Cognition Digital Twins for Personalized Information Systems of Smart Cities: Proof of Concept

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Abstract: Amid the rapid development of information communication technologies (ICTs), residents of future smart cities are expected to be exposed to unprecedented amounts of real-time information on a daily basis. The cognitive overload driven by an excess of complex information has become a potential issue. Nonetheless, standardized information systems are still widely used, despite individual differences in information intake. To set a foundation for the intelligent information systems of smart cities, this paper introduces methods and tools for a cognition-driven, personalized information system, which acknowledges individual differences in information preference and helps reduce the cognitive load in daily lives and at work. The proposed method includes the use of virtual reality (VR) to simulate complex tasks paired with the digital twin modeling of workers' cognitive reactions to different information formats and contents in VR simulation. Collected data are then used to build a personal digital twins model of information-driven cognition, or Cog-DT. A human subject experiment was performed with a simulated industrial facility shutdown maintenance task as a proof of concept of Cog-DT. The latest neuroimaging technology and analysis methods were applied to model unique cognitive processes pertaining to information processing. Results indicate that cognitive activities driven by different information stimuli in the work context are distinguishable and modelable with Cog-DT methods and tools. This study is expected to contribute to digital twin literature by testing a human-centered, individual-level digital twin modeling method of cognitive activities. It also sets a preliminary foundation for developing personalized information systems for the smart cities of the future.
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Introduction

According to the United Nations (UN), over 55% of the world population inhabited cities in 2008, with the percentage expected to rise to 68% by 2050 (UN 2019). Cities play a major role in societal and economic development worldwide and have a profound impact on the environment (Lam and Fu 2019; Mori and Christodoulou 2012). Given the importance of cities to human development, research communities and policy makers have never stopped to explore fundamental paradigm changes to improve the functions, quality and management of modern cities. In the last two decades, the concept of the "smart city" has gained popularity in scientific discussion (Hall et al. 2000; Hollands 2008; Kwak 2019; Nam and Pardo 2011; Neirotti et al. 2014). Although smart cities do not have an official definition (Nam and Pardo 2011), their most commonly associated characteristics in literature are smart information and communication technology (ICT), social inclusion and social capital, environmental sustainability, and community-centered activities for smart growth (Albino et al. 2015; Nam and Pardo 2011). Particularly, a fully integrated ICT infrastructure in all aspects of city life has commonly been considered a key element of smartness (Ahmad et al. 2019; Cocchia 2014; Dameri and Cocchia 2013). It is believed that the wide use of ICT can make the critical infrastructure components and services of a city more intelligent (Chourabi et al. 2012). Owing to its unique significance, various ICT-focused concepts are often used interchangeably with smart city, such as digital city (Cocchia 2014), information city (Sproull and Patterson 2004), and intelligent city (Komninos 2013). The present smart city literature has mostly focused on discussing the technical and engineering basis of ICT (e.g., computing architecture, sensing networks, and cyberphysical systems and the benefits of increased processing power and data analytics to future smart cities (Sanchez et al. 2014; Tang et al. 2015; Arasteh et al. 2016; Gurgen et al. 2013; Hancke et al. 2013; Zanella et al. 2014). Although the advancing ICT has made data sensing, collection, and real-time analytics much easier (Guo et al. 2017), the issue of information overload has arisen. An excess of information can lead to cognitive overload (Eppler and Mengis 2004), causing decreased performance (Sweller 1988) or prejudices in decision-making, such as stereotyping (i.e., relying on personal experience instead of facts) (Banaji and Greenwald 1994). For smart city residents, there is a foreseeable gap between the constant torrent of information enabled by ICT and their limited information-processing capability. Information overload can make it difficult for residents to maintain

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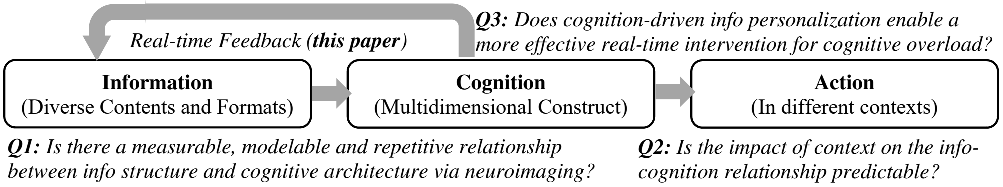


Fig. 1. Three scientific challenges in the form of unanswered questions, based on information-processing theory by Sowa (1983).

cognitive functions in important decision-making, such as disaster response, transportation decisions, and those related to professional work (Du et al. 2019a, 2019b, 2016, 2017; Klann and Geissler 2012). There is an urgent need to develop an intelligent information system that is adaptive to the information-processing capability of each person for more effective control of cognitive load in important decision-making.

Each person is unique in how he or she processes information intake: some may be easily burdened by visuospatial information, whereas others may be resistant to verbal instruction (Cornoldi et al. 1991). The information-taking behavior of the same person may also change dramatically in different cognitive states, such as a bias toward visuospatial information during periods of emotional turmoil (Holmes and Bourne 2008). This indicates that methods for controlling information-induced cognitive load should vary by person and case. The human-computer interaction (HCI) literature has long recognized the importance of personalized information in promoting effective communication (e.g., information filtering theory) (Gerjets and Scheiter 2003; Hanani et al. 2001; Oviatt 2006; Sherman and Frost 2016) and has proposed various approaches for personalizing information in various contexts (Gajos et al. 2010; Jannach and Kreutler 2005; Khriyenko 2018; Khushraj and Lassila 2005; Liang et al. 2014; Liu et al. 2003; Soh et al. 2017). Most approaches are driven by learning the indirect and lagging evidence of cognitive profile to filter information, such as user modeling. As a subdivision of human-computer interaction, user modeling refers to the process of customization and adaptation of a system or the user interface (UI) to the user's specific needs. In other words, the system presents the right information at the right time in the right way (Abel et al. 2011; Berkovsky and Freyne 2015; Fink and Kobsa 2002; Shen et al. 2005; Yin et al. 2015). However, according to the information-processing theory (Sowa 1983) (Fig. 1), these behavioral responses are, at most, indirect evidence of complex cognitive processes, often affected by other emotional and motivational factors (Ross 1979). Directly measuring human cognitive status presents a major challenge.

This research relies on direct cues of human cognitive processes related to information processing as a leading indicator of possible cognitive overload. Cognitive process refers to the process of acquiring knowledge through experiences, senses, and learning (Flower and Hayes 1981). Because it relates to the direct measure of neural activities, an information system based on cognitive processes can adapt to a person's needs proactively instead of passively. To address the need of modeling and predicting cognitive processes at an individual level, this paper introduces the concept of cognition digital twins (Cog-DT), i.e., a digital replica of information-driven cognition (Boschert and Rosen 2016). Cog-DT models, monitors, and predicts a person's cognitive status through the processing of diverse types of information. We propose that it should become a key component of the future ICT infrastructure in smart cities. To provide a potential solution for the complex issue of modeling the precise cognitive processes related to information processing (Cabeza and Nyberg 2000), we used a recent advancement in neuroimaging: functional near-infrared spectroscopy (fNIRS) (Ferrari and Quaresima 2012). The mapped cognitive activities then are used to build a personal digital twin model for the specific individual, which can be used to predict the cognitive status in real time and maneuver a large number of possible information adjustment strategies to control the cognitive load. To test the concept, we will investigate a personalized information system for industrial facility shutdown maintenance (e.g., power plants), an event in which the entire facility is shut down for a short period of time for renewal (Duffuaa and Ben Daya 2004; Yussef et al. 2019). Industrial facility shutdown maintenance often requires workers to process a large amount of information under extreme mental pressure and thus is a suitable application to test the proposed personalized information system. In addition, it plays a critical role in maintaining the sustainable infrastructure systems for smart cities.

In the reminder of this paper, we will introduce the theoretical background of this study, the method for developing the proposed system, and a set of virtual reality (VR) experiments as a proof for the concept. The limitations and future agenda will be introduced at the end.

Literature Review

Industrial Facility Shutdown Maintenance

According to ASCE (2017), the US infrastructure system received a low grade of D+ in 2017, projecting a more than $2.0 trillion investment to fix the problems (ASCE 2018). As a result, industrial facility shutdown maintenance work has become more intensive (Wang et al. 2019). Data from the Energy Information Administration (EIA 2018) shows that, in the first 6 months of 2018, there were 7,783 planned outages in the United States due to industrial shutdown maintenance works. During a shutdown maintenance, workers are always under extreme pressure (Duffuaa and Ben Daya 2004). To minimize the impact of the shutdown schedule, the work is usually done in a 24/7 manner (Daley 2008; Valentin et al. 2018). On average, shutdown maintenance workers work 12 h a day, 7 days a week (Ben-Daya et al. 2009). In addition, owing to the growing complexity of engineered facilities, workers often need to digest a large amount of dynamic engineering information in a very short period (Fig. 2). Many mistakes in facility shutdown operations are related to the miscommunication, misunderstanding, and misuse of information (Anderson et al. 2011a; Carper 1987; New Civil Engineer 2010; Gordon 1998; j5 International 2017; Meshkati 2016; Rozenfeld et al. 2010; Toole 2002). There is a pressing need for the understanding of the causes and constructs of workers' cognitive load in stressful and complex shutdown maintenance works and the best mitigation methods (Liu et al. 2017).

Cognitive Load and Information Intake

The cognitive load theory (CLT) (Kalyuga 2009; Paas et al. 2003; Sweller 1994, 2010) divides the overall cognitive load into

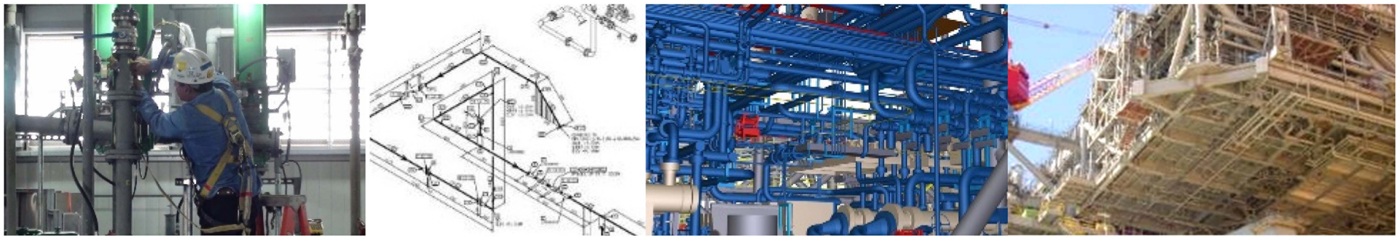


Fig. 2. Engineering information for shutdown maintenance work is becoming increasingly complex, resulting in a more challenging task for workers.

three main components: the *intrinsic cognitive load* (related to the complexity of tasks), the *extraneous cognitive load* (affected by how information is presented), and the *germane cognitive load* (devoted to construction of schemas—permanent knowledge about patterns). Baddeley and colleagues found a "dual channels" process in human cognition related to information processing, where different mental activities are activated when people are processing two distinct categories of information: phonological information (i.e., auditory verbal information or visually presented language) and visuospatial information (i.e., the visually presented information about objects and space) (Baddeley 1992, 2000, 2003, 2012; Baddeley and Hitch 1974; Miyake and Shah 1999; Moreno and Mayer 2007). In addition, a *central executive* cognitive process also takes place to bind information into coherent episodes, shift between tasks or retrieval strategies, and select between attention and inhibition (Sridharan et al. 2008). Based on the dual channels framework, Mayer (2002) proposed a multimedia learning theory to describe various mental constructs pertaining to information processing, including sensory (which receives stimuli and stores it for a very short period of time), working (where we actively process information to create mental constructs), and long-term (the repository of all things learned) memories (Mayer 2002), as illustrated in Fig. 3.

Because of the difficulty of measuring cognitive loads caused by different information stimuli, literature tends to investigate cognitive load as a single entity [Chang and Wang 2010; D. Cyganski and R. J. Duckworth, "Search and rescue method and system," US Patent No. 9476963B2 (2016); Haapalainen et al. 2010; Kim and Irizarry 2019; Klatzky et al. 2006; Progri et al. 2007]. Indicators such as task performance (e.g., errors) and psychometrics (e.g., NASA TLX surveys) are typically used to measure cognitive load (Cabeza and Nyberg 2000; Meilinger et al. 2008; Sweller 1988). As a result of the rapid development of neuroimaging technologies, it is possible to map brain activities that are directly related to different types of cognitive loads (Cabeza and Nyberg 2000; Sauseng et al. 2005). For example, neuroimaging studies found that phonological information often triggers *Broca's area* (involved in speech production) in addition to supplementary and *premotor areas* (involved in movement) in the *frontal cortex* cognitive (Sahin et al. 2009). These advancements in neural science have inspired this study to investigate a method called Cog-DT that measures, models, and even predicts information-driven cognitive processes at the individual level, serving as the core of an intelligent information system. In order to better explain the rationale and need for Cog-DT, we examined digital twins literature and identified the point of departure.

Digital Twins

The advancements of computational, informational, and communication technologies have driven the birth and evolution of digital twins (DTs). A DT, originating from the manufacturing industry, is the concept of designing, testing, manufacturing, and applying a virtual copy of a physical system (Grieves and Vickers 2017; Li et al. 2018). Grieves and Vickers (2017) defined a DT to be a set of virtual information constructs that are designed to fully describe a potential or existing physical manufactured product. In its ultimate form, they believed that a DT should be able to provide all information relating to the product, from the microatomic level to the macrogeometrical level. Even without such details, a DT can still be a holistic digital representation of an individual product that contains the attributes and behaviors of the real-life object though modeling and data (Haag and Anderl 2018). Such a DT can simulate the product's actual behavior in a deployed environment. In the manufacturing industry, a DT has been regarded as a critical component of production systems to achieve Industry 4.0 (Uhlemann et al. 2017a, b). The potential application of DTs spans many stages and areas, including design (Lu et al. 1997; Maropoulos and Ceglarek 2010; Rosen et al. 2015), manufacturing (Schleich et al. 2017; Tao et al. 2018), service (Tao et al.

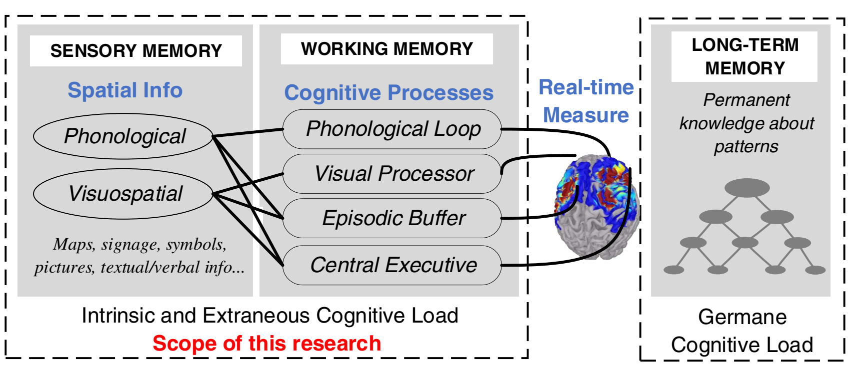


Fig. 3. Information-cognition relationships are complex. (Adapted from Baddeley 2000, 2012; Baddeley and Hitch 1974.)

2018), simulation (Boschert and Rosen 2016), data management (Abramovici et al. 2016; Uhlemann et al. 2017a, b), and life-cycle analysis (Quintana et al. 2010; Tuegel et al. 2011).

Recently, the concept of DTs has started to expand into the conceptualization and development of smart cities. This is an unprecedented growth of the concept of DTs, from the manufacturing system, which usually has a relatively small and clearly defined boundary, to large, open, and complex urban systems (Park et al. 2017). A smart city DT, as argued by Mohammadi and Taylor (2017), is a digital replica of a city that includes its infrastructure, human dynamics, spatial and temporal information flow, and physical and virtual connectivity. Powered by data from citywide the internet of things (IoT) and analytical capacities, a smart city DT will be able to explore what-if scenarios that can contribute to sustainable growth, socioeconomic resilience, and better infrastructure performance (Mohammadi and Taylor 2019; Rouse and Serban 2011).

Our review on the existing DT literature has identified a potential gap of modeling resident behaviors at the individual level. Most DT studies focus on modeling the processes and behaviors at the system level. To achieve the promise of smart city DTs, the digital representations of urban residents need to reflect the complexities of human nature, especially for the purpose of simulating decision-making and human behavior. One critical perspective of incorporating individuality is modeling the cognitive processes in a DT (Boschert and Rosen 2016). No two persons share the same cognition processes, and thus personalized systems are needed (Cabeza and Nyberg 2000). These systems, built on cutting-edge technology in human sensing, neuroimaging, data mining, and cognitive mapping, will be able to maneuver a large amount of data in real time, map cognitive processes, evaluate cognitive loads, develop control strategies, and provide effective feedback. Developing such personalized information systems will be a critical step to creating cognitive digital twin models.

Proposed Cognition Digital Twins for Personalized Information Systems

Overview

Building a cognition-driven, personalized information system does not only involve information filtering and presenting. A tailored information system can only respond to a person's needs in searching, digesting, and using information necessary for the successful completion of a task if the profile is based on historical data. An information system without a robust database and analytical system to store, process, and analyze an individual's actions cannot support effective training or action during operations, even if it is equipped with the most advanced visualization technologies. To establish the basis of information personalization, we propose using Cog-DT, a cognitive profile model of information-taking preference and behavioral patterns at the individual level. This personalized information system dynamically and automatically customizes UI to specific users based on their unique Cog-DT model. The Cog-DT model can be tracked by quantifying individual reactions to different types, quantities, and display methods of information during VR training. Cognitive data of individuals can be integrated as a necessary part of their personal files. Just as personality can be used to model the behavioral patterns of a person, the unique information-taking patterns captured by the Cog-DT model also exhibit individual differences and help tailor UI to reduce their cognitive load. Fig. 4 illustrates the concept map of a Cog-DT enabled

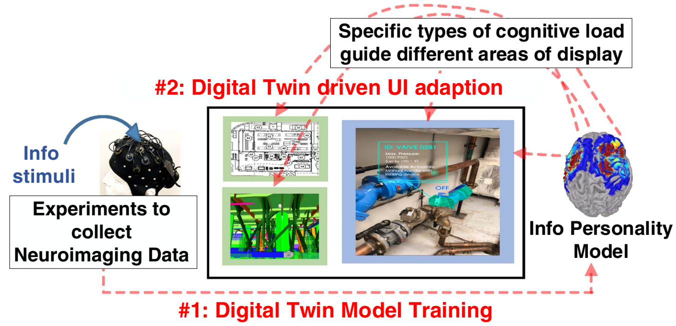


Fig. 4. Concept map of Cog-DT–enabled personalized information system.

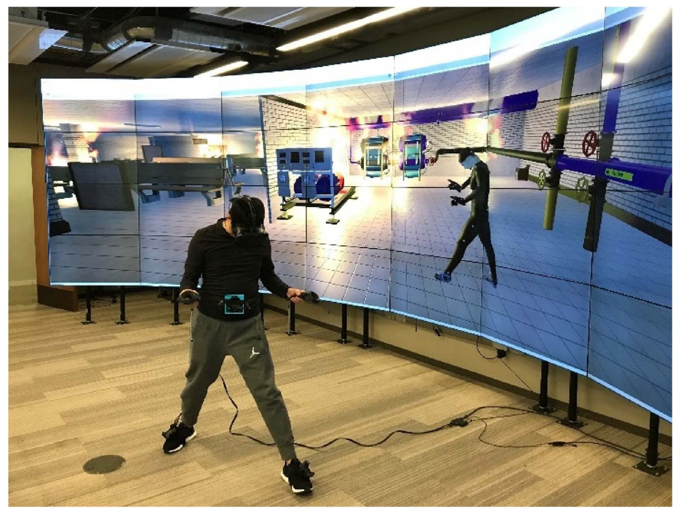


Fig. 5. VR simulation platform for information personality data collection.

information system. A detailed explanation to the concept map is provided in the rest of this section.

Step 1: VR Training to Collect Raw Data about Information Personality

The first step is using a VR training platform to collect the personal cognitive process of information intake. The key is the development of VR model modules that accurately reconstruct various facility shutdown scenarios for training purposes. We have developed a VR training platform (Fig. 5) to include valuable field knowledge (Du et al. 2018a, b; Shi et al. 2016, 2017).

To examine how specific individuals react to the perceived information, we need to collect the real-time cognitive load (CL) during training. Cog-DT highlights the importance of differentiating separate types of CL as a multidimensional construct. Based on the cognitive load theory and Baddeley's model of working memory (Baddeley 2012), Cog-DT measures cognitive load as a summation of intrinsic CL (related to task difficulty) and extraneous CL (related to received information). Although psychometrics-based cognitive load measurements [e.g., NASA TLX Survey Task Load Test (Hart 2006)] have been well validated, they have rarely been used as a working instrument in real-time monitoring. The proposed Cog-DT features the real-time monitoring of (and adaptation to) a person's cognitive status. Psychometric-based methods

Table 1. Real-time cognitive load metrics

Category	Real-time cognitive sensing	Evidence
Neuroimaging	1. Functional near-infrared spectroscopy (fNIRS): A noninvasive brain imaging method quantifying brain blood changes using near-infrared light; less affected by motions. 2. Electroencephalogram (EEG): A noninvasive brain imaging method monitoring electrical changes on the skin; can be affected by motions.	Anderson et al. (2011b), Antonenko et al. (2010), Cabeza and Nyberg (2000), Fehrenbacher and Djamasbi (2017), Ferrari and Quaresima (2012), Gevins et al. (2016), Gregson et al. (1993), Haapalainen et al. (2010), and Sauseng et al. (2004, 2005)
Physiological	1. Gaze focus (GF): Gaze focus tracking over points of interest. 2. Eye movement frequency (EMF): Pixels moved per second. 3. Eye blink rate (EBR): Eye blinks per minute. 4. Pupillary dilation (PD): Task-invoked pupillary response in diameter change. 5. Electrocardiogram (ECG)[a]: The electrical activity of the heart. 6. Respiratory (RES)[a]: Total volume and respiratory rate. 7. Galvanic skin response (GSR): Electrical resistance change of the skin. 8. Heat flux rate (HFR)[a]: Rate of skin heat transfer. 9. Electromyography (EMG)[a]: Muscle activities. 10. Heart rate-blood pressure product (RPP)[a]: Heart rate and systolic blood pressure.	Brunken et al. (2003), Chen et al. (2012), Engström et al. (2005), Fehrenbacher and Djamasbi (2017), Ferreira et al. (2014), Fredericks et al. (2005), Grassmann et al. (2016), Haapalainen et al. (2010), Hess and Polt (1964), Hyönä et al. (2007), Kahneman and Beatty (1966), Klingner et al. (2011), Nourbakhsh et al. (2012), Paas et al. (2003), Recarte and Nunes (2000), Scholey et al. (1999), Shi et al. (2007), Van Gerven et al. (2004), Verner et al. (2013), and Zekveld et al. (2011)
Ergonomic	1. Tapping frequency (TF): The tapping frequency of feet and fingers. 2. Gait patterns (GP)[a]: Gait variability such as change to stride length.	Kee et al. (1983), Martin and Bajcsy (2011), Sprenger et al. (2011), and Tracy and Albers (2006)

[a]Metrics that may be significantly affected by bodily movement but are still worthy of testing with sensor fusion.

can only measure cognitive load after the task is done. In this scenario, it would be too late to execute any real-time interventions to prevent the occurrence of cognitive overload. To overcome this challenge, Cog-DT uses a comprehensive CL index based on a variety of psychological and neurobiological metrics, including neuroimaging, physiological, and ergonomic metrics. Based on a comprehensive literature review, the 14 metrics for real-time CL measurement metrics are used as listed in Table 1.

Step 2: Digital Twin Modeling of Human Cognition

Whereas most existing DT models concentrate on replicating physical processes and systems, this research will focus on reproducing human cognitive processes in cyber simulation. The proposed Cog-DT is modeled and implemented in two phases. Phase 1 is for modeling the fundamental patterns of the person's cognitive reactions to different information stimuli, which we call "information personality" in this research. This is done by obtaining neuroimaging data during VR training. We use fNIRS to track the hemodynamic reactions of representative brain areas (i.e., the activation levels of these brain areas) in simulated information-processing tasks. Once the data are collected, a base model will be built to formulate a person's possible cognitive reaction patterns (measured as the hemodynamic reaction strength) in different information-processing scenarios. Phase 2 pertains to the monitoring of a person's real-time cognitive status using portable fNIRS and optimizing the formats and contents of delivered information to minimize cognitive load. The hemodynamic reactions of the brain will be continuously tracked and compared with the base model developed in Phase 1, and an optimization algorithm (e.g., gradient descent) will identify the best strategy for reducing real-time hemodynamic reactions of brain areas related to specific types of information.

To collect the data for the Cog-DT modeling, a controlled Sternberg working memory test (Sternberg 1969) is used to (1) standardize the modeling of information personality and cognitive activities and (2) collect continuous data about the complete picture of the cognitive impacts of different kinds of information. Participating workers are asked to finish a dual task: (1) primary task—Sternberg working memory test. As illustrated in Fig. 6(a), workers are asked to take a Sternberg working memory test, which involves the presentation of a list of information items to memorize (encoding period; 2 s in total), followed by a memory retention period (2 s) during which the subject must maintain the list of items in memory, and a retrieval period (2 s) in which the workers answer if a given item appears. Between the two sessions is a short fixation phase (0.5 s). The Sternberg test is repeated 300 times for each worker (32.5 min in total). The working memory accuracy is used as a direct indicator of cognitive load, as suggested by the literature (Brunken et al. 2003; Engle 2016; Jonides et al. 1997; Tracy and Albers 2006). According to Mayer's multimedia learning theory, adjustable information items include symbols, orientation (spatial information), words, letters, numbers, shapes and combinations; (2) secondary task—pipe maintenance. As shown in Fig. 6(b), while the worker is taking the Sternberg test, he or she will also be asked to maintain a pipe skid following a given procedure with 20 steps.

The data gained from the Sternberg tests will first inform a quantitative model of information personality. The cognitive load and multimedia learning theories indicate that the two most relevant dimensions of information to a person's cognitive load (Baddeley 2000, 2012; Baddeley and Hitch 1974) are information quantity (intrinsic cognitive load) and information type (extraneous cognitive load). Hence, the proposed system focuses on modeling information personality from these two dimensions. The first dimension, denoted as I_q, refers to how much meaningful content is delivered in a message, that is, the information that is directly relevant and contributing to the task. The second dimension, denoted as I_t, indicates whether the information is more abstractly displayed (such as textual instructions) or more visually displayed (such as an interactive map). The outcome is the measure of a specific type of cognitive load CL_i. The ground truth about each type of CL_i is built upon the corresponding Sternberg test scores. Data from the experiments will be used in a multivariate regression analysis to find the information personality function $\mathrm{CL}_i = f(I_q, I_t)$, as illustrated in Fig. 7. The dots show the current cognitive load measures (hypothetical), and the arrows indicate the most efficient way of reducing cognitive load.

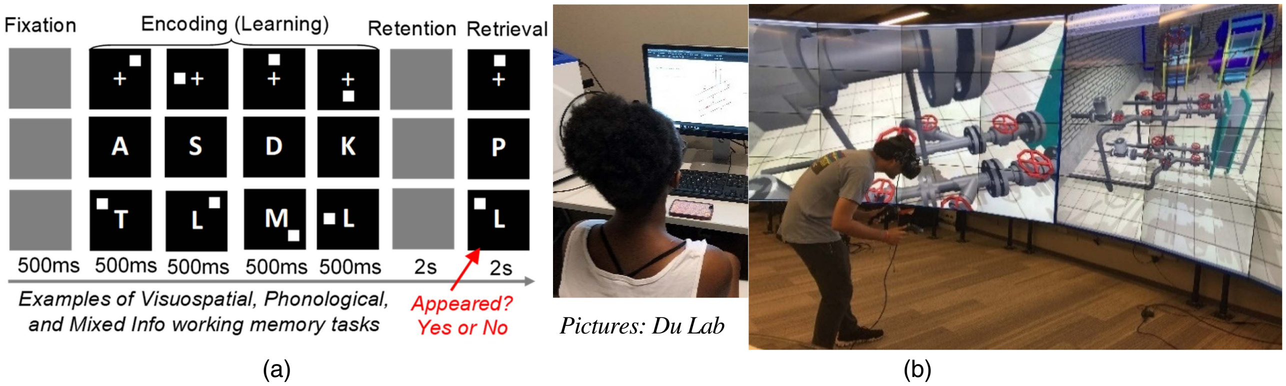


Fig. 6. Examining the relationship between information and cognitive load based on a revised Sternberg working memory test; test subjects will finish the Sternberg test while maintaining a pipe skid: (a) primary task—Sternberg working memory test. Test subjects need to memorize the info provided and answer if it appeared based on memory and (b) secondary task—VR pipe maintenance task. Test subjects will be asked to maintain a pipework following given instructions. We programmed motion tracking and interaction function.

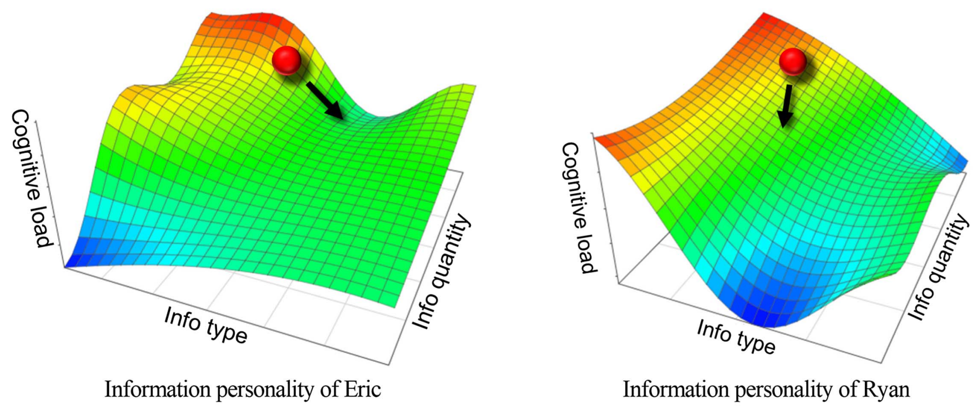


Fig. 7. Two hypothetical examples of information personality.

For Cog-DT, cognitive load is measured by brain activation patterns as reactions to different information stimuli. Cognition literature shows that specific brain areas are activated at different levels in information-processing tasks, depending on what kinds of information are overloaded. Our system monitors 18 brain areas concurrently and pictures the overall patterns of brain activity. We apply a multivariate analysis to correspond to the activation levels of the 18 brain areas with a specific information stimulus or combinations of multiple types of information (e.g., phonological and visuospatial information). The "heat map" of brain activation, mathematically modeled in our study, represents the cognitive reaction pattern.

The modeling of information personality only reflects the static general pattern of a person's information-cognition relationship. In order to achieve a real-time intervention, we also need to be able to predict the dynamic changes of cognitive activities, that is, where the current cognitive status is and where it is going. Little has been done to model and predict the continuous changes of raw neuroimaging data. As a result, we propose to use a recurrent neural network (RNN) (Mikolov et al. 2010) to fit and predict the fNRIS raw data. Fig. 8 illustrates an example of the fNIRS data prediction in Channel 5 of Participant 12. Channel 4 in our experiment measures the activation level in the middle frontal gyrus of the brain's frontal cortex, which plays a role in sensory information retrieval (Stark et al. 2010). The x-axis shows the time interval of fNIRS data sampling. Because the sampling rate is 7.8125 data points per second, each interval refers to 1/7.8125 s. The y-axis shows the relative brain activation level measured as hemodynamic responses (levels of oxygen consumption). Specifically, a reading of 0 refers to the baseline of brain activation, with the reading being established by measuring brain activities when a test subject is completely relaxed. The values in the y-axis show how much more or less oxygen was consumed at a certain point as a ratio to the baseline reading. For example, a value of 2.0 means the current oxygen consumption is twice as high as the baseline. Given the features of fNIRS data, we used a sliding window of 40 s to predict the oxygen consumption level in the next 20 s. The example shown in Fig. 8 indicates that RNN can predict significant changes to oxygen consumption within the next 20 s, and thus is an effective prediction tool for potential cognitive overload.

Step 3: Adaptive Information Based on Digital Twin Models of Human Cognition

Ultimately, the personalized information system will customize information based on the Cog-DT model of each individual to reduce the risk of cognitive overload. Specifically, the Cog-DT model will help determine: (1) what information format should be presented, considering symbols, orientation (spatial information), words, letters, numbers, shapes, and combinations; (2) when the information should be presented (time); and (3) how the information should be presented (the syntactical issue). Percentages of standardized and

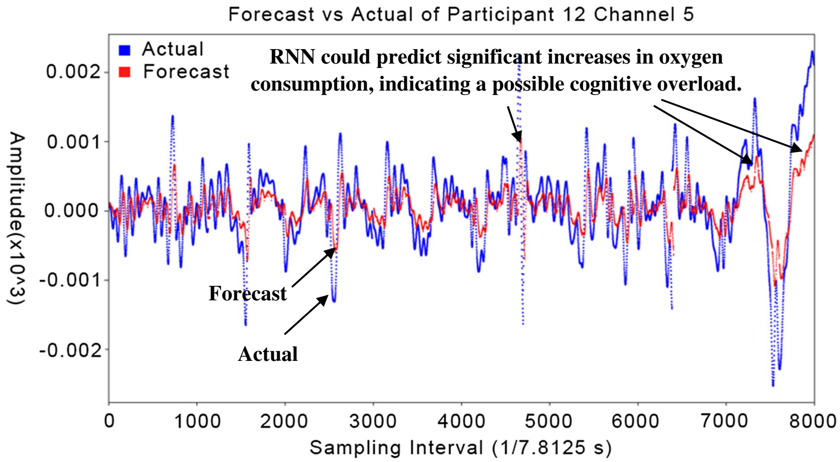


Fig. 8. Example of predicting cognitive activities (fNIRS) with RNN.

personalized information will also be determined based on personal data. The engineering information display options are defined for a specific cognitive load according to (1) m categorical levels of information quantity I_q and (2) n categorical options of information type I_t. By converting continuous values of the two information dimensions I_q and I_t into categorical options, the optimization search will be much easier. Then, the display options will be deployed in different areas of the display device (i.e., a headset), with each area showing a certain type of information. The information quantity and type of each display area will be dynamically adjusted based on the real-time measure of each corresponding type of cognitive load, as well as the established Cog-DT model. Based on the unique nature of information personality, a gradient descent algorithm will be applied to find the most effective way of reducing cognitive load by adjusting the specific display design. Eventually, this personalized information system will feature in a closed loop of model training, model implementation, and model improvement, as illustrated in Fig. 4. The graphic attributes of the display will also be adjusted according to Cleveland and McGill's graphic perception theory (Cleveland and McGill 1984), with elements including shading, color saturation, volume, area, positions, and so on.

Fig. 9. Setting up fNIRS for one of the subjects.

Human Subject Experiment to Test Cog-DT

In this section, we introduce a study ($n = 16$) testing the concept of digital models of human cognition. Specially, we will present the cognitive data collection setup for collecting training data for the digital twin model, the analysis of cognitive patterns under different information stimuli, and the feasibility of the prediction of cognitive activities. The findings are foundational to the further testing of the proposed personalized information system.

Cognitive Data Collection Setup

In this study, we used NIRx Sport 2 (NIRx, Berlin), a portable fNIRS device to collect real-time brain activities (NIRx 2019), as illustrated in Fig. 9. fNIRS maps brain activities through hemodynamic (blood) responses associated with neuron behavior (Izzetoglu et al. 2004). Given its accuracy and portability, fNIRS has been successfully implemented as a control signal for brain-computer interface (BCI) systems (Coyle et al. 2007). NIRx Sport 2 is a multimodal brain and physiological assessment system with 64-channel NIRS imaging capabilities including automatic gain control, plus eight-channel E*G analog recording capabilities. It has been proven effective in scanning brain activities in various studies (Hu et al. 2016; Ivkovic et al. 2014; Strangman et al. 2018; Zhang et al. 2014). The challenge we faced was integrating fNIRS devices with VR devices. Our system requires neuroimaging data collection and VR experiments to happen simultaneously, but most off-the-shelf products do not consider this necessity. The VR headset used in this research originally had a plastic cap that conflicted with the cap of the NIRx system. We replaced the plastic cap with a strap. We also redesigned the NIRx cap to give enough space for the VR headset straps. It was added in the revised manuscript. Fig. 9 shows that the two systems are working together effectively.

Then the 16 test subjects were asked to perform: (1) a Sternberg test (Fig. 10) and (2) a VR pipe maintenance task (Fig. 11), as previously discussed. Each experiment lasted for about 1.0–1.5 h, and the fNIRS data were continuously collected. Fig. 12 illustrates the different engineering information instructions provided in the experiment.

Data Collection

The data on the fNIRS and other psychological aspects (not shown in this paper) listed in Table 1 were collected in the experiments. The 18 channels monitored in our experiment covered the frontal

Fig. 10. Establishing the baseline of digital twin cognition modeling using Sternberg tests.

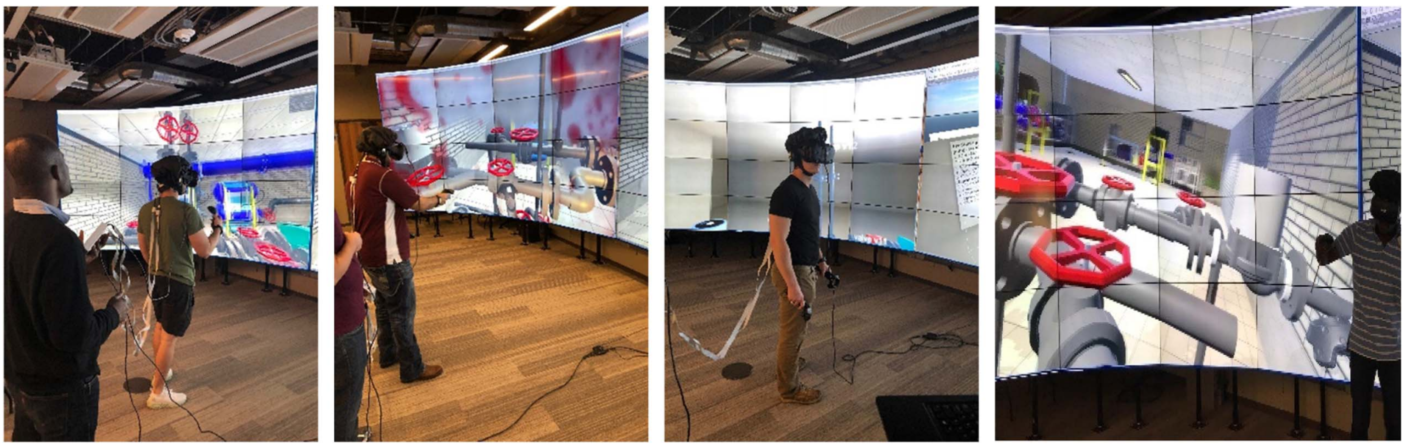
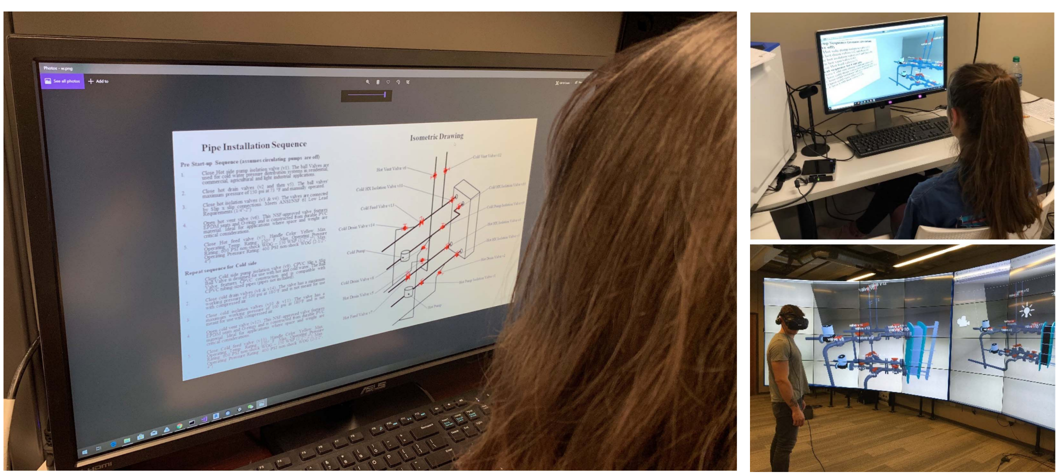


Fig. 11. Collecting brain activity data while performing VR training and pipe maintenance tasks.



Test subject learning the task instructed as isometric drawing (2D) and written instruction (phonological).

Test subject learning procedures in 3D and VR.

Fig. 12. Different types of engineering information were given.

cortex and premotor and motor cortex areas, which are believed to correspond to memory, logical thinking, and skill acquisition (Cabeza and Nyberg 2000). Fig. 13 illustrates the changes in oxygen consumption in the 18 channels over 40 s, and Fig. 14 shows the oxygen consumption of both sides of the brain over 25 min when exposed to the following information stimuli: symbols, orientation (spatial information), words, letters, numbers, shapes and combinations, which we call "base information components"

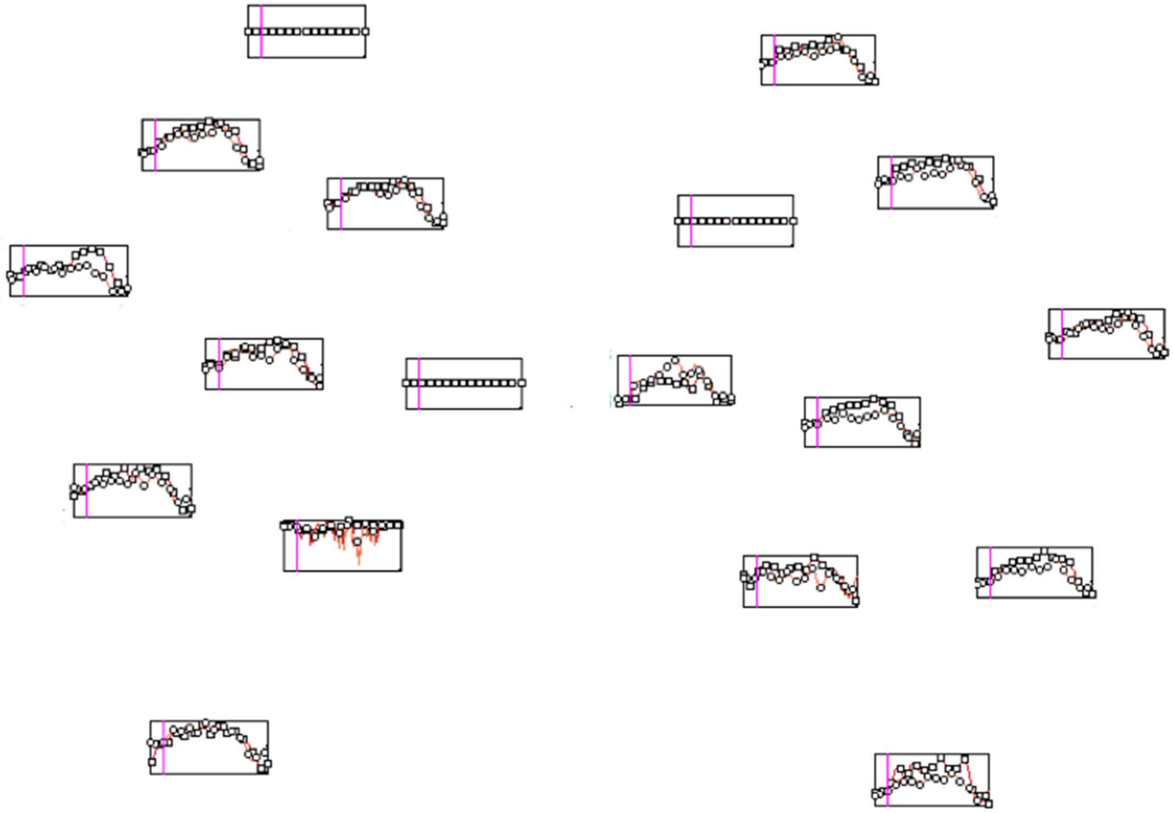


Fig. 13. Temporal data of 18 channels (18 brain areas) of Subject 03 over 40 s; X is seconds, Y is oxygen consumption measures in mol/L.

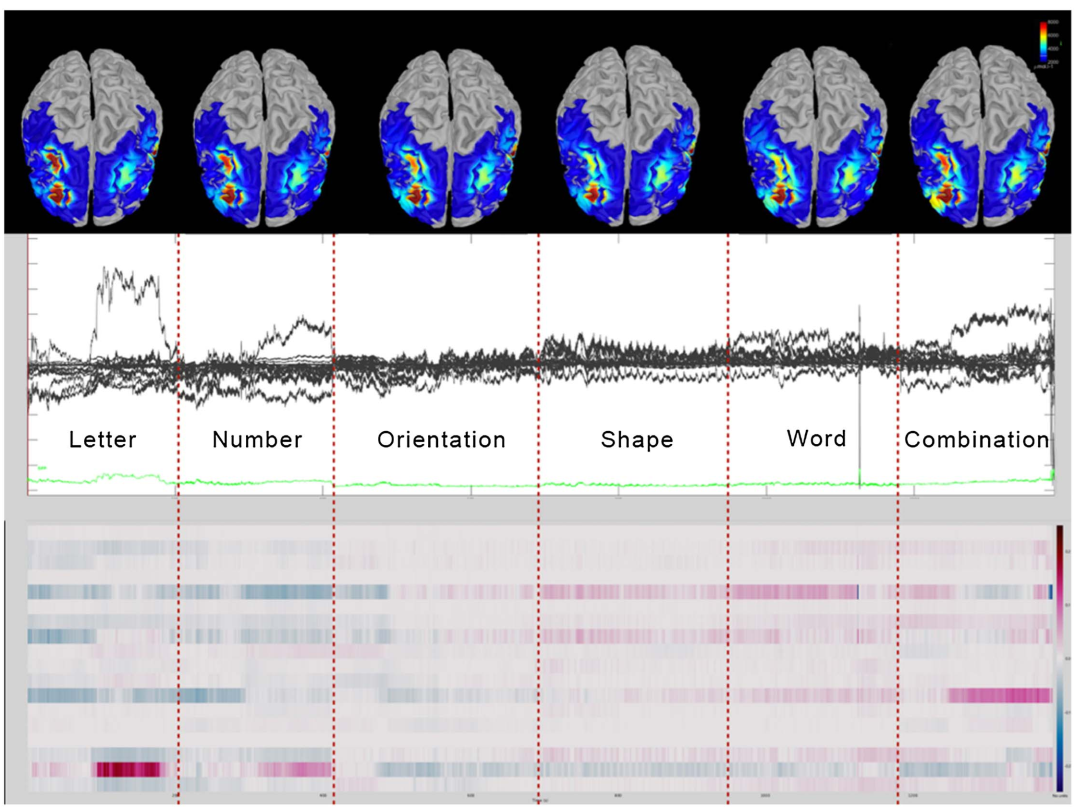


Fig. 14. Brain activity (18 channels) change of Subject 03 over 25 min; X = time (s), and Y = oxygen consumption (mmol/L).

in this research. The assumption is that once we successfully model the cognitive patterns for these base information components, we can test the predictivity in a much more realistic setup.

Data Analysis

Two analyses were performed to test the concept of Cog-DT. First, we performed a classification analysis to test if there were identifiable differences in the cognitive patterns (measured by fNIRS data) among seven information stimuli (data labels): Phonological-letters, Phonological-numbers, Spatial-orientations, Visual-shapes, Visual-symbols, Phonological-words, and mixed information. Each of the 18 channels tracked by fNIRS represents a dimension in the data space, and each type of information stimuli represents the data label. Then, a multivariate discriminant analysis (Kennedy et al. 1980) was used to classify the classes. An important point is that the raw fNIRS data should be processed with a hemodynamic response function (HRF) before the classification analysis to reflect the real brain activities (Lindquist et al. 2009). In neural science, hemodynamics refers to the body's reactions to physical and mental activities by homeostatically adjusting its blood flow to deliver resources (such as oxygen and glucose) to stressed brain areas to continue their functions (Iadecola 2004). HRFs are the proven shapes of nutrition change curves that correspond to known blood flow patterns that are essential for the maintenance of neurons, astrocytes, and other cells of the brain. The procedure of HRF analysis is to: (1) divide the continuous raw fNIRS data into sections called "events," which represent the beginning and ending of the information stimulus in our experiment; (2) overlay the established HRF of memory and skill-gaining cognitive processes on each of the event sections; and (3) perform a F-test to examine the similarity between the raw fNIRS data and the HRF. Results are shown as a number from 0 to 1, showcasing different levels of brain area activation under the external stimuli. The processed data were then used in the multivariate discriminant analysis. Our results indicate that there are identifiable differences among the seven information stimuli shown as excellent prediction rates of the classification analysis, as shown in Table 2.

Afterward, we also performed RNN analyses to test the predictability of the cognitive activities measured as the fNIRS oxygen consumption data. RNN was selected because it has been proven to be a highly effective way of analyzing time series data (Connor et al. 1994). Compared to other methods, RNN is more robust to the noise in the data and can capture the nonlinearity more effectively (Ho et al. 2002). Fig. 15 illustrates the RNN prediction of the 18 channels of Subject 12's fNIRS data.

Table 2. Classification results of 14 subjects

Subject ID	Percent misclassified	—2LogLikelihood
1	7.284	50.6144
2	6.662	7.92326
3	8.596	80.4007
4	4.636	45.8853
5	5.298	75.4885
6	4.636	56.6448
7	6.662	6.53595
8	8.609	84.3487
9	4.636	43.1822
10	9.272	170.38
11	7.947	105.973
12	9.986	18.8986
13	3.3112	57.2329
14	6.6225	72.2801

Note: Data from two subjects are missing because of quality issues.

Discussion and Conclusions

This paper introduces the methods, procedures, and tools for a cognition-driven, personalized information system as a key component of the intelligent ICT for future smart cities. Knowing that ICT advancements and smart city technologies will generate an unprecedented amount of information for residents and professional workers, a personalized information system is proposed as a solution for potential cognitive overload issues. The core component of the personalized information system is Cog-DT, a digital replica of a person's cognitive process in relation to information processing. Cog-DT includes a VR platform that collects information preference data during training, contains the modeling and optimization algorithm of DT modeling of human cognitions, and has an adaptive UI design based on real-time cognitive load measures and Cog-DT models. By dynamically adjusting the contents and formats of presented information, the personalized information system is expected to reduce the real-time cognitive load of individuals while still maintaining an effective performance.

Our results indicate that the specific types of cognitive loads related to different information stimuli are distinguishable and modelable. This finding sets a solid foundation for the proposed Cog-DT and is expected to advance smart city and DT knowledge in two ways. First, Cog-DT echoes the urgent need for a personalized information system to tackle the potential information overload issues driven by the unprecedented accessibility to large amounts of real-time information in future smart cities. Existing literature has recognized the importance of optimizing information systems to control cognitive load (Campbell et al. 2008; Kruijff et al. 2014; Nunez 2017; Reeves et al. 2004). Yet, most literature only focuses on giving generalized design recommendations rather than providing personalized solutions. Their assumption is that certain principals of design will work well with the overall population (Reeves et al. 2004). However, this assumption is questionable because cognitive science literature has already discovered that individual-level differences in receiving information are major contributors to varying task performances (Cornoldi et al. 1991). Cog-DT employs neuroimaging technologies and algorithms to track and model the cognitive profiles of individuals. The data will then be used to guide the dynamic change of information content and format for the specific individual. This personalized information system solution will transform the ICT into an adaptive framework.

Second, this study tests the concept of using digital twin modeling for human cognition. Although digital twins have gained popularity, most applications focus on reproducing physical processes and systems, such as Boschert and Rosen (2016), Glaessgen and Stargel (2012), and Tao et al. (2018). Simulating human behaviors has been investigated, such as evacuation behaviors (Zheng et al. 2009), yet little has been done to examine if human cognition is modelable and able to be simulated with digital twins. This work is one of the first efforts on cognitive digital twins.

Several limitations of the current study have been identified as potential topics for future investigation. First, it must be admitted that neurocentric cognitive prediction is still constrained by limited knowledge on brain functions (Blakemore and Decety 2001; Haggard 2008). The literature finds that, given complex tasks and changing environments, the variability of neurophysiological data is often too far beyond a modelable level to generate any effective

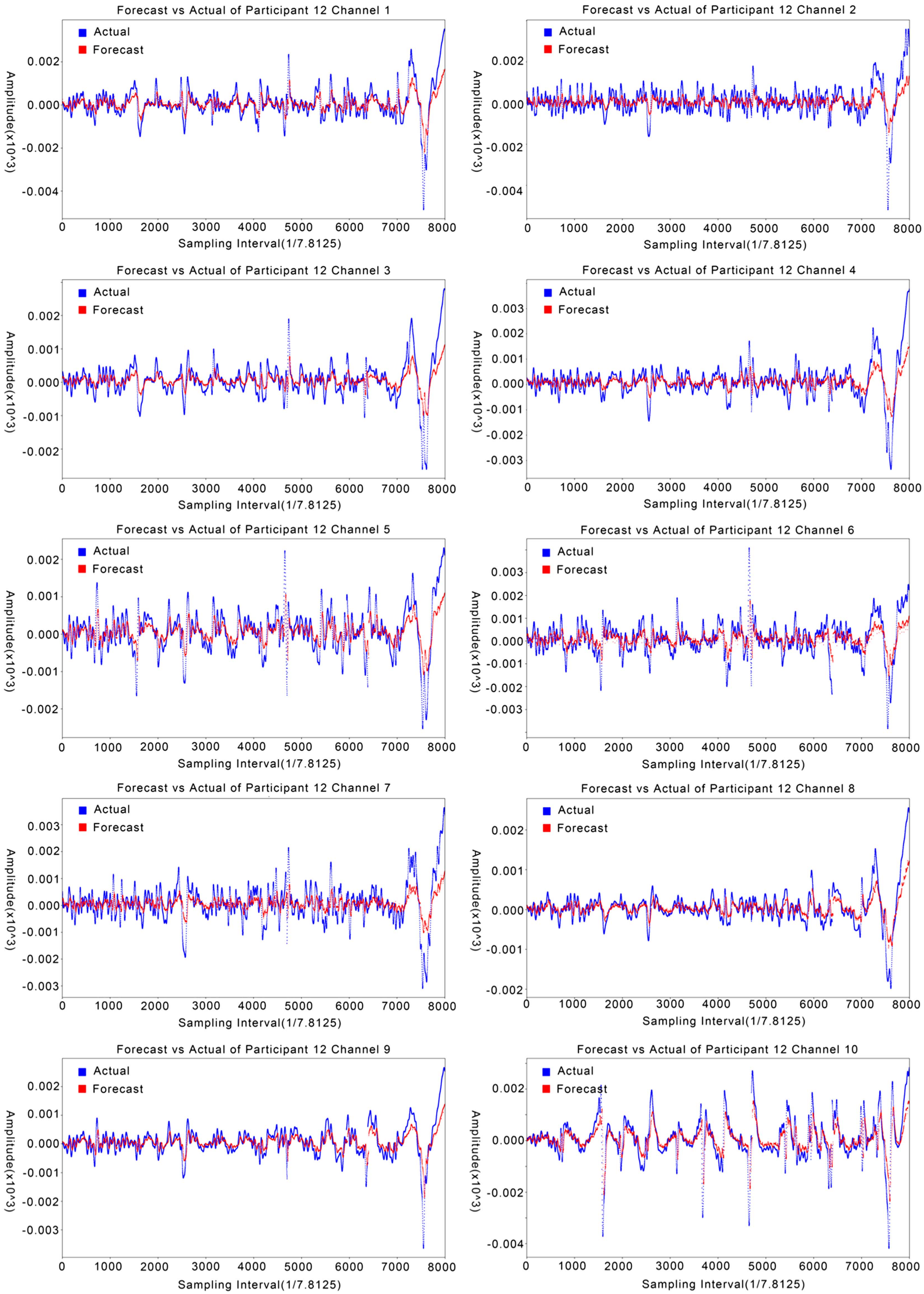


Fig. 15. RNN fit and predication of fNIRS raw data (Subject 12).

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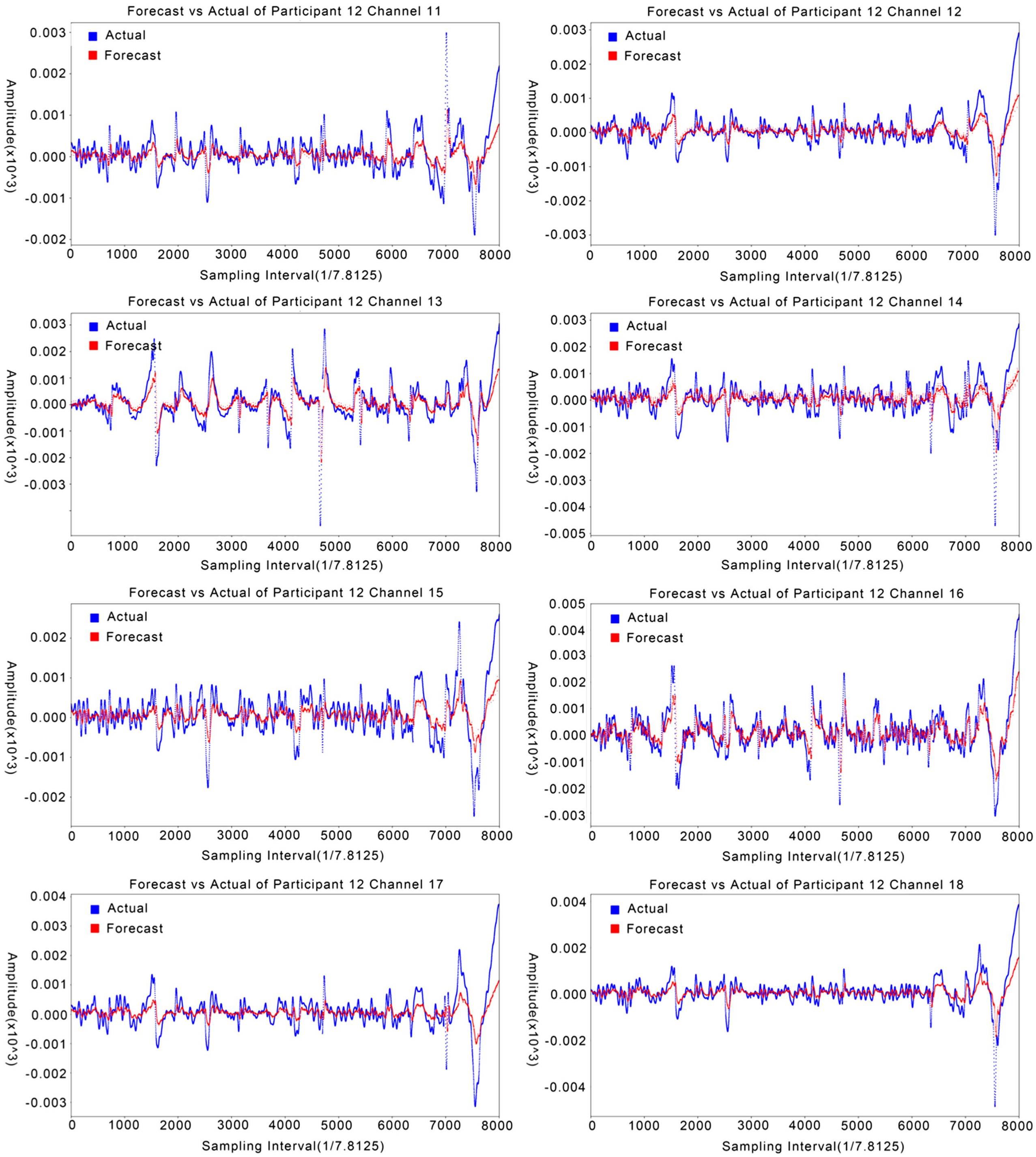

Fig. 15. (*Continued.*)

intent prediction mode (Marcos et al. 2013). The future agenda of this study will be focusing on the validation of the proposed cognitive modeling and simulating with advancements in neural science and deep learning. We also expect a more thorough experiment to reveal what types of information are more suitable to be presented in two-dimensional (2D), three-dimensional (3D), and VR environments. Second, we recognize the importance of identifying the minimum number and variety of worker training data for Cog-DT modeling; however, the answer can be very complex and is beyond the scope of the current study. Specifically, the minimum data requirement varies across people, driven by how much variation is observed in cognitive data. This paper focuses on introducing the framework, method, and tools for modeling a person's cognitive process (which are foundational to the personalized information system). Determining the specific data requirements for each individual deserves future investigation. Third, although we recognize that a detailed introduction to the functionality, algorithms, and specific UI designs of the proposed personalized information system will be helpful, this paper focuses on introducing the framework and tools for developing Cog-DT and corresponding information system, and thus such intricacies are in the agenda of the future. In the future, we will also incorporate environmental simulations, such as temperature, ventilation, and so on, in the VR platform to help trigger realistic behaviors.

Data Availability Statement

Some or all data, models, or code generated or used during the study are available in a repository or online in accordance with funder data retention policies (Du et al. 2019b).

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