



Functional Near-Infrared Spectroscopy as a Personalized Digital Healthcare Tool for Brain Monitoring

Zephaniah Phillips V^a

Raymart Jay Canoy^b

Seung-ho Paik^{a,c}

Seung Hyun Lee^d

Beop-Min Kim^e

^aGlobal Health Technology Research Center, College of Health Science, Korea University, Seoul, Korea

^bProgram in Biomicro System Technology, College of Engineering, Korea University, Seoul, Korea

^cKLIEN Inc., Seoul Biohub, Seoul, Korea

^dInterdisciplinary Program in Precision Public Health, Korea University, Seoul, Korea

^eDepartment of Bio-Convergence Engineering, Korea University, Seoul, Korea

The sustained growth of digital healthcare in the field of neurology relies on portable and cost-effective brain monitoring tools that can accurately monitor brain function in real time. Functional near-infrared spectroscopy (fNIRS) is one such tool that has become popular among researchers and clinicians as a practical alternative to functional magnetic resonance imaging, and as a complementary tool to modalities such as electroencephalography. This review covers the contribution of fNIRS to the personalized goals of digital healthcare in neurology by identifying two major trends that drive current fNIRS research. The first major trend is multimodal monitoring using fNIRS, which allows clinicians to access more data that will help them to understand the interconnection between the cerebral hemodynamics and other physiological phenomena in patients. This allows clinicians to make an overall assessment of physical health to obtain a more-detailed and individualized diagnosis. The second major trend is that fNIRS research is being conducted with naturalistic experimental paradigms that involve multisensory stimulation in familiar settings. Cerebral monitoring of multisensory stimulation during dynamic activities or within virtual reality helps to understand the complex brain activities that occur in everyday life. Finally, the scope of future fNIRS studies is discussed to facilitate more-accurate assessments of brain activation and the wider clinical acceptance of fNIRS as a medical device for digital healthcare.

Keywords functional near-infrared spectroscopy; digital healthcare; optical monitoring; cerebral oxygenation; diffuse optics.

INTRODUCTION

Digital healthcare involves the intersection of new technologies with the field of healthcare. As described in the Global Strategy on Digital Health published by the World Health Organization, the aim of this intersection is to “improve health for everyone, everywhere by accelerating the development and adoption of appropriate, accessible, affordable, scalable and sustainable person-centric digital health solution.”¹ Considerable attention has been given to concepts such as artificial intelligence (AI) and telehealth applications as person-orientated digital healthcare solutions. However, the role of brain monitoring tools that are appropriate for personalized digital healthcare solutions in the field of neurology should not be overlooked. Advanced brain monitoring tools can be considered the cornerstone of digital healthcare in neurology due to the dependence of AI and telehealth applications on high-quality input data.

The growth of digital healthcare in neurology requires real-time, portable, and cost-effective brain monitoring devices, and thus functional near-infrared spectroscopy (fNIRS) has received attention from researchers and neurologists as a suitable tool for realizing the goals of digital healthcare. fNIRS and its three-dimensional imaging extension, diffuse op-

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Correspondence

Zephaniah Phillips V, PhD
Global Health Technology Research Center,
College of Health Science,
Korea University,
145 Anam-ro, Seongbuk-gu,
Seoul 02841, Korea
Tel +82-2-940-2771
E-mail zphillips@korea.ac.kr

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tical tomography (DOT), are optical-based methods that are capable of measuring blood oxygenation levels using near-infrared light. fNIRS can serve as a practical alternative to the currently employed bulky and movement-restricting methods such as functional magnetic resonance imaging (fMRI) and magnetoencephalography. fNIRS brain monitoring can be performed in real time and at the bedside, making it suitable for patients who cannot be transported or who experience difficulties in constrained environments.^{2,3} Although the spatial resolution of fNIRS is lower than that of other modalities, the fNIRS signal have been found to be strongly correlated with blood-oxygen-level-dependent (BOLD) signals.^{3,4} fNIRS can also act as a complementary tool to electroencephalography (EEG). Simultaneous fNIRS and EEG measurements have improved the understanding of the relationship between the electrical activity of neurons and blood oxygen delivery to the brain.⁵

The structure of this review paper is as follows. First, there is a brief review the principles of fNIRS to investigate its utilization as an advanced brain monitoring tool for digital healthcare in neurology. Then, fNIRS research trends are highlighted that are driving toward a more-personalized understanding of the brain. These trends include multimodal brain monitoring and naturalistic experimental paradigms. To support the notion that these trends are shaping current fNIRS studies, recent research that best demonstrates its application for digital healthcare in neurology is reported.

BASIC PRINCIPLES AND TECHNIQUE DEVELOPMENTS

fNIRS optical brain monitoring is based on photons generated by a near-infrared light source (i.e., laser or light-emitting diode) propagating through the skin, scalp, and cerebral spinal fluid to reach the cerebral tissue. An optical window exists in the near-infrared range (600–1,000 nm) where absorption by water and lipids are minimized, allowing photons to pass through the skin and scalp. Light absorption in this range is primarily associated with oxygenated hemoglobin (HbO) and deoxygenated hemoglobin (Hb), making it possible to resolve changes in cerebral blood oxygenation (i.e., HbO and Hb) and total blood volume (HbT).⁶ Most commercial fNIRS systems are the continuous-wave type, which continuously illuminates the region of interest and measures intensity variations to resolve the changes in hemodynamic concentrations relative to baseline levels.⁷

Since photons must pass through the skin and scalp before reaching the brain, the fNIRS signal can be considered as a combination of non-event-related hemodynamics (skin and scalp) and event-related hemodynamics (brain activa-

tion). The source–detector (SD) distance must be appropriately controlled in order to ensure that the measured signal includes photons that pass through the brain tissue. Monte Carlo simulations of photon propagation have indicated that an SD separation of 25–35 mm can reliably monitor brain activation in adults.⁶ Shorter SD distances are only considered sensitive to hemodynamics changes in superficial areas. These short SD channels can be used to regress superficial hemodynamics from farther channels to isolate hemodynamics related to brain activation. However, the inhomogeneity of superficial hemodynamics should be considered when performing such regression.⁸

SD distance is just one of the many factors that needs to be considered when designing and conducting an experiment using fNIRS. Other experimental factors along with an overview of best practices for fNIRS studies has been published as a useful guide for conducting research using fNIRS.⁹

The typical fNIRS signal in response to brain activation can be generated using gamma functions, which have been shown to accurately model BOLD and fNIRS signals (Fig. 1).^{10,11} This generated signal can reveal blood vessel dynamics and changes in cerebral metabolism via temporal changes in the three fNIRS parameters being measured: HbO, Hb, and HbT. There is a rapid increase of oxygen consumption at the time of initial brain stimulation, resulting in a rapid increase in Hb and a decrease in HbO.^{12,13} The following large increase of HbO and HbT reflect a delivery of blood oxygen to the brain to support neural activity. An additional increase in blood velocity washes out the Hb in the blood vessels and increases HbO until blood oxygen saturation peaks in the blood vessels.¹⁰ HbO and HbT peak once cerebral metabolic demands are met, and then decrease to coincide with the

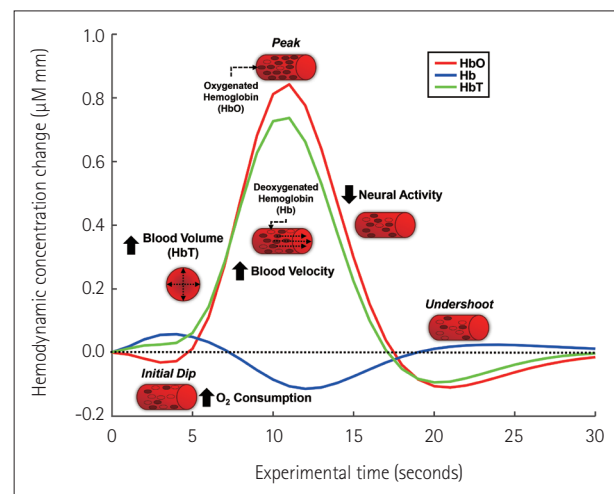


Fig. 1. Generated functional near-infrared spectroscopy signals and corresponding physiological blood vessel changes. Hb, deoxygenated hemoglobin; HbO, oxygenated hemoglobin; HbT, total blood volume.

decrease in neural activity. Lastly, a post stimulus undershoot is observed due to the rapid decrease in HbT while oxygen is still being consumed. This undershoot has been observed more often in optical monitoring than in BOLD signals.¹⁴

Recent software advancements have greatly facilitated the modeling, processing, and analysis of fNIRS data. This includes a three-dimensional Monte Carlo program to model photon propagation that can be run entirely in a web browser,¹⁵ along with continuous updates to the HOMER and AtlasViewer programs for fNIRS data handling.¹⁶ These software have also facilitated DOT reconstruction of cerebral hemodynamics without the need for prior knowledge of image reconstruction algorithms. Anatomically guided reconstruction of hemodynamics changes using DOT allows for gyrus-specific localization to pinpoint impairment and better understand the regional cerebral effects of diseases such as autonomic dysfunction.¹⁷

Fig. 2 presents an overview of DOT reconstruction to demonstrate how software advancements work together to reconstruct localized brain activation. The first step is to model the source and detector layout of the fNIRS system relative to the brain anatomy. When individual magnetic resonance imaging (MRI) scans are unavailable, the Colin27 MRI template can be used to model sources and detectors onto the anatomy using the AtlasViewer program (Fig. 2A).¹⁸ According to the channel layout, the photon propagation of each channel through the layered medium is simulated using the

Monte Carlo method. The browser-based Monte Carlo eXtreme program can be used for layer segmentation, photon simulation, and calculating fluence rates (Fig. 2B).¹⁵

The optical properties of the brain layers used to simulate photon propagation are listed in Table 1. Each optical property quantifies the behavior of light within the measured tissue, such as the absorption coefficient, which quantifies the effectiveness of photon absorption for a specific chromophore, and the scattering coefficient, which quantifies the photon-scattering characteristic.¹⁰ The optical properties in Table 1 have been used in previous studies on cerebral hemodynamics reconstruction.¹⁹ The sensitivity matrix is calculated after simulating photon propagation in each channel, and three-dimensional reconstruction of cerebral hemodynamics is then performed (Fig. 2C).¹⁸ The sensitivity profile of the channel measures the degree to which a change of absorption in a specific area is reflected in the measured signal. Sensitivity values can provide a better understanding of the brain regions that contribute most to the measured fNIRS signal, and they have been used to optimize probe positioning.^{18,20} The exact methods for inverting the photon propagation model, calculating the sensitivity profile, and linearizing the reconstruction method can be found elsewhere.²¹⁻²³

These software advancements have made data processing more widely available, and led to the standardization of data formats for use in studies on fNIRS.²⁴ Consistent visualization techniques using HOMER and AtlasViewer software

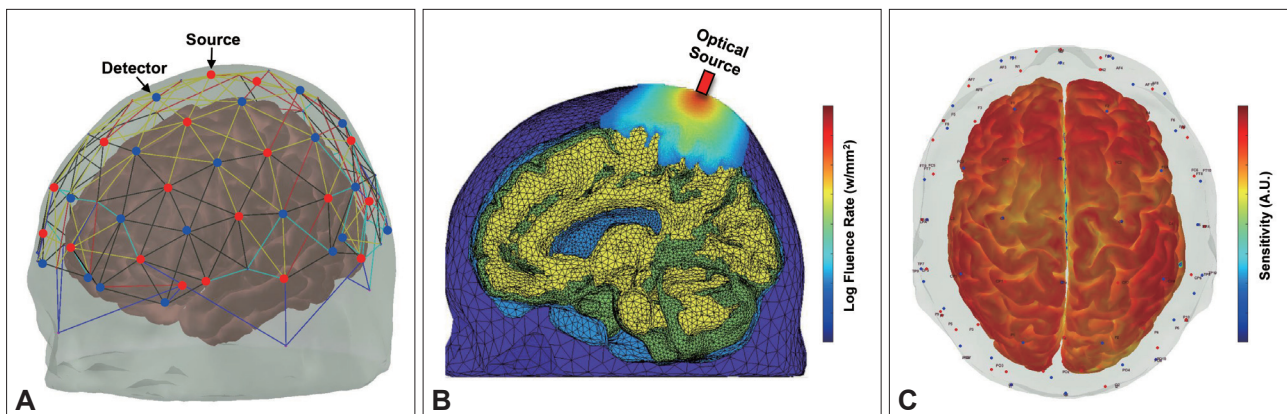


Fig. 2. Example of diffuse optical tomography processing steps: (A) probe modeling (red dot, source; blue dot, detector), (B) photon propagation modeling and fluence rate through a layered Colin27 template, and (C) probe sensitivity calculation.

Table 1. Summary of optical properties of the human head for modeling photon propagation

| Tissue type | Absorption coefficient (mm^{-1}) | Scattering coefficient (mm^{-1}) | Anisotropy factor (g) | Refractive index (n) |
|---------------------|--|--|--------------------------|-------------------------|
| Scalp and skull | 0.019 | 7.8 | 0.89 | 1.37 |
| Cerebrospinal fluid | 0.004 | 0.009 | 0.89 | 1.37 |
| Gray matter | 0.02 | 9.0 | 0.89 | 1.37 |
| White matter | 0.08 | 40.9 | 0.84 | 1.37 |

also allow for easier comparisons of the results obtained by different research groups. Due to these reasons, the applications of fNIRS have spread from only basic research and preliminary clinical studies to interdisciplinary research fields, such as sports science,²⁵ social neuroscience,²⁶ and neuro-marketing.²⁷ Furthermore, the growing trend of multimodal monitoring using fNIRS has enhanced the capabilities and accuracy of cerebral monitoring in these fields.

MULTIMODAL MONITORING

Cerebral dysfunction can be assessed directly by cerebral monitoring using fNIRS, which is more accurate than using blood pressure and heart rate measurements alone.²⁸ However, considering a more holistic health solution, a single brain monitoring modality for assessing cerebral hemodynamics is not adequate in the context of whole-body changes. Multimodal brain monitoring can therefore assess the relationship between various physiological phenomena. Due to the portability and miniaturization of fNIRS, as well as the lack of crosstalk between fNIRS and other systems (e.g., EEG),²⁹ multimodal monitoring has become one of the biggest trends in studies on fNIRS. Multimodal monitoring is important for digital healthcare because it produces a large amount of complementary data to improve the accuracy of AI systems.³⁰ It also reveals potential individual confounding factors for more-accurate brain studies³¹ and for exploring cause-and-effect relationships between physiological phenomena.³²

The various types of physiological parameters that can be monitored are best demonstrated in the study titled “Effect of short-term colored-light exposure on cerebral hemodynamics and oxygenation, and systemic physiological activity.”³³ That study analyzed the relationships between cerebral parameters and various systemic physiological parameters based on changes in colored light. For this purpose, cerebral oxygenation was monitored using a frequency-domain fNIRS system (ISS ImageNet) to measure oxygen saturation, HbO, Hb, and HbT. A wide range of systemic parameters were also measured, including the partial pressure of exhaled CO₂ (using the Nellcor N1000 gas analyzer), mean arterial pressure, systolic blood pressure, diastolic blood pressure, pulse pressure, pulse transit time, heart rate, heart rate variability (using the SOMNOtouch noninvasive blood-pressure monitor), electrodermal activity (using a skin-conductance bio-feedback device), and skin conductance level. The main finding of that study was that passive activities such as short-term light exposure can induce color-dependent responses in cerebral hemodynamics and cardiorespiratory changes. That study coined the term systemic-physiology-augment-

ed fNIRS (SPA-fNIRS) for the simultaneous measurement of systemic physiological parameters for assisting, complementing, and improving fNIRS measurements.

Subsequent SPA-fNIRS studies have demonstrated the importance of neurosystemic monitoring in identifying potential confounding factors that could mask brain activity. Because the fNIRS signal is a combination of systemic changes and cerebral hemodynamics, non-event-related systemic responses may result in false positives when analyzing fNIRS data.³¹ SPA-fNIRS studies have observed the resting-state asymmetry of frontal cerebral oxygenation and the dependence of resting-state hemodynamics on various systemic physiological parameters, the season of the year, and the time of day.³⁴ Those study results highlighted the importance of considering individual baseline physiological differences before evaluating differences across subjects. SPA-fNIRS studies have also explored the relationships between experimental conditions and neurosystemic parameters, such as the effect of continuous light exposure on systemic and brain physiology³⁵ and the effect of colored-light exposure on brain responses during verbal fluency tasks.³⁶ Those findings supported the need for continuous neurosystemic monitoring to properly control for factors that could influence experimental results. Finally, comparisons of cerebral and systemic physiological parameters between different participants produced evidence of synchronization due to eye contact,³⁷ which could be an important factor when performing hyperscanning studies (i.e., the simultaneous continuous fNIRS monitoring of multiple participants). Continuous and simultaneous neurosystemic monitoring can improve the accuracy of fNIRS measurements by identifying individual physiological characteristics and isolating physiological changes unrelated to brain activation.

Hardware improvements, such as system miniaturization, have not only increased the accessibility of fNIRS, but has allowed it to be combined with various brain monitoring modalities. Tables 2 and 3 present information on ten major recent studies that combined fNIRS systems with other brain monitoring modalities. The tables list the types of hardware used in the multimodal systems, the physiological parameters simultaneously measured, the fNIRS data acquisition rate, and the number of fNIRS channels. As indicated in the tables, fNIRS systems have been successfully combined with various other types of system, ranging from other brain monitoring tools (e.g., diffuse correlation spectroscopy and EEG) to stimulation tools (e.g., transcranial direct-current stimulation). These multimodal systems provide a wide range of neurosystemic parameters for quantifying different aspects of physiological changes. These parameters can also be used to derive new indirect parameters, such as those for

Table 2. Summary of multimodal research performed using fNIRS

| Systems | fNIRS channels | fNIRS data Acq. Rate (Hz) | Parameters measured | Ref. |
|---|--|---------------------------|--|------|
| CW-NIRS, EEG, accelerometer (support for ECG, electromyography) | Up to 6 | 16.66 | EEG power, HbO, Hb, X-Y-Z position, ECG | 38 |
| FD-NIRS, tDCS | 2 | 10 | μ_a , reduced μ_s' , (possibly HbO, Hb, HbT, STO ₂) | 39 |
| CW-NIRS, head PPG, chest ECG, seismocardiography, accelerometry | 116 channels (1.5 cm) 4 channels (3.5 cm) | 2 | HR, pre-ejection period, pulse arrival time, PTT, head PPG amplitude, HbO, Hb, HbT | 40 |
| MREG, EEG, CW-NIRS, NIBP, respiration belt, fingertip PPG, anesthesia monitoring | 10 | 10 | MREG, EEG power bands, HbO, Hb, HbT, BP, RR, PPG, respired CO ₂ , ECG | 41 |
| CW-NIRS, ECoG, negative-temperature-coefficient thermistors (separate monitoring of physiological activities) | 6 | 200 | HbO, Hb, HbT, ECoG power bands, cortical surface temperature, BP, HR | 42 |

BP, blood pressure; CW, continuous wave; ECG, electrocardiography; ECoG, electrocorticography; EEG, electroencephalography; FD, frequency domain; fNIRS, functional near-infrared spectroscopy; Hb, deoxygenated hemoglobin; HbO, oxygenated hemoglobin; HbT, total blood volume; HR, heart rate; MREG, magnetic resonance encephalography; NIBP, noninvasive blood pressure; NIRS, near-infrared spectroscopy; PPG, photoplethysmography; PTT, pulse transit time; RR, respiratory rate; STO₂, tissue oxygenation saturation; tDCS, transcranial direct-current stimulation; μ_a , absorption coefficient; μ_s' , scattering coefficient.

Table 3. Summary of multimodal research performed using fNIRS

| Systems | fNIRS channels | fNIRS data Acq. Rate (Hz) | Parameters measured | Ref. |
|---|----------------|---------------------------|---|------|
| FD-NIRS, gas analyzer, continuous NIBP monitor, skin conductance measuring device | 16 | 2 | Mayer wave amplitude, STO ₂ , HbO, Hb, HbT, RR, partial pressure of exhaled CO ₂ , MAP, systolic BP, diastolic BP, PP, PTT, HR, high frequency of HR variability, low frequency of HR variability, electrodermal activity, skin conductance, cardiac output, pulse respiration quotient | 33 |
| CW broadband NIRS, EEG | 16 | 0.35 | HbO, Hb, cytochrome-C-oxidase, EEG power bands, relative power, relative cost (metabolism) | 43 |
| Time-domain NIRS, DCS | 1 | 1 | μ_a , μ_s' , HbO, Hb, STO ₂ , blood flow index | 44 |
| EEG, EOG, CW-NIRS | 133 | 8.13 | EEG power bands, HbO, Hb, HbT, EOG | 45 |
| EEG, CW-NIRS, DCS, FD-NIRS, bedside monitoring of arterial BP | 1 | 5 | HbO, Hb, HbT, tissue oxygen index, relative cerebral blood flow, relative oxygen metabolism rate, EEG power bands, MAP | 46 |

BP, blood pressure; CW, continuous wave; DCS, diffuse correlation spectroscopy; EEG, electroencephalography; EOG, electrooculography; FD, frequency domain; fNIRS, functional near-infrared spectroscopy; Hb, deoxygenated hemoglobin; HbO, oxygenated hemoglobin; HbT, total blood volume; HR, heart rate; MAP, mean arterial pressure; NIBP, noninvasive blood pressure; NIRS, near-infrared spectroscopy; PP, pulse pressure; PTT, pulse transit time; RR, respiratory rate; STO₂, tissue oxygenation saturation; μ_a , absorption coefficient; μ_s' , scattering coefficient.

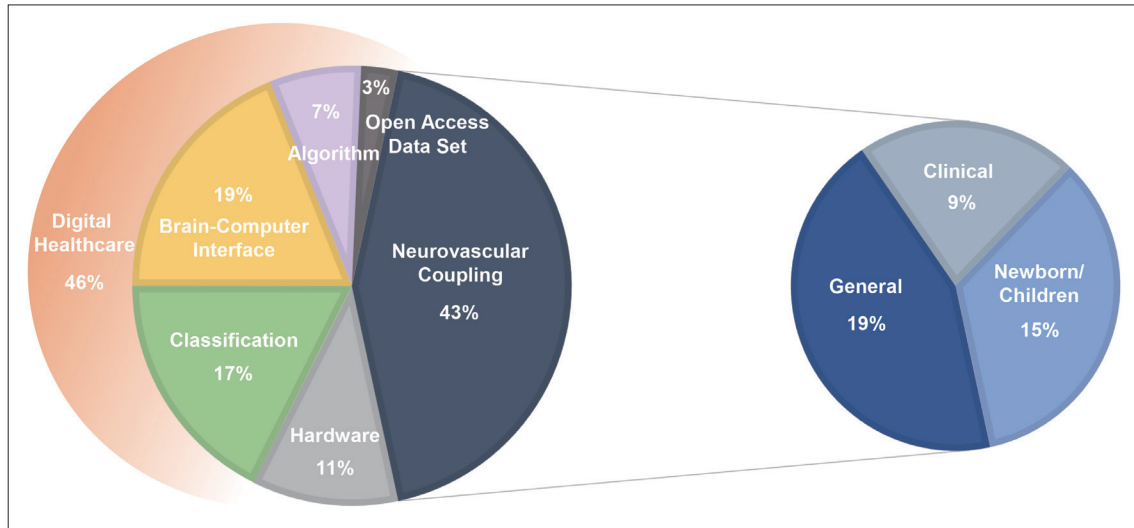


Fig. 3. The distribution of fNIRS-EEG applications according to relevant applications that were surveyed among 75 recent fNIRS-EEG studies. EEG, electroencephalography; fNIRS, functional near-infrared spectroscopy.

quantifying cerebral metabolism. Hardware and power-capacity improvements have also resulted in both higher data acquisition rates (up to 16.66 Hz) and more fNIRS channels (up to 133).

The fNIRS-EEG system is the most common combination for a multimodal fNIRS systems. Various reviews of the hardware integration, data processing, and interpretation of fNIRS and EEG multimodal systems can be found elsewhere.⁴⁷⁻⁴⁹ To investigate further into fNIRS-EEG systems and explore the type of applications, the first 75 fNIRS-EEG articles were surveyed when performing a Google Scholar search using the keywords “fNIRS” and “EEG.” Conference proceedings were omitted and the publication date range was limited to 2018–2022 in order to focus on recently studied fNIRS and EEG applications. After reviewing the list of publications, the following six major categories were created: 1) neurovascular coupling (NVC), 2) algorithm, 3) brain-computer interface (BCI), 4) classification, 5) hardware, and 6) open-access data sets (Fig. 3).

The NVC studies primarily consisted of clinical neurology studies and basic neurological research that explored the relationship between neural electrical signals and cerebral blood oxygenation in both patients and healthy participants. They aimed to understand brain functioning in the presence of various stimuli or neurological disease. NVC studies can be further divided into three subcategories: 1) general studies on healthy adult participants, 2) studies on newborns/children, and 3) clinical studies on patients. The proportions of studies among the NVC subcategories demonstrate that fNIRS-EEG multimodal systems have been equally useful for healthy adults (19%) and newborns/children (15%); however, relatively fewer of these systems have been implement-

ed in clinical settings (9%).

The algorithm, BCI, and classification categories, and open-access data sets can be considered as general digital healthcare studies because they directly intersect with technology. Research in these categories has facilitated the accurate classification of fNIRS data, the interactions between humans and computers, and the sharing of data sets among research groups to benchmark classification accuracy and improve algorithm development of digital healthcare technologies. The survey found that these studies accounted for 46% of fNIRS-EEG multimodal studies. It was interesting that this percentage was only slightly higher than that of the NVC studies combined (43%). The practical split between digital healthcare studies and general neurological research supports the idea that fNIRS has progressed toward being both a suitable medical modality for digital healthcare and a reliable brain monitoring tool for neurological studies. Many of the surveyed studies that directly contributed to the progress in digital healthcare were conducted using naturalistic experimental paradigms, which is the second major trend driving fNIRS studies.

NATURALISTIC EXPERIMENTAL PARADIGMS

The high motion tolerance of fNIRS when detecting artifacts allows subjects to engage in dynamic movements during brain-activation studies, such as those that involve the tilt-table test⁵⁰ and freely moving animals.⁵¹ fNIRS as a digital healthcare tool for unrestrained brain monitoring provides two major benefits: 1) the capability of monitoring participants in a natural environment and 2) providing neurofeed-

back during virtual reality (VR) experiences. These benefits allow for more practical studies of brain activation with real-life implications, which will be further discussed in this section.

Participants in a natural environment experience a diverse set of visual and auditory stimuli, and so the brain responses measured in this condition often reflect complex connections between multiple cortices. However, typical task-evoked stimuli only target individual cortices. These experimental paradigms are also often repetitive, thereby failing to fully engage the participant with the task.⁵² Instead of task-evoked stimuli, naturalistic experimental paradigms involve real-life scenarios that contain a mixture of visual and auditory stimuli, often along with narrative components. The brain responses and whole-brain mapping in naturalistic experimental paradigms are best discussed by Fishell et al.⁵² in their publication titled “mapping brain function during naturalistic viewing using high density diffuse optical tomography” that was published in 2019. In that study, a wide field of view DOT system monitored whole-brain responses during naturalistic movie watching. It demonstrated the ability to separate stimuli-specific brain responses for concurrent audio and visual stimuli while watching a movie. For this purpose, a feature-decomposition strategy was used to map brain activation to specific features (i.e., visual cues such as faces, bodies, and hands, and audio cues such as speaking). That study presented the effectiveness of naturalistic experimental paradigms for DOT studies and their ability to isolate brain responses during multisensory experiences.

The naturalistic experimental paradigm extends beyond movie watching and has practical use in the ergonomics and sports-science fields. fNIRS has been increasingly used in ergonomics experiments to quantify parameters that are difficult to measure, such as cognitive workload. Cognitive workload is an important parameter for assessing the feasibility of robotic assistance technology in everyday life. For example, fNIRS studies have found that using an exoskeleton induces functional connectivity changes in participants, indicating that the reduced physical effort required when lifting with the aid of an exoskeleton may be offset by the greater cognitive workload imposed by the robotic assistance.⁵³ fNIRS also has the capability to accurately detect and communicate the intended movements of the participant to the exoskeleton despite the increased cognitive workload.⁵⁴ Furthermore, cognitive workload measurements can be utilized to understand brain function during dynamic wheelchair usage. fNIRS studies of wheelchair users found reduced hemodynamics activation when navigating simple environments (lower cognitive workload), but increased when navigating through complex environments with various obstacles (high-

er cognitive workload). The brain was also less active when wheelchair users used assistive software to support movement, indicating that the software can reduce the cognitive workload imposed on the user.⁵⁵

In the sports-science field, fNIRS monitoring has been used to study brain function during cooperative activities and training. A hyperscanning approach yielded evidence of interpersonal neural synchronization during joint drawing tasks among basketball teammates. However, the same synchronization was not observed in college students who did not participate in cooperative sports.⁵⁶ Altered brain function was also observed in endurance athletes during cycling, including reduced Hb production compared with controls; however, no evidence of improved neural efficiency was observed in those athletes.⁵⁷ In contrast, fNIRS measured the same functional connectivity while slackline athletes were standing or walking, demonstrating their high level of balance.⁵⁸ These applications highlighted for the advancement of ergonomics and sports science demonstrate the potential usefulness of fNIRS for the everyday person.

Naturalistic environments can also be replicated in VR, which is a key topic in digital healthcare. VR allows researchers to develop immersive environments and carefully control experimental parameters to design more-insightful experimental protocols. VR headsets combined with fNIRS allow real-time assessments of brain activation in realistic yet customized environments, and the delivery of real-time neurofeedback for more-effective and personalized training.

The enhanced efficacy of VR therapy was demonstrated by Cho et al.⁵⁹ in 2022, in which a VR environment was used to administer prism adaptation (PA) therapy to test unilateral spatial neglect. Since PA therapy often requires a large physical space, VR provides the opportunity to conveniently administer such therapy. Using the multisensory environment of VR and real-time fNIRS brain monitoring, researchers adjusted the therapy treatment according to user responses. This allowed for measurements of activated attentive networks and quantification of the effectiveness of the therapy. Similar benefits were demonstrated in a fNIRS study that measured cognition during life-support training for emergency preparedness. Monitoring cerebral blood oxygenation during training allowed researchers to assess the effectiveness of emergency-situation training.⁶⁰

Efficacy can be measured not only for therapy and training but also for prescription medication for cognitive disorders. Simultaneous VR and fNIRS monitoring was used to monitor brain oxygenation changes in students with attention deficit hyperactivity disorder (ADHD) in a classroom setting. This experiment was designed to measure the efficacy of prescription medication in controlling impulsive re-

sponses to new scenarios.⁶¹ The VR and fNIRS monitoring results also indicated better focusing ability in healthy participants and participants with ADHD, as well as higher user satisfaction with the experimental protocol.⁶²

Reinforced learning can be integrated into VR environments through real-time fNIRS monitoring that provides neurofeedback. In a study that exposed participants with ADHD to a VR classroom environment, neurofeedback was utilized to help their self-regulation of cognitive behavior. The feedback included visual or acoustic cues, such as lighting changes in the classroom, which were immediately presented to the participant upon the performance of certain behaviors, in order to correct them or act as positive reinforcement.⁶³ VR feedback based on the fNIRS signal was found to help participants of all ages with ADHD to concentrate, sit still, endure boredom, and inhibit impulsive behavior.^{63,64} Besides alleviation of cognitive dysfunction, neurofeedback can be used as guidance for the user, including paced breathing to localize brain activity during mindful breathing.⁶⁵

FUTURE OUTLOOK

While the future of fNIRS for digital healthcare in neurology is promising, certain outstanding issues need to be addressed before it can become widely accepted in clinics. One of the biggest obstacles to fNIRS monitoring is the lack of an accepted data-processing pipeline for effectively removing noise, such as systemic noise and motion artifacts.⁶ The use of different processing pipelines makes it difficult to compare results among studies, because each noise-removal algorithm offers varying capabilities in removing motion artifacts, temporal drift, and non-event-related hemodynamics. Many reviews have investigated various fNIRS processing pipelines, with each having its own benefits and drawbacks depending on the characteristics of the participants.⁶⁶⁻⁶⁹ In the case of motion artifacts, most researchers agree that correcting motion artifacts is a better approach than simply rejecting trials.⁷⁰ Wavelet filtering combined with another algorithm (i.e., spline interpolation) was the most effective correction method for reducing motion artifacts in cognitive studies⁷¹ and infant data.⁷⁰

For a reliable assessment of cerebral hemodynamics, the basic fNIRS processing pipeline should include steps such as channel rejection, motion artifact removal, and superficial hemodynamics removal.⁹ To reach a consensus on the best processing pipeline, the capabilities of the different types must be objectively measured. In this sense, realistic data-generation algorithms are needed to provide both noisy data and the ground-truth hemodynamics response as a basis for comparing the effectiveness of recovering the ground-truth

data.⁷² The lack of a consensus-based approach for basic fNIRS processing may lead to results that are difficult to interpret or unreliable.^{31,73}

Tremendous progress has been made toward fNIRS becoming a viable alternative to fMRI as well as a complementary monitoring tool to EEG, thereby making it one of the most appropriate tools for achieving the goal of personalizing digital healthcare. Researchers are constantly finding innovative ways to perform multimodal monitoring with fNIRS, which affords clinicians and patients access to more data and allows for a personalized assessment of the health of the whole body. Researchers are also designing experiments with fNIRS that allow participants to freely engage with multi-sensory environments that closely mimic naturalistic, everyday conditions. Lastly, fNIRS combined with innovative technologies such as VR allows researchers to work within a digital space to objectively measure performance and provide feedback to the individual.

Availability of Data and Material

The datasets generated or analyzed during the study are available from the corresponding author on reasonable request.

ORCID iDs

| | |
|----------------------|---|
| Zephaniah Phillips V | https://orcid.org/0000-0001-7357-7589 |
| Raymart Jay Canoy | https://orcid.org/0000-0003-2371-2900 |
| Seung-ho Paik | https://orcid.org/0000-0001-6993-3229 |
| Seung Hyun Lee | https://orcid.org/0000-0002-1109-6787 |
| Beop-Min Kim | https://orcid.org/0000-0002-1056-5078 |

Author Contributions

Conceptualization: Zephaniah Phillips V, Seung-ho Paik, Seung Hyun Lee, Beop-Min Kim. Supervision: Beop-Min Kim. Writing—original draft: Zephaniah Phillips V. Writing—review & editing: Zephaniah Phillips V, Raymart Jay Canoy.

Conflicts of Interest

The authors have no potential conflicts of interest to disclose.

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