of interest.

References

1. Angles, R., Gutierrez, C.: Survey of graph database models. ACM Computing Surveys (CSUR) **40**(1), 1–39 (2008)
2. Armbrust, M., Fox, A., Griffith, R., Joseph, A.D., Katz, R., Konwinski, A., Lee, G., Patterson, D., Rabkin, A., Stoica, I., Zaharia, M.: A view of cloud computing. Communications of the ACM **53**(4), 50–58 (2010)
3. Arrieta, A.B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., García, S., Gil-López, S., Molina, D., Benjamins, R., et al.: Explainable artificial intelligence (xai): Concepts, taxonomies, opportunities and challenges toward responsible ai. Information Fusion **58**, 82–115 (2020)
4. Atzori, L., Iera, A., Morabito, G.: The internet of things: A survey. Computer Networks **54**(15), 2787–2805 (2010)
5. Badue, C., Guidolini, R., Carneiro, R.V., Azevedo, P., Cardoso, V.B., Forechi, A., Jesus, L., Berriel, R., Paixao, T.M., Mutz, F., et al.: Self-driving cars: A survey. Expert Systems with Applications **165**, 113816 (2021)
6. Bailin, S.C., Truszkowski, W.: Ontology negotiation between intelligent information agents. The Knowledge Engineering Review **17**(1), 7–19 (2002)
7. Balazs, J.A., Velásquez, J.D.: Opinion mining and information fusion: a survey. Information Fusion **27**, 95–110 (2016)
8. Bannister, F., Connolly, R.: The trouble with transparency: A critical review of openness in e-government. Policy & Internet **3**(1), 1–30 (2011)
9. Becker, J., Brackbill, D., Centola, D.: Network dynamics of social influence in the wisdom of crowds. Proceedings of the National Academy of Sciences **114**(26), E5070–E5076 (2017)
10. Borgatti, S.P., Mehra, A., Brass, D.J., Labianca, G.: Network analysis in the social sciences. Science **323**(5916), 892–895 (2009)
11. Borge-Holthoefer, J., Arenas, A.: Semantic networks: Structure and dynamics. Entropy **12**(5), 1264–1302 (2010)
12. Boubela, R.N., Kalcher, K., Huf, W., Našel, C., Moser, E.: Big data approaches for the analysis of large-scale fmri data using apache spark and gpu processing: a demonstration on resting-state fmri data from the human connectome project. Frontiers in Neuroscience **9**, 492 (2016)
13. Camacho, D., Panizo-LLedot, A., Bello-Orgaz, G., Gonzalez-Pardo, A., Cambria, E.: The four dimensions of social network analysis: An overview of research methods, applications, and software tools. Information Fusion **63**, 88–120 (2020)
14. Charles, A.S., Falk, B., Turner, N., Pereira, T.D., Tward, D., Pedigo, B.D., Chung, J., Burns, R., Ghosh, S.S., Kebschull, J.M., et al.: Toward community-driven big open brain science: Open big data and tools for structure, function, and genetics. Annual Review of Neuroscience **43**, 441–464 (2020)
15. Chen, S., He, Z., Han, X., He, X., Li, R., Zhu, H., Zhao, D., Dai, C., Zhang, Y., Lu, Z., et al.: How big data and high-performance computing drive brain science. Genomics, Proteomics & Bioinformatics **17**(4), 381–392 (2019)
16. Chen, T., Guestrin, C.: Xgboost: A scalable tree boosting system. In: Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining, pp. 785–794 (2016)

17. Cohen, J.D., Daw, N., Engelhardt, B., Hasson, U., Li, K., Niv, Y., Norman, K.A., Pillow, J., Ramadge, P.J., Turk-Browne, N.B., et al.: Computational approaches to fmri analysis. Nature Neuroscience **20**(3), 304–313 (2017)
18. Craddock, R.C., James, G.A., Holtzheimer, P.E., III., Hu, X.P., Mayberg, H.S.: A whole brain fmri atlas generated via spatially constrained spectral clustering. Human Brain Mapping **33**(8), 1914–1928 (2012)
19. Dabney, W., Kurth-Nelson, Z., Uchida, N., Starkweather, C.K., Hassabis, D., Munos, R., Botvinick, M.: A distributional code for value in dopamine-based reinforcement learning. Nature **577**(7792), 671–675 (2020)
20. De Caux, R., Smith, C., Kniveton, D., Black, R., Philippides, A.: Dynamic, small-world social network generation through local agent interactions. Complexity **19**(6), 44–53 (2014)
21. Dhar, V.: Data science and prediction. Communications of the ACM **56**(12), 64–73 (2013)
22. Ding, J., Petzoldt, A.: Current state of multivariate cryptography. IEEE Security Privacy **15**(4), 28–36 (2017)
23. do Nascimento, N.M., de Lucena, C.J.P.: Fiot: An agent-based framework for self-adaptive and self-organizing applications based on the internet of things. Information Sciences **378**, 161–176 (2017)
24. Doan, A., Ramakrishnan, R., Halevy, A.Y.: Crowdsourcing systems on the world-wide web. Communications of the ACM **54**(4), 86–96 (2011)
25. Dosenbach, N.U., Nardos, B., Cohen, A.L., Fair, D.A., Power, J.D., Church, J.A., Nelson, S.M., Wig, G.S., Vogel, A.C., Lessov-Schlaggar, C.N., et al.: Prediction of individual brain maturity using fmri. Science **329**(5997), 1358–1361 (2010)
26. Epstein, B.: What are social groups? their metaphysics and how to classify them. Synthese **196**(12), 4899–4932 (2019)
27. Esser, S.K., Merolla, P.A., Arthur, J.V., Cassidy, A.S., Appuswamy, R., Andreopoulos, A., Berg, D.J., McKinstry, J.L., Melano, T., Barch, D.R., et al.: Convolutional networks for fast, energy-efficient neuromorphic computing. Proceedings of the National Academy of Sciences **113**(41), 11441–11446 (2016)
28. Eth, D.: The technological landscape affecting artificial general intelligence and the importance of nanoscale neural probes. Informatica **41**(4) (2017)
29. Fan, L., Li, H., Zhuo, J., Zhang, Y., Wang, J., Chen, L., Yang, Z., Chu, C., Xie, S., Laird, A.R., et al.: The human brainnetome atlas: a new brain atlas based on connectional architecture. Cerebral Cortex **26**(8), 3508–3526 (2016)
30. Faraj, S., Jarvenpaa, S.L., Majchrzak, A.: Knowledge collaboration in online communities. Organization Science **22**(5), 1224–1239 (2011)
31. Faroukhi, A.Z., El Alaoui, I., Gahi, Y., Amine, A.: Big data monetization throughout big data value chain: a comprehensive review. Journal of Big Data **7**, 3 (2020)
32. Feldman, R.: Techniques and applications for sentiment analysis. Communications of the ACM **56**(4), 82–89 (2013)
33. Fong, R.C., Scheirer, W.J., Cox, D.D.: Using human brain activity to guide machine learning. Scientific Reports **8**(1), 1–10 (2018)
34. Friedewald, M., Raabe, O.: Ubiquitous computing: An overview of technology impacts. Telematics and Informatics **28**(2), 55–65 (2011)
35. Gao, C., Su, Z., Liu, J., Kurths, J.: Even central users do not always drive information diffusion. Communications of the ACM **62**(2), 61–67 (2019)
36. Gu, Z., Xu, B., Li, J.: Service data correlation modeling and its application in data-driven service composition. IEEE Transactions on Services Computing **3**(4), 279–291 (2010)
37. Guzdial, M.: Human-centered computing: a new degree for licklider's world. Communications of the ACM **56**(5), 32–34 (2013)
38. Herschel, M., Diestelkämper, R., Lahmar, H.B.: A survey on provenance: What for? what form? what from? The VLDB Journal **26**(6), 881–906 (2017)
39. Hlinka, O., Hlawatsch, F., Djuric, P.M.: Distributed particle filtering in agent networks: A survey, classification, and comparison. IEEE Signal Processing Magazine **30**(1), 61–81 (2013)
40. Hochreiter, S., Schmidhuber, J.: Long short-term memory. Neural Computation **9**(8), 1735–1780 (1997)
41. Holzinger, A.: Interactive machine learning for health informatics: when do we need the human-in-the-loop? Brain Informatics **3**(2), 119–131 (2016)
42. Iqbal, A., Khan, R., Karayannis, T.: Developing a brain atlas through deep learning. Nature Machine Intelligence **1**(6), 277–287 (2019)

43. Jaimes, A., Gatica-Perez, D., Sebe, N., Huang, T.S.: Guest editors' introduction: Human-centered computing-toward a human revolution. Computer **40**(5), 30–34 (2007)
44. Ji, S., Pan, S., Cambria, E., Marttinen, P., Yu, P.S.: A survey on knowledge graphs: Representation, acquisition, and applications. IEEE Transactions on Neural Networks and Learning Systems **33**(2), 494–514 (2022)
45. Jordan, M.I., Mitchell, T.M.: Machine learning: Trends, perspectives, and prospects. Science **349**(6245), 255–260 (2015)
46. Kambatla, K., Kollias, G., Kumar, V., Grama, A.: Trends in big data analytics. Journal of Parallel and Distributed Computing **74**(7), 2561–2573 (2014)
47. Kassak, O., Kompan, M., Bielikova, M.: Acquisition and modelling of short-term user behaviour on the web: A survey. Journal of Web Engineering **17**(5), 23–70 (2018)
48. Kiar, G., Gorgolewski, K.J., Kleissas, D., Roncal, W.G., Litt, B., Wandell, B., Poldrack, R.A., Wiener, M., Vogelstein, R.J., Burns, R., et al.: Science in the cloud (sic): A use case in mri connectomics. Giga Science **6**(5), gix013 (2017)
49. Kirkpatrick, J., Pascanu, R., Rabinowitz, N., Veness, J., Desjardins, G., Rusu, A.A., Milan, K., Quan, J., Ramalho, T., Grabska-Barwinska, A., et al.: Overcoming catastrophic forgetting in neural networks. Proceedings of the National Academy of Sciences **114**(13), 3521–3526 (2017)
50. Knoblock, C.A., Szekely, P.: Exploiting semantics for big data integration. Ai Magazine **36**(1), 25–38 (2015)
51. Kotseruba, I., Tsotsos, J.K.: 40 years of cognitive architectures: core cognitive abilities and practical applications. Artificial Intelligence Review **53**(1), 17–94 (2020)
52. Kotsiantis, S.B., Zaharakis, I.D., Pintelas, P.E.: Machine learning: a review of classification and combining techniques. Artificial Intelligence Review **26**(3), 159–190 (2006)
53. Koukaras, P., Tjortjis, C., Rousidis, D.: Social media types: introducing a data driven taxonomy. Computing **102**(1), 295–340 (2020)
54. Kuai, H., Chen, J., Tao, X., Imamura, K., Liang, P., Zhong, N.: Exploring the brain information processing mechanisms from functional connectivity to translational applications. In: International Conference on Brain Informatics, pp. 99–111. Springer (2021)
55. Kuai, H., Zhang, X., Yang, Y., Chen, J., Shi, B., Zhong, N.: Thinking-loop: The semantic vector driven closed-loop model for brain computing. IEEE Access **8**, 4273–4288 (2020)
56. Kuai, H., Zhong, N.: The extensible data-brain model: Architecture, applications and directions. Journal of Computational Science, 101103 (2020)
57. Kuai, H., Zhong, N., Chen, J., Yang, Y., Zhang, X., Liang, P., Imamura, K., Ma, L., Wang, H.: Multi-source brain computing with systematic fusion for smart health. Information Fusion **75**, 150–167 (2021)
58. LeCun, Y., Bengio, Y., Hinton, G.: Deep learning. Nature **521**(7553), 436–444 (2015)
59. Lee, J., Han, W.S., Kasperovics, R., Lee, J.H.: An in-depth comparison of subgraph isomorphism algorithms in graph databases. Proceedings of the VLDB Endowment **6**(2), 133–144 (2012)
60. Legg, S., Hutter, M.: A collection of definitions of intelligence. In: Advances in Artificial General Intelligence: Concepts, Architectures and Algorithms, volume 157 of Frontiers in Artificial Intelligence and Applications, pp. 17–24. IOS Press (2007)
61. Lemm, S., Blankertz, B., Dickhaus, T., Müller, K.R.: Introduction to machine learning for brain imaging. Neuroimage **56**(2), 387–399 (2011)
62. Li, B., Li, S., Nallanathan, A., Zhao, C.: Deep sensing for future spectrum and location awareness 5g communications. IEEE Journal on Selected Areas in Communications **33**(7), 1331–1344 (2015)
63. Li, M., Wang, X., Gao, K., Zhang, S.: A survey on information diffusion in online social networks: Models and methods. Information **8**(4), 118 (2017)
64. Liakos, P., Ntoulas, A., Labrinidis, A., Delis, A.: Focused crawling for the hidden web. World Wide Web **19**, 605–631 (2016)
65. Lieto, A., Bhatt, M., Oltramari, A., Vernon, D.: The role of cognitive architectures in general artificial intelligence (2018)
66. Liu, F., Shi, Y., Li, P.: Analysis of the relation between artificial intelligence and the internet from the perspective of brain science. Procedia Computer Science **122**, 377–383 (2017)
67. Liu, J.: Autonomous agents and multi-agent systems. World Scientific (2001)
68. Liu, J.: Web intelligence (wi): What makes wisdom web? In: Proceedings of the 18th International Joint Conference on Artificial Intelligence, IJCAI'03, p. 1596-1601. Morgan Kaufmann Publishers Inc., San Francisco, CA, USA (2003)
69. Liu, J., Jing, H., Tang, Y.: Multi-agent oriented constraint satisfaction. Artificial Intelligence **136**(1), 101–144 (2002)

70. Liu, X., Ma, Y., Huang, G., Zhao, J., Mei, H., Liu, Y.: Data-driven composition for service-oriented situational web applications. IEEE Transactions on Services Computing **8**(1), 2–16 (2014)
71. Lnenicka, M., Komarkova, J.: Big and open linked data analytics ecosystem: Theoretical background and essential elements. Government Information Quarterly **36**(1), 129–144 (2019)
72. Macal, C.M.: Everything you need to know about agent-based modelling and simulation. Journal of Simulation **10**(2), 144–156 (2016)
73. Macías-Escrivá, F.D., Haber, R., del Toro, R., Hernandez, V.: Self-adaptive systems: A survey of current approaches, research challenges and applications. Expert Systems with Applications **40**(18), 7267–7279 (2013)
74. Mahmud, R., Kotagiri, R., Buyya, R.: Fog computing: A taxonomy, survey and future directions. In: Internet of everything, pp. 103–130. Springer (2018)
75. Mao, Y., You, C., Zhang, J., Huang, K., Letaief, K.B.: A survey on mobile edge computing: The communication perspective. IEEE Communications Surveys & Tutorials **19**(4), 2322–2358 (2017)
76. Markram, H.: The blue brain project. Nature Reviews Neuroscience **7**(2), 153–160 (2006)
77. Martins, N.R., Angelica, A., Chakravarthy, K., Svidinenko, Y., Boehm, F.J., Opris, I., Lebedev, M.A., Swan, M., Garan, S.A., Rosenfeld, J.V., et al.: Human brain/cloud interface. Frontiers in neuroscience **13**, 112 (2019)
78. McRorie, M., Sneddon, I., McKeown, G., Bevacqua, E., de Sevin, E., Pelachaud, C.: Evaluation of four designed virtual agent personalities. IEEE Transactions on Affective Computing **3**(3), 311–322 (2012)
79. Mnih, V., Heess, N., Graves, A., Kavukcuoglu, K.: Recurrent models of visual attention. In: Proceedings of the 27th International Conference on Neural Information Processing Systems - Volume 2, NIPS'14, p. 2204-2212. MIT Press, Cambridge, MA, USA (2014)
80. Pan, Z., Park, C., Brietzke, E., Zuckerman, H., Rong, C., Mansur, R.B., Fus, D., Subramaniapillai, M., Lee, Y., McIntyre, R.S.: Cognitive impairment in major depressive disorder. CNS Spectrums **24**(1), 22–29 (2019)
81. Pinyol, I., Sabater-Mir, J.: Computational trust and reputation models for open multi-agent systems: a review. Artificial Intelligence Review **40**, 1–25 (2013)
82. Pot, E., Monceaux, J., Gelin, R., Maisonnier, B.: Choregraphe: a graphical tool for humanoid robot programming. In: RO-MAN 2009-The 18th IEEE International Symposium on Robot and Human Interactive Communication, pp. 46–51. IEEE (2009)
83. Pouyanfar, S., Sadiq, S., Yan, Y., Tian, H., Tao, Y., Reyes, M.P., Shyu, M.L., Chen, S.C., Iyengar, S.S.: A survey on deep learning: Algorithms, techniques, and applications. ACM Computing Surveys (CSUR) **51**(5), 1–36 (2018)
84. Power, J.D., Cohen, A.L., Nelson, S.M., Wig, G.S., Barnes, K.A., Church, J.A., Vogel, A.C., Laumann, T.O., Miezin, F.M., Schlaggar, B.L., et al.: Functional network organization of the human brain. Neuron **72**(4), 665–678 (2011)
85. Precup, D.: Building knowledge for ai agents with reinforcement learning. In: Proceedings of the 18th International Conference on Autonomous Agents and MultiAgent Systems, AAMAS '19, p. 6. International Foundation for Autonomous Agents and Multiagent Systems, Richland, SC (2019)
86. Ren, J., Guo, H., Xu, C., Zhang, Y.: Serving at the edge: A scalable iot architecture based on transparent computing. IEEE Network **31**(5), 96–105 (2017)
87. Ritchie, K.: Social structures and the ontology of social groups. Philosophy and Phenomenological Research **100**(2), 402–424 (2020)
88. Sheth, A., Anantharam, P., Henson, C.: Semantic, cognitive, and perceptual computing: Paradigms that shape human experience. Computer **49**(3), 64–72 (2016)
89. Silver, D., Huang, A., Maddison, C.J., Guez, A., Sifre, L., Van Den Driessche, G., Schrittwieser, J., Antonoglou, I., Panneershelvam, V., Lanctot, M., et al.: Mastering the game of go with deep neural networks and tree search. Nature **529**(7587), 484–489 (2016)
90. Sisinni, E., Saifullah, A., Han, S., Jennehag, U., Gidlund, M.: Industrial internet of things: Challenges, opportunities, and directions. IEEE Transactions on Industrial Informatics **14**(11), 4724–4734 (2018)
91. van Steen, M., Tanenbaum, A.S.: A brief introduction to distributed systems. Computing **98**(10), 967–1009 (2016)
92. Stronge, A.J., Rogers, W.A., Fisk, A.D.: Web-based information search and retrieval: Effects of strategy use and age on search success. Human Factors **48**(3), 434–446 (2006)
93. Tolosana, R., Vera-Rodriguez, R., Fierrez, J., Morales, A., Ortega-Garcia, J.: Deepfakes and beyond: A survey of face manipulation and fake detection. Information Fusion **64**, 131–148 (2020)

94. Tomazela, B., Hara, C.S., Ciferri, R.R., de Aguiar Ciferri, C.D.: Empowering integration processes with data provenance. Data & Knowledge Engineering **86**, 102–123 (2013)
95. Tsai, C.W., Lai, C.F., Chao, H.C., Vasilakos, A.V.: Big data analytics: a survey. Journal of Big data **2**(1), 1–32 (2015)
96. Walker, E.Y., Cotton, R.J., Ma, W.J., Tolias, A.S.: A neural basis of probabilistic computation in visual cortex. Nature Neuroscience **23**(1), 122–129 (2020)
97. Wang, Y., Li, Q., Liu, L., Zhou, Z., Ruan, Z., Kong, L., Li, Y., Wang, Y., Zhong, N., Chai, R., et al.: Teravr empowers precise reconstruction of complete 3-d neuronal morphology in the whole brain. Nature Communications **10**(1), 1–9 (2019)
98. Willett, F.R., Avansino, D.T., Hochberg, L.R., Henderson, J.M., Shenoy, K.V.: High-performance brain-to-text communication via handwriting. Nature **593**(7858), 249–254 (2021)
99. Xintong, G., Hongzhi, W., Song, Y., Hong, G.: Brief survey of crowdsourcing for data mining. Expert Systems with Applications **41**(17), 7987–7994 (2014)
100. Yan, Y., Qian, Y., Sharif, H., Tipper, D.: A survey on smart grid communication infrastructures: Motivations, requirements and challenges. IEEE communications Surveys & Tutorials **15**(1), 5–20 (2012)
101. Yao, Y.Y., Zhong, N., Liu, J., Ohsuga, S.: Web intelligence (wi) research challenges and trends in the new information age. In: Zhong, N., Yao, Y., Liu, J., Ohsuga, S. (eds.) Web Intelligence: Research and Development, pp. 1–17. Springer, Berlin (2001)
102. Yu, H., Shen, Z., Leung, C., Miao, C., Lesser, V.R.: A survey of multi-agent trust management systems. IEEE Access **1**, 35–50 (2013)
103. Yuan, X., Lee, J.H., Kim, S.J., Kim, Y.H.: Toward a user-oriented recommendation system for real estate websites. Information Systems **38**(2), 231–243 (2013)
104. Yue, Y.G., He, P.: A comprehensive survey on the reliability of mobile wireless sensor networks: Taxonomy, challenges, and future directions. Information Fusion **44**, 188–204 (2018)
105. Zhang, Y.D., Dong, Z., Wang, S.H., Yu, X., Yao, X., Zhou, Q., Hu, H., Li, M., Jiménez-Mesa, C., Ramirez, J., et al.: Advances in multimodal data fusion in neuroimaging: Overview, challenges, and novel orientation. Information Fusion **64**, 149–187 (2020)
106. Zheng, Z., Xie, S., Dai, H.N., Chen, X., Wang, H.: Blockchain challenges and opportunities: A survey. International Journal of Web and Grid Services **14**(4), 352–375 (2018)
107. Zhong, N.: Developing intelligent portals by using wi technologies. In: Wavelet Analysis and Its Applications, and Active Media Technology: (In 2 Volumes), pp. 555–567. World Scientific (2004)
108. Zhong, N.: Web intelligence meets brain informatics: An impending revolution in wi and brain sciences. In: Szczepaniak, P.S., Kacprzyk, J., Niewiadomski, A. (eds.) Advances in Web Intelligence, pp. 23–25. Springer, Berlin (2005)
109. Zhong, N.: How to make "web intelligence (wi) meets brain informatics (bi)" successfully? In: 30th Annual International Computer Software and Applications Conference (COMPSAC'06), vol. 1, pp. 24–25 (2006)
110. Zhong, N.: Ways to develop human-level web intelligence: A brain informatics perspective. In: Franconi, E., Kifer, M., May, W. (eds.) The Semantic Web: Research and Applications, pp. 27–36. Springer, Berlin (2007)
111. Zhong, N., Bradshaw, J.M., Liu, J., Taylor, J.G.: Brain informatics. IEEE Intelligent Systems **26**(5), 16–21 (2011)
112. Zhong, N., Chen, J.: Constructing a new-style conceptual model of brain data for systematic brain informatics. IEEE Transactions on Knowledge and Data Engineering **24**(12), 2127–2142 (2011)
113. Zhong, N., Hu, J., Motomura, S., Wu, J.L., Liu, C.: Building a data-mining grid for multiple human brain data analysis. Computational Intelligence **21**(2), 177–196 (2005)
114. Zhong, N., Liu, J., Yao, Y.: Envisioning intelligent information technologies through the prism of web intelligence. Communications of the ACM **50**(3), 89–94 (2007)
115. Zhong, N., Liu, J., Yao, Y.: Web intelligence (wi). Wiley Encyclopedia of Computer Science and Engineering pp. 1–11 (2007)
116. Zhong, N., Liu, J., Yao, Y., Ohsuga, S.: Web intelligence (wi). In: Proceedings 24th Annual International Computer Software and Applications Conference. COMPSAC2000, pp. 469–470. IEEE Computer Society (2000)
117. Zhong, N., Liu, J., Yao, Y., Wu, J., Lu, S., Qin, Y., Li, K., Wah, B.: Web intelligence meets brain informatics. In: Zhong, N., Liu, J., Yao, Y., Wu, J., Lu, S., Li, K. (eds.) Web Intelligence Meets Brain Informatics, pp. 1–31. Springer, Berlin (2007)
118. Zhong, N., Ma, J., Liu, J., Huang, R., Tao, X.: Wisdom web of things. Springer International Publishing (2016)

119. Zhong, N., Ma, J.H., Huang, R.H., Liu, J.M., Yao, Y.Y., Zhang, Y.X., Chen, J.H.: Research challenges and perspectives on wisdom web of things (w2t). The Journal of Supercomputing **64**(3), 862–882 (2013)
120. Zhong, N., Yau, S.S., Ma, J., Shimojo, S., Just, M., Hu, B., Wang, G., Oiwa, K., Anzai, Y.: Brain informatics-based big data and the wisdom web of things. IEEE Intelligent Systems **30**(5), 2–7 (2015)
121. Zuo, X.N., Ehmke, R., Mennes, M., Imperati, D., Castellanos, F.X., Sporns, O., Milham, M.P.: Network centrality in the human functional connectome. Cerebral Cortex **22**(8), 1862–1875 (2012)