Opportunities and Limitations of Mobile Neuroimaging Technologies in Educational Neuroscience

Tieme W.P. Janssen[1] ⓘ**, Jennie K. Grammer[2]** ⓘ**, Martin G. Bleichner[3]** ⓘ**, Chiara Bulgarelli[4]** ⓘ**,
Ido Davidesco[5]** ⓘ**, Suzanne Dikker[6]** ⓘ**, Kaja K. Jasińska[7]** ⓘ**, Roma Siugzdaite[8]** ⓘ**, Eliana Vassena[9]** ⓘ**,
Argiro Vatakis[10]** ⓘ**, Elana Zion-Golumbic[11]** ⓘ**, and Nienke van Atteveldt[1]** ⓘ

ABSTRACT— As the field of educational neuroscience continues to grow, questions have emerged regarding the ecological validity and applicability of this research to educational practice. Recent advances in mobile neuroimaging technologies have made it possible to conduct neuroscientific studies directly in naturalistic learning environments. We propose that embedding mobile neuroimaging research in a cycle (Matusz, Dikker, Huth, & Perrodin, 2019), involving lab-based, seminaturalistic, and fully naturalistic experiments, is well suited for addressing educational questions. With this review, we take a cautious approach, by discussing the valuable insights that can be gained from mobile neuroimaging technology, including electroencephalography and functional near-infrared spectroscopy, as well as the challenges posed by bringing neuroscientific methods into the classroom. Research paradigms used alongside mobile neuroimaging technology vary considerably. To illustrate this point, studies are discussed with increasingly naturalistic designs. We conclude with several ethical considerations that should be taken into account in this unique area of research.

[1]Department of Clinical, Neuro- & Developmental Psychology, Vrije Universiteit
[2]Graduate School of Education and Information Studies, University of California Los Angeles
[3]Department of Psychology, University of Oldenburg
[4]Centre for Brain and Cognitive Development, Birkbeck University of London
[5]Department of Educational Psychology, University of Connecticut
[6]NYU Max Planck Center for Language, New York University
[7]Department of Applied Psychology and Human Development, University of Toronto
[8]Department of Psychology, Cambridge University
[9]Donders Institute for Brain, Cognition and Behaviour, Radboud University
[10]Psychology Department, Panteion University
[11]Gonda Brain Research Center, Bar-Ilan University

Address correspondence to Tieme W.P. Janssen, Vrije Universiteit Clinical Neuropsychology Section, Van der Boechorststraat 7, 1081 BT Amsterdam, The Netherlands; e-mail: twp.janssen@vu.nl.

Tieme W.P. Janssen and Jennie K. Grammer contributed equally to this work.

Martin G. Bleichner, Chiara Bulgarelli, Ido Davidesco, Suzanne Dikker, Kaja K. Jasińska, Roma Siugzdaite, Eliana Vassena, Argiro Vatakis, and Elana Zion-Golumbic (arranged in alphabetical order) contributed equally to this work.

Over the past 20 years, there has been a marked increase in the use of neuroscientific methods to examine student learning. In this relatively short period, a great deal has been revealed about the neural processes associated with educationally relevant skills. As the field of educational neuroscience has developed, it has emerged as an inherently interdisciplinary enterprise, drawing on theories and methods from education, psychology, and cognitive neuroscience (Thomas, Ansari, & Knowland, 2019). Theoretical models that characterize development in the school context emphasize the role of complex and dynamic interactions between students and teachers for growth (Eccles & Roeser, 2011). Although these complex processes are what researchers aim to study in the classroom, educational neuroscience has historically fallen short of this goal.

This is in large part because the majority of educational neuroscience research is based on traditional laboratory-based methods (e.g., functional magnetic resonance imaging [fMRI] and electroencephalography [EEG]). While these methods help elucidate cognitive processes that

cannot be directly observed through student behavior, their use involves artificially reducing the world to a small number of variables for experimental manipulation ("systematic design") studied in isolated individuals. This reductionist approach affords researchers experimental control over phenomena of interest; however, neuroscientific methods are often seen as incommensurate with educational theory and impose limitations on the generalizability to learning and teaching in real life (Van Atteveldt, Van Kesteren, Braams, & Krabbendam, 2018). Although informed by—and sometimes conducted in collaboration with—educators, educational neuroscience is often limited in the extent to which it can fully capture dynamic real-world classroom experiences and, in turn, inform educational practice (Bowers, 2016). In this review, we discuss the promise afforded by *real-world neuroscience* methods, and in particular, those made possible by advances in mobile neuroimaging technologies, for understanding student learning in educational settings.

What Is Real-World Neuroscience?
Cognitive and social skills do not develop in isolation. Rather they are formed through the multitude of experiences and dynamic interactions that an individual has with other people, as well as with the rich stimuli that make up our daily environments. However, this real-world complexity can be inherently at odds with the way research is conducted in a laboratory setting.

Take, for example, the experience of an elementary school student learning a new concept in mathematics. To examine this in a traditional lab-based investigation, the student might come to the university laboratory and individually participate in a computerized task, carefully designed to elicit neural responses associated with a particular aspect of learning mathematics. As is shown on the far left side of Figure 1, in this setting, it is possible to track the progression of learning and to tightly control the context in which learning occurs. In contrast, assessing the learning of mathematics in the classroom would involve accounting for multisensory input, social interactions with teachers and peers, active learning involving a two-way exchange of information, and all kinds of distractions inherent to being in a classroom. This distinction—between the experience of a student in a laboratory versus in a classroom—is central to understanding the unique contributions of
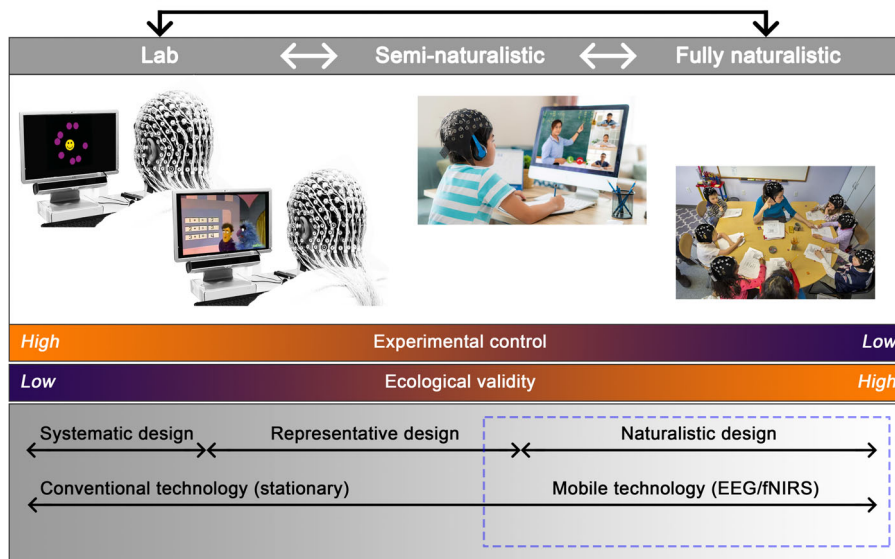

Fig. 1. The three-stage cyclical model for educational neuroscience. Research in educational neuroscience covers a broad range of paradigms with different trade-offs between experimental control and ecological validity, which can be achieved in different ways. In contrast to the systematic design, researchers can increase their efforts to "*bring the real-world to the lab*" by the careful sampling of the target ecology ("representative design"). The current review focuses on "*bringing the lab to the real-world*" using mobile neuroimaging technology, which is another approach to real-world neuroscience (blue rectangle). One important challenge is to develop new paradigms that work well outside the lab ("naturalistic design"). Research at all stages of the cycle is needed in educational neuroscience; lab studies are needed to provide a basis for more naturalistic research, with the latter providing ground for previously established knowledge or for formulating new hypotheses that can be tested in more controlled lab or seminaturalistic environments. Note that not all neuroeducational research conforms to these categories; for example, some reliability studies use typical ERP designs ("systematic design") outside the lab with mobile electroencephalography (e.g., while walking or cycling). Further note that this is a revised version of the cycle by Matusz et al. (2019), incorporating Brunwik's terminology, the need for naturalistic paradigms and the focus on mobile neuroimaging technology.

research drawn from a range of paradigms in educational neuroscience.

Even when experiments are designed to mimic the experiences that students have in school, it is challenging to simulate dynamic aspects of classroom ecologies including the varied sensory inputs, social interactions with familiar teachers and peers, student autonomy and agency, and authentic academic experiences (e.g., challenging assignments and cumulative units of instruction) that are naturally occurring in the classroom setting. Indeed, there is reason to suspect that the cognitive processes observed in the laboratory setting vary from those employed in authentic social interactions (Risko, Richardson, & Kingstone, 2016) and that while this highly controlled research provides important insight into these processes, this work cannot address the complexities of how and when they are applied in the real world (Osborne-Crowley, 2020).

The goal of real world or "real-life" (Shamay-Tsoory & Mendelsohn, 2019) neuroscience is to increase the *ecological validity* of neuroscience investigations. There is a recent discussion (Holleman, Hooge, Kemner, & Hessels, 2020) about the definition of ecological validity and real-life experiments, which is useful to consider with respect to our current goal. This discussion is more a revival, as Hammond (1998) already argued that ecological validity is often conflated with *representative design* (Brunswik, 1955). According to Brunswik, researchers should not only aim for proper sampling of participants (to represent a target population) but also aim for proper sampling of stimuli, tasks, and situations (to represent a specific target ecology). Holleman et al. (2020) argue that the words "real-world" and "ecological validity" are often used superficially and suggest that researchers should more clearly specify and describe the particular contexts of behavior in which they are interested (*target ecology*).

The Continuum of Real-World Neuroscience

There are a number of ways that researchers can begin examining neural processes in real-world settings. As an initial step in this direction, researchers have begun to examine neural processes in response to real-world stimuli. For example, Cantlon (2020) provides an example of how the same research group examining numerical cognition progressed from a traditional lab neuroimaging study to a more representative paradigm to validate their theory. Starting with a typical fMRI lab paradigm, 4-year-old children were presented with dot arrays with the same number of elements and element shape; however, in some of the trials, there was a deviant stimulus in either the number of elements (number deviants) or local element shape (shape deviants; Cantlon, Brannon, Carter, & Pelphrey, 2006). The results indicated that the intraparietal sulcus (IPS), previously associated with numerical processing, showed greater activation for the number deviants.

Children's early math skills develop in part through informal learning opportunities including watching educational programs. To examine the extent to which the IPS is involved in numerical processing when children are engaged in these types of everyday activities, in their subsequent fMRI study (Cantlon & Li, 2013), they aimed to have more naturalistic stimuli by using a 20-min episode of Sesame Street about mathematics, reading, and other topics. Children's IPS responses were higher during mathematics content than during non-numerical content. Moreover, the maturity of children's neural time courses in the IPS, compared to adults, predicted their mathematics test performance better than traditional fMRI measures. The right IPS showed an overall higher maturity and more specificity for mathematics than the left IPS, which is consistent with previous studies, suggesting that the comparison of analog quantities (more strongly related to the right IPS) develops earlier than the processing of precise symbolic representations of numerical values (more strongly related to the left IPS). A recent study similarly examined neural alignment between novice college students and experts while they watched math lectures and completed an open-question exam in the fMRI scanner. Results indicated that neural alignment with other students and experts predicted exam performance, even on a more fine-grained question-by-question basis within individual students (Meshulam et al., 2021).

The principles of representative design are also increasingly used in lab-based functional near-infrared spectroscopy (fNIRS) studies. For example, in one investigation, adult students watched a lecture on astronomy and completed related quiz questions (Oku & Sato, 2021). Using this experimental design with representative stimuli allowed researchers to measure activation in the prefrontal cortex and examine how this was related to quiz accuracy. Others have used fNIRS in combination with virtual reality (VR) neuropsychological tests to approximate real-life contexts in the laboratory, to address questions about working memory (Jang et al., 2021) and reading development (Blume et al., 2020) for children with Attention-Deficit/Hyperactivity Disorder (ADHD) in the context of virtual classrooms. The combination of fNIRS and VR-based real-life context allowed researchers to assess brain activity while controlling the classroom setting to limit any extraneous factors.

These examples improve our understanding of brain development and learning in more naturalistic contexts. Future studies may further inform us about learning disabilities and other individual differences, potentially aiding the development of educational programs. Otherwise, these findings may help us to understand why existing programs are more or less effective. We think that validating earlier findings with more naturalistic paradigms is a crucial step.

Especially encouraging is when findings not only replicate but also improve prediction of real-world outcomes.

The previous examples highlight (1) the ways in which neuroscience can be used to address questions relevant to education (e.g., what are the neural processes associated with numeracy, and how does exposure to real-world educational videos relate to these processes?) and (2) how researchers can iterate between traditional lab tasks and novel paradigms to understand neural processes in naturalistic contexts.

In-line with these examples, we argue that the most useful model for educational neuroscience is cyclical, as some of us previously outlined in Matusz et al. (2019). The three-stage cyclical model comprises (1) tightly controlled lab-based studies, (2) seminaturalistic research conducted either in the laboratory or in controlled field settings, which are designed to be representative of classroom experiences, and (3) fully naturalistic studies. Educationally relevant studies exist on a continuum of two dimensions, experimental control and ecological validity, which generally have an antagonistic relationship, see Figure 1. By iterating across stages and methods, it is possible to generate complementary and converging evidence that—considered collectively—can yield comprehensive, neuroscientifically informed evidence to address complex educational questions. In this way, research relevant to education can be construed broadly, ranging from work focused on "low-level" learning-related behaviors and single cognitive constructs (Willingham & Lloyd, 2007), such as numerical processing, attention, or memory, to more complex educational processes like advanced mathematical problem solving or social interactions.

Educational neuroscience studies in lab environments can be made more naturalistic using the principle of representative design, that is, by "bringing the real world to the lab." This is a valuable and promising approach. In this review, however, we instead focus on "bringing the lab to the real world" (stages 2 and 3). Specifically, we discuss the potential of neuroscientific work conducted directly in real-world settings, including schools, homes, and community-based settings. The aim is to probe neural and behavioral processes in the contexts in which they realistically occur and—in the specific case of educational neuroscience—to increase the translational potential of neuroscientific findings for educational practice.

Mobile Neuroimaging

Advances in mobile neuroimaging technology, namely mobile EEG and mobile fNIRS, have played a key role in bringing the lab to the real world. Mobile systems are small, lightweight, battery-powered, and can be worn by participants without being tethered by wires to an amplifier or other recording devices (for examples of mobile EEG systems, see Lau-Zhu, Lau, & McLoughlin, 2019; for

examples of fNIRS systems, see Quaresima & Ferrari, 2019; see Table 1 for more details on the EEG and fNIRS techniques). Wearing mobile technology, student learning would ideally be investigated while they are able to freely move about the classroom and engage with the world around them, while data on behavioral and brain processes are being continuously acquired. In this review, it will become apparent that currently, the most "real-world" educational neuroscience studies come close to this ideal, but with the inherent trade-offs that have to be made to retain some experimental control.

CURRENT STATE OF AFFAIRS

Mobile neuroimaging systems have been used in a variety of research settings, both inside and outside the lab, because they allow more natural behaviors in participants. However, research paradigms that are used alongside mobile EEG/fNIRS vary considerably in how naturalistic they are. To illustrate this point, we will discuss exemplar studies with increasingly naturalistic designs, covered in the following sections: (2.1) lab paradigms in mobile labs, (2.2) lab paradigms in naturalistic settings, (2.3) online paradigms in educational technology, and (2.4) naturalistic paradigms in naturalistic settings. For Section 2.4, we will focus on studies that used mobile EEG/fNIRS *outside* the lab in *educational settings*, as indicated by the blue rectangle in Figure 1. In doing so, we highlight the strengths of these approaches and challenges that need to be addressed in future research. Where possible, we will address how research findings may be indirectly relevant for the classroom.

In the final section of this review, we will address ethical considerations of mobile technologies and present recommendations for future research. fNIRS has been scarcely used in educational settings, therefore this review comprises mostly mobile EEG examples, though many methodological and ethical challenges are similar for both techniques.

Lab Paradigms in Mobile Labs

Mobile technologies have the potential to significantly increase inclusion in science for communities that have largely remained excluded from scientific research. Most neuroimaging research to date takes place at universities and hospitals. These settings inherently create barriers to an inclusive and comprehensive science of the human brain. There are socioeconomic and cultural factors that prevent many people from participating in neuroimaging research. Moreover, university campus laboratories can be unfamiliar, difficult to navigate, and potentially intimidating to visit for individuals and families who may have never been there before. These obstacles have a cumulative effect in neuroscience; much of our understanding of human brain

Table 1

Comparison of Lab-Based and Mobile-Based EEG and fNIRS Techniques

	EEG		fNIRS	
	Lab EEG	Mobile EEG	Lab fNIRS	Mobile fNIRS
Nature of signal	Changes in electrophysiological activity of neurons. Depends on changes in voltage that follow from the synchronized firing of neurons that are oriented parallel to the cortical surface. This measurement mostly captures cortical activity (not subcortical).	Similar to lab EEG	Levels of oxygenated and deoxygenated hemoglobin in blood vessels in the brain, mainly cortical areas (maximum depth 2 cm). Changes in oxyH and deoxyH levels are taken as a sign of increased brain activity.	Similar to lab fNIRS
Equipment	A cap is placed on the participant's head. A number of electrodes are attached to the cap at different locations (e.g., 32, 64, or 128 channels). Most systems require conductive gel or saline and are wired to an amplifier.	Mobile systems are small, lightweight, battery-powered, and can be worn by participants without being tethered by wires to an amplifier. While many consumer "headsets" only contain small numbers of electrodes (1–14), research-grade systems can have better scalp coverage (16–128). Both dry and wet (saline and gel) electrodes may be used.	A number of sensors, called optodes, are placed on the participant's head attached to a cap. The number of sensors depends on the "montage" (i.e., combination of sensors depending on which cortical area one wants to record). Most studies measure only part of the cortex (e.g., frontal).	Mobile systems are small, lightweight, battery-powered, and can be worn by participants without being tethered to a recording device. Compared to lab fNIRS, usually less optodes are used.
Additional equipment	Two computers may be used, one for recording EEG and another for presenting stimuli. The participant generally sits on a chair facing a computer screen and provides responses with a keyboard or button box.	EEG data may be recorded on the device or transmitted via Bluetooth to a nearby device (e.g., laptop or smartphone). Some companies offer mobile devices for presenting stimuli that are synced with the EEG.	Two computers may be used, one for recording fNIRS, and another for presenting stimuli. The participant generally sits on a chair facing a computer screen and provides responses with keyboard or button box	fNIRS data may be recorded on the device, or transmitted via Bluetooth to a nearby device (e.g., laptop or smartphone).
Context	Participants are very restricted in acting naturally. Ideally, the room is shielded to avoid electromagnetic interference.	Participants have more room to act naturally; however, in many studies, this is still limited due to data quality issues. Environments outside the lab can contain more electrical noise, which can be partially counteracted with active electrodes and shielding.	Participants are restricted in acting naturally, but fNIRS allows more movement than EEG. Ideally, a dark room to avoid additional light sources.	Participants have more room to act naturally; however, even though fNIRS is more robust to motion artifacts, naturalistic paradigms need to take increased motion artifacts into account when moving out of the lab.
Data quality	EEG data contains artifacts from many different sources, both physiologic (e.g., ocular, muscle) and nonphysiologic (e.g., cable and body movement, AC interference).	All sources of artifacts can be more common when measured outside the lab, therefore large portions of EEG may be rejected (~30–70%). Mobile systems with active electrodes and shielding can reduce some artifacts. Higher number of electrodes allow ICA, which can be used to identify and remove some types of artifacts (e.g., ocular, muscle, movement), without rejecting some EEG epochs. Larger number of trials or a longer period of recording is recommended to account for data loss.	fNIRS is relatively robust to subjects' motions. This does not mean that the technique is insensitive to motion artifacts, especially in certain populations (e.g., infants and children). There are a range of correction methods available that are effective in recovering most trials affected by motion artifacts (Di Lorenzo et al., 2019).	Fibreless systems are more robust to motion artifacts. Fibreless systems with high coverage or whole-head measurements have a higher chance of producing motion artifacts due to the weight of the probe holder. Increased artifacts can also occur due to daylight in naturalistic environments, but this can be minimized by using shading caps or using optical detectors with a high dynamic range, or by including a reference detector.

Table 1
Continued

	EEG		fNIRS	
	Lab EEG	*Mobile EEG*	*Lab fNIRS*	*Mobile fNIRS*
Analysis options	It is possible to study ERP, which are voltage changes that are time-locked to experimental events, which allow investigating specific cognitive functions (e.g., inhibition). It is also possible to study changes in time-frequency spectra, both spontaneous and related to task events. For both ERP and trial-specific EEG analyses it is necessary to have a sufficient number of trials to assess following data cleaning and processing.	ERPs are feasible to study using lab paradigms in naturalistic settings (see Section 2.2), but this is more difficult otherwise (see Section 2.4). Real-world learning situations are relatively unstructured, meaning that relevant events are not pre-established, relatively rare, and not always have clear onsets. Hyperscanning of multiple interacting students is a promising approach for mobile EEG.	Task-related hemodynamic changes (e.g., during working memory vs. control). Both block designs and event-related designs are possible. Rest activity is also possible to record.	Block designs are used more often in naturalistic contexts with mobile fNIRS.
Advantages	High temporal resolution (milliseconds): possibility to measure electrophysiological changes in brain activity in real time.	Similar to lab EEG.	Reasonable spatial resolution (~1 cm). Possible to determine the cortical source of the measured signal	Similar to lab fNIRS, although the scalp coverage may be smaller.
	Noninvasive.	Similar to lab EEG.	Noninvasive.	Similar to lab fNIRS.
	Direct measure of neural activity.	Similar to lab EEG.	Child-friendly and can be used for people who cannot go into the MRI scanner (e.g., people who have contraindications for the MRI scanner, such as metal implants, etc).	Similar to lab fNIRS.
Disadvantages	Low spatial resolution: not possible to make fine anatomical inference on the source of the signal (although dense systems with >64 channels allow for complex source modeling).	Due to the lower number of electrodes in most mobile EEG systems, source modeling may be less feasible or accurate.	Low temporal resolution. The hemodynamic response is slow, and hence relevant events need to be at least 3 s apart (and ideally longer) to be distinguishable in an event-related design.	Similar to lab fNIRS.
	Preparation time for cap setup is long.	Dry EEG systems are fast to setup but have lower signal quality. Most systems have fewer electrodes (shorter preparation).	Because of the optic measurement, hair color and skin type can affect signal quality. Preparation time is still long.	Similar to lab fNIRS.
	Very sensitive to physiological noise (many artifacts).	Similar to lab EEG.	Indirect measure of neural activity.	Similar to lab fNIRS.
	Impossible to measure subcortical activity.	Similar to lab EEG.	Impossible to measure subcortical activity.	Similar to lab fNIRS.

Note. AC = alternating current; EEG = electroencephalography; ERP = event-related potentials; fNIRS = functional near-infrared spectroscopy; ICA = independent component analysis; MRI = magnetic resonance imaging.

development is effectively based on a nonrepresentative sample (Henrich, Heine, & Norenzayan, 2010). With mobile techniques, neuroimaging studies can take place virtually anywhere; in schools (Grammer, Carrasco, Gehring, & Morrison, 2014; Pietto et al., 2018) and in communities that are distant to a university or hospital-based lab, or at home. From a methodological standpoint, such studies may employ typical lab paradigms in "pop-up labs" (e.g., empty classroom and living room), allowing researchers to examine the links between neural processes and educational outcomes (Kim et al., 2016) with more representative samples.

Mobile neuroimaging tools have also successfully been used to study child development beyond high-income countries (HICs), where the majority of neuroimaging laboratories exist. For example, Jasińska and Guei (2018) developed a field neuroimaging protocol for use in rural sub-Saharan Africa, Côte d'Ivoire, to better understand the reading development of primary-school children growing up in environments with a high-risk of illiteracy. fNIRS techniques have also been used to evaluate the impact of early risk on infant and child development in global health settings. In rural Gambia (Blasi, Lloyd-Fox, Katus, & Elwell, 2019; Lloyd-Fox et al., 2014; Papademetriou et al., 2014), in an urban slum in Bangladesh (Perdue et al., 2019; Storrs, 2017), and in India (Wijeakumar, Kumar, Delgado Reyes, Tiwari, & Spencer, 2019), researchers have used fNIRS to study infant cognition and gain new insights into how environmental factors such as nutrition and sanitation contribute to brain development.

Lab Paradigms in Naturalistic Settings
One way researchers have taken mobile technologies into the real world involves employing lab paradigms in naturalistic settings. At first sight, it may seem paradoxical to combine typical lab paradigms with mobile neuroimaging. However, validating laboratory paradigms in the real world, and validating mobile technology using well-established laboratory paradigms, is a crucial step in the development of real-world neuroscience.

EEG Investigations
Validity and reliability studies of mobile EEG systems typically focus on replicating well-known and robust EEG features, such as certain event-related potential (ERP) components or power spectra features, outside the lab. Although conducted in real-world settings, many of the same considerations and limitations present in laboratory studies are relevant (e.g., trial count, data quality, and loss; for additional details, see Table 1). Most of these studies focus on the P300 (or P3) component, which is a broad and large positive deflection in the ERP, maximal at parieto-central scalp locations, and is sensitive for subjective probability,

motivational significance, and attention (Nieuwenhuis, De Geus, & Aston-Jones, 2011).

It is common for mobile EEG studies to have participants walk or cycle a predetermined route on the university campus, while they listen and count or respond to infrequent oddball tones through a headphone to obtain ERPs (De Vos, Gandras, & Debener, 2014; Debener, Minow, Emkes, Gandras, & de Vos, 2012; Ladouce, Donaldson, Dudchenko, & Ietswaart, 2019; Zink, Hunyadi, Van Huffel, & Vos, 2016). Validity is typically assessed by comparing the oddball P300 during an outdoor condition with a sitting condition. Although data loss can be high outdoors (e.g., over 40% in Ladouce et al., 2019), the remaining artifact-free trials can produce reliable P300 effects. Interestingly, P300 amplitudes tend to be reduced in outdoor conditions, despite similar data quality for remaining trials. De Vos et al. (2014) reported a 30% P300 reduction in a walking condition, probably because of more distraction. P300 reduction effects may also be caused by increased processing demands in real-life scenarios (Zink et al., 2016), which were recently shown to be multisensory, involving both visual and inertial processing (Ladouce et al., 2019).

Lau-Zhu et al. (2019) provide a more elaborative discussion on the reliability and validity of mobile EEG systems. They conclude that higher-quality research-grade gel-based mobile systems, which are more similar to those used in laboratory research and require a larger financial investment, can produce the expected signal (e.g., oddball P300, power spectra). In contrast, while less expensive consumer-grade systems are more affordable and can be used more easily by participants, they can be useful under more limited circumstances due to issues with data quality. Considering that data loss can be high outside the lab, we recommend accounting for this with a larger number of trials. Sufficient scalp coverage is also recommended, as it allows independent component analysis to separate brain and nonbrain (artifact) sources, retaining parts of the EEG that would otherwise have been rejected.

Currently, most mobile headsets are clearly visible and this may reduce the compliance of students or reduce the realism of the learning context. To address this, there are recent efforts toward developing "transparent EEG," such as c-shaped electrode arrays (cEEGrid), which sit around the ears and are near-invisible (Debener, Emkes, De Vos, & Bleichner, 2015). Hölle and Bleichner (2021) demonstrated the feasibility of transparent EEG in combination with a sporadic oddball paradigm (stimuli presented on average once a minute), which was designed to interfere minimally with the participants' normal office routine for over 5 hr. Because transparent EEG can be worn comfortably for extended periods, it may even become feasible to rely entirely on responses to naturally occurring events that are relatively infrequent. In addition, by recording more EEG data, higher

EEG data exclusion rates in naturalistic environments can be mitigated. Together, these advantages may allow ERP research of natural events.

Not only reliability studies use more typical lab paradigms. Ko, Komarov, Hairston, Jung, and Lin (2017) investigated sustained attention with conventional EEG systems during regular university lectures using an experimental task to examine attentional processes. Specifically, while students followed these lectures, they were instructed to press a corresponding button on a smartphone when they saw simple geometric objects, which unexpectedly appeared on the lecture slides (>1 min between stimuli). Slower response times, which were interpreted as lower sustained attention, were preceded by increased delta and theta, and decreased beta power, indicating mental fatigue. Notable is that this situation is in fact a dual-task, requiring divided attention between the lecture content and lab task. More generally, this is the case when using lab paradigms in naturalistic situations (Hölle & Bleichner, 2021). While these examples have their own use cases, at the same time, they show that the use of lab paradigms impose a real limit to how "natural" real-world neuroscience can be, as they involve the same artificial stimuli and tasks frequently used in the lab.

fNIRS Investigations

Similar approaches have been applied to fNIRS technology. Mobile fNIRS devices have paved the way for new studies that examine both spatial and temporal patterns of neural activation during a variety of cognitive tasks during daily life activities, leveraging the specific advantages of fNIRS relative to both fMRI and EEG/ERP (Table 1). In recent years, the fNIRS field has seen increased development of miniature, wireless, wearable devices used in naturalistic and real-world settings (Scholkmann et al., 2014), and increasingly sophisticated devices with a greater number of source-detector pairs have since become available, which permit simultaneous measurement of brain activity in multiple brain regions (see Pinti et al., 2018 for a review).

Many of the mobile fNIRS studies published to date involve a motor-cognitive dual-task walking protocol, whereby participants are asked to perform a secondary cognitive task while walking. For example, studies have been conducted where participants complete cognitive tasks such as serial subtractions (Maidan et al., 2016; Mirelman et al., 2014; Nieuwhof et al., 2016), counting forward (Mirelman et al., 2014; Nieuwhof et al., 2016), verbal letter fluency (Doi et al., 2013), or reciting digits (Nieuwhof et al., 2016) while freely moving. These studies all involved indoor protocols; however, other studies have been conducted outside in everyday-life contexts (Balardin et al., 2017; McKendrick, Mehta, Ayaz, Scheldrup,

& Parasuraman, 2017; Pinti et al., 2015). Challenges still remain in limiting artifacts due to body movements, as well as limiting systemic interferences that arise from the influence of other physiological factors (see Pinti et al., 2018 for a discussion). However, strategies for minimizing the impact of these factors on data quality, such as adding acceleration measurements, are useful for interpreting data collected from participants during free movement.

Online Paradigms in Educational Technology

When considering the continuum of real-world neuroscience (see Figure 1), online learning environments can provide a framework for more naturalistic educational stimuli, while retaining more control relative to real classrooms. Mobile EEG systems are increasingly used in educational technology research. Of 22 studies reviewed by Xu and Zhong (2018), all used off-the-shelf consumer-grade systems, with 82% opting for a Neurosky system with only one dry electrode on the forehead. The majority (91%) of the authors used automatically calculated indices of "meditation" or "attention" provided by the system's proprietary algorithms, instead of (pre)processing the raw EEG data themselves. For these studies, it shows that the focus is more on technology (applications) than neuroscience (understanding). For example, mobile EEG was used in *attention monitoring and alarm mechanisms* in e-learning environments, *intelligent tutoring systems*, *neurofeedback training*, or for evaluating e-learning *instructional designs* and educational entertainment, also called "*edutainment*." A typical example (Chen & Wang, 2018) would be an online English course in which native Chinese speakers wear mobile EEG systems, while the instructor receives alerts when there are low-attention states ("No # student lacks concentration"), who subsequently sends out an alarm message to the student ("Your attention is now low. Please pay more attention to the course! Cheer up!").

While our review concerns *research approaches* with mobile neuroimaging, we deemed it important to mention these application approaches as well to aid our ethical discussion in Section 3. EEG frequency bands are often used in these proprietary algorithms purporting to measure student mental states, but it should be noted that the interpretation of EEG data is not straightforward. For example, frequency bands do not readily correspond to specific processes, the functional correlates may depend on the location (e.g., 8–13 Hz over the motor cortex, also called *mu* oscillations, are different from 8–13 Hz over visual areas) and depend on the specific task, and especially when analyzed in individuals, they are very prone to artifacts. While we see merit in some of the more research-oriented studies, also in respect to the push toward more blended learning, and more recently the reliance on online learning

due to the COVID-19 pandemic (Dhawan, 2020; Rapanta, Botturi, Goodyear, Guàrdia, & Koole, 2020), we think that the application-focused studies should receive a healthy dose of skepticism and more ethical scrutiny (more on this in Section 3).

Naturalistic Paradigms in Naturalistic Settings

While mobile technologies are advancing fast, the key challenge in the coming years is to design naturalistic paradigms (naturalistic design, Figure 1) that allow us to take full advantage of the technology. As set out by Nastase et al. (2020, p. 1): " … the world outside the laboratory is not amenable to many of the assumptions of classical experimental design; real-world ecological variables are often multidimensional, sometimes nonlinear, and interact in unexpected ways." The tension between mobile technology and typical lab paradigms was clearly illustrated in Section 2.2. Although the stimuli were presented in a real-life context, they were still unrelated to this context, the participants remained limited in their responses, and they were unable to affect their situation. Shamay-Tsoory and Mendelsohn (2019) named these person-dependent and situation-dependent limitations.

Compared to the lab, real-world learning situations are relatively unstructured, meaning that relevant events are not pre-established, relatively rare, and not always have clear onsets (e.g., presentation of learning material, distracting noises, receiving teacher feedback, interacting with peers). Therefore, naturalistic paradigms cannot easily isolate specific neurocognitive processes (e.g., feedback processing), because these require many repeated and controlled occurrences of events to separate signal from noise. In the case of mobile EEG, these limitations hinder calculating averaged ERPs to naturally occurring events. However, naturalistic paradigms can use personal or environmental events to segment neuroscientific data, where more general cognitive "states" (e.g., engagement, attention) can be explored. Furthermore, the timing and nature of classroom activities can be decided beforehand, effectively resulting in a blocked design. One example is a recent mobile EEG study (Dikker et al., 2020) into the effects of school class times on adolescent attention, including four types of teaching over three-time points (morning, mid-morning, and afternoon). Results corroborated previous findings, showing worse performance and higher alpha power (inversely related to attention) in the early morning, indicating mid-morning to be the best time to learn.

Other investigations have experimentally manipulated instruction to examine the impact of aspects of the classroom environment on attention. For example, in their work with college students, Grammer, Xu, and Lenartowicz (2021) measured EEG oscillatory power collected when students engaged in different types of classroom instruction (instructor initiated: lecture and video watching; student-initiated: group work and independent work). They found that occipital alpha, theta, and gamma power differed significantly across instructional activities, revealing that attention was highest during student-initiated activities, followed by lecture. Notably, this pattern of findings stood in contrast to standardized behavioral observations, which revealed a different pattern in student attention as a function of teacher instruction. For example, student attention was rated as lowest during group activities, whereas EEG data indicated that this was a period when attention was high. Overall, the contrast between behavioral and neural data indicates the EEG measures provided additional and unique information that was not immediately available through observing behavior alone. Although these types of investigations are still quite limited in number and work needs to be done before their findings can be translated directly to recommendations for instructional practice, they highlight the ways in which EEG can be employed to understand the impact of instruction on student cognition, providing additional insight that cannot be gained by examining behavior in the classroom.

We recognize that over the past 30 years, isolating ERPs has been one of the most fruitful analysis approaches in laboratory-based EEG research. As discussed in Section 2.2, this can be achieved outside the lab with typical lab paradigms, but it is quite incompatible with naturalistic paradigms. However, recent methodological developments may contribute to the analysis of spontaneous events in real-world learning situations. Su, Hairston, and Robbins (2018) described and tested a method called "automated event detection," which identifies stereotypical responses in the EEG (based on a trained classifier) and then asked the reverse question, "which stimulus triggered this EEG response?." This proof of concept study still used a typical oddball paradigm, with known timings of stimuli to validate the algorithm. A similar approach is being developed for fNIRS with the Automatic IDentification of functional Events method (Pinti et al., 2017), where not only synthetic and lab-based, but also real-world fNIRS data were validated. For the real-world data, 3/4 of the events were recovered during a complex real-world prospective memory experiment conducted outside the lab. The authors suggest that the main advantage of this method is to support the behavioral analysis of video recordings by statistically detecting functional event onsets from fNIRS data, which both saves time and is more accurate. Combined with mobile neuroimaging systems that can be comfortably worn for longer periods, this might allow to collect sufficient numbers of events for ERP research. Note, however, that there would still be limited experimental control.

The main challenge for naturalistic classroom paradigms is to balance naturalism with experimental control. As will

become apparent, the few "real-world" studies that were conducted in classrooms, still imposed considerable constraints to have some control over confounds (e.g., movement). An additional challenge is that educational or cognitive neuroscientists may not have enough expertise in what constitutes real-world learning and classroom processes, and their theories may also fall short in this dimension. A shift toward more transdisciplinarity, including research-practice partnerships, may therefore be needed for real-world educational neuroscience to advance (Youdell, Lindley, Shapiro, Sun, & Leng, 2020).

Hyperscanning

As it stands now, hyperscanning studies seem to approach the goal of marrying mobile EEG/fNIRS technology with naturalistic paradigms most effectively. The term "hyperscanning" describes situations in which brain activity is recorded from two or more people simultaneously. Usually, some form of interbrain connectivity analysis is applied to the data (Ayrolles et al., 2020; Hirsch, Noah, Zhang, Dravida, & Ono, 2018). Most hyperscanning studies share the goal to move from first-person neuroscience to "second-person neuroscience" (Schilbach et al., 2013), thus investigating dynamic social exchanges rather than one person in isolation. Evidently, this is important in classrooms where there is a continuous interaction among students and between students and teachers. Most hyperscanning studies involve laboratory simulations of particular social contexts, but there are a few notable exceptions in the field of educational neuroscience, demonstrating the potential of mobile technology to move to more naturalistic research.

In a pioneering study by Dikker et al. (2017), mobile EEG was recorded in 12 high-school students over one semester. Each class included four teaching styles that are typical for schooling: teacher reads aloud, educational video, teacher lecture, and group discussion. The findings suggested that brain-to-brain synchrony was driven by a combination of stimulus properties (teaching style) and individual differences (student focus, teaching style preference, teacher likeability, and personality traits). Moreover, face-to-face interaction prior to class not only increased brain-to-brain synchrony during class but also seemed to serve as an "activator" for interpersonal relationship features (Dikker et al., 2017). Thus, brain-to-brain synchrony predicted both student class engagement and social dynamics. Another recent hyperscanning study with undergraduates underscores the relative sensitivity of this measure for real-world outcomes; brain-to-brain synchrony, but not self-reported group identification, predicted collective performance among teams (Reinero, Dikker, & Van Bavel, 2021). fNIRS methods have also been used to examine synchrony in the brain activity of pre-schooler/teacher dyads during

a math game (Barreto et al., 2021) and between adult learner/teacher dyads during a conceptual learning task involving new psychology concepts (Pan et al., 2020). In both of these cases, the goal was to examine how understanding synchrony between learners and teachers might inform understanding of student outcomes.

It is important to emphasize that the interpretation of brain-to-brain synchrony remains complex and ambiguous. Low-level processing significantly affects brain-to-brain synchrony through common visual (Poulsen, Kamronn, Dmochowski, Parra, & Hansen, 2017) or auditory input, and common motor output (Hamilton, 2020). This means that brains similarly synchronize to stimuli and movement even without higher-order processing. For example, fNIRS hyperscanning experiments of live eye-to-eye contact suggest that mutual eye contact may play a critical role in natural interpersonal interactions (Hirsch, Zhang, Noah, & Ono, 2017). There is, however, evidence for higher-order processes contributing to the strength of brain-to-brain synchrony. Based on fMRI, fNIRS, and EEG hyperscanning evidence, Jiang, Zheng, and Lu (2021) proposed that two processes—shared representation and interpersonal predictive coding—might facilitate successful interpersonal verbal communication and underlie brain-to-brain synchrony during interactive speech. Interpersonal predictive coding is probably specifically associated with time-lagged brain-to-brain synchrony between two individuals, which seems especially relevant for teacher-student interactions. Furthermore, shared attention seems to modulate brain-to-brain synchrony (Dikker et al., 2017). When students are engaged, they pay attention to the same source (e.g., teacher's voice). This leads to synchronized brain activity through a process called entrainment, that is, the "locking" of brain waves to the rhythmic features of auditory and audiovisual input from the environment (Zion Golumbic, Poeppel, & Schroeder, 2012).

The shared attention hypothesis is especially relevant for educational neuroscience, as it predicts that brain-to-brain synchrony is associated with learning. Although brain-to-brain synchrony predicted learning in lab environments (Cohen et al., 2018; Cohen & Parra, 2016), this was in noninteracting students (they were separately measured). The only study with a group of students, similar set-up as Dikker et al. (2017), failed to demonstrate such an association (Bevilacqua et al., 2019). However, the link between brain-to-brain synchrony and learning was only globally assessed, without pinpointing when exactly information was presented. This was addressed in a recent simulated classroom experiment in the lab (Davidesco et al., 2019). Following a common approach in laboratory memory research, the researchers marked periods in which certain information was presented by the teacher and compared brain-to-brain synchrony during the periods where retained information was presented to periods where

unretained information was presented. Retained items were associated with higher brain-to-brain synchrony. In addition, student-to-teacher brain synchrony best predicted learning when adjusting for a ~200 millisecond lag in the students' brain activity relative to the teacher's brain activity, probably reflecting speech processing (Davidesco et al., 2019) and/or interpersonal predictive coding (Jiang et al., 2021).

What Can We Learn From These Naturalistic Hyperscanning Studies?

Although the mechanisms behind brain-to-brain synchrony are complex, it seems to be a sensitive marker for processes relevant for education: engagement, shared attention, social dynamics, collective performance, and learning. We do think that a more detailed understanding of brain-to-brain synchrony using EEG and fNIRS methodology (Brockington et al., 2018) could benefit educational research. For instance, researchers could increase their efforts to track behavior (Hamilton, 2020) and the stimulus environment in classrooms alongside brain activity. Similar to Poulsen et al. (2017) and Davidesco et al. (2019), video and audio recordings of the classroom could be synchronized with brain data. In addition, the behavior could be tracked with eye-tracking, transcripts, and coding of speech. This approach may help to delineate lower- (e.g., shared stimulus environment) and higher-order (e.g., shared attention) moderators of brain-to-brain synchrony, leading to a better specification of higher-order mechanisms that are relevant in the classroom. Conversely, by reverse engineering, periods of high brain-to-brain synchrony can be identified as functional events, forming the basis for exploring behavioral correlates ("brain-first approach"; Pinti et al., 2017). The *causal role* of interbrain synchrony on social interaction needs more attention as well, for example, by adequate experimental designs and computational tools (Moreau & Dumas, 2021) or by multibrain stimulation (Novembre & Iannetti, 2021).

These first pioneering studies demonstrated that the classroom lends itself well as a stage for real-world neuroscience experiments. Compared to, for example, shopping in a busy street, activities in a classroom naturally have structure and are confined to a specific space and time and group composition. Naturalistic paradigms can be built on this structure as demonstrated (Bevilacqua et al., 2019; Dikker et al., 2017); however, striking the right balance between ecological validity and experimental control remains a challenge. Although the previous examples are currently the most extreme on the continuum (see right side of Figure 1), close inspection of the research reveals that true "realism" still suffers because of necessary experimental control.

For example, in Dikker et al. (2017), the actual teaching during each class was relatively short (13 min over four

different activities) compared to usual classes, and they followed the same structure over the semester, providing limited room for spontaneity and variety. Even though students were instructed to minimize overt movement during the recordings, EEG rejection rates due to artifacts were high (~40–60%), especially for classroom activities that involve extensive student interaction, such as group discussions. In a follow-up study, EEG activity was collected only during lectures and videos, and "students were instructed to reserve questions and discussion for after the recording session was over. Thus, minimal to no conversational exchange occurred between students and their teacher during the EEG recordings" (Bevilacqua et al., 2019, p. 404). Furthermore, the teacher in this study was requested to remain seated throughout the lecture and minimize head movement, which resulted in less naturalistic teaching.

These challenges may be addressed by collecting data long enough to end up with sufficient clean data or to have sufficient data to average out artifacts. Additionally, some of these problems are likely to improve by advancements in hardware (e.g., better shielding, less electrode movement, and dual-electrodes motion artifact cancellation; Nordin, Hairston, & Ferris, 2018), advances in artifact identification and removal, but other problems may remain inherent to research outside the lab, such as limited control over and limited occurrences of unstructured events.

In conclusion, brain-to-brain synchrony provides an *implicit*, *unobtrusive*, and *continuous* measure that captures important aspects of interpersonal interactions and motivation in classrooms. This may be used as an objective marker with unique predictive value (Reinero et al., 2021), in conjunction with behavioral and self-report measures, to better understand these complex processes. In addition, brain-to-brain synchrony may be suitable in the future as an outcome measure to test school interventions and teaching methods or to even inform the development of new neuroscience-informed interventions before they are used at scale. We like to reiterate that we do not expect such naturalistic hyperscanning studies to be sufficient for informing innovations in teaching; rather, these studies have a place in the cycle that we discussed in the first section.

REFLECTION AND WAYS FORWARD

Overpromising

Although mobile brain technologies provide exciting new research avenues, there have been several critiques to this emerging field of research. Some argue that the use of mobile technology is currently being advocated in an overly optimistic way, which comes with the risk that limitations and challenges do not get the attention they should (Hessels, Niehorster, Holleman, Benjamins, & Hooge, 2020). A

question that should always be answered first is whether the use of mobile technology is justified for a specific study and what insights it will add, given the challenges with regard to data quality and analysis. To be able to answer this question, researchers should be educated and trained in using the technology. This point is also made in Parada and Rossi (2017). They stress the importance of discussing the theoretical and methodological need for using mobile equipment. Theory-guided and hypothesis-driven experiments are important even in the most naturalistic settings. And even if a study is more exploratory, it should be avoided at any rate that researchers are uninformed, collect terabytes of data using portable devices, only to find out that the analyses are far from straightforward and lack a theoretical foundation (Hessels et al., 2020). The use of mobile technology should not be presented as a "simple solution" to the limited ecological validity of lab-based research. One step in the right direction is to use mobile technology as part of the cycle (Figure 1), not as a standalone "replacement" of lab research.

Brain Data: Commercial (Mis)Use

Another cause of concern is when (unintentional) over-promising is not done by researchers, but by commercial parties. Given the wide availability of consumer-grade mobile systems that are easy to use, there are companies advertising wearable EEG bands to businesses or to schools as tools to monitor their employees' or students' focus levels. They claim that this technology enables personalized interventions that improve workplace productivity and academic achievement. These applications send "attention levels" to workplace supervisors or teachers in a dashboard in real time, who can use them to recommend short breaks or lower workload if focus drops and stress increases. A video published by the Wall Street Journal (WSJ, 2019) documents a Chinese primary school where this type of technology was implemented in their classes. Besides a lack of empirical evidence for the rational and accuracy of translating EEG signals into "attention levels," such applications give rise to serious privacy and consent issues (Minielly, Hrincu, & Illes, 2020). Indeed, data collection at the Chinese school was shut down based on parents' privacy concerns.

In addition to applications aimed to measure brain signals in a work or school setting for monitoring employees or students, the research described in Section 2.3 has also found its way to commercial "neuro-adaptive learning platforms," which use neural data to personalize learning. Such examples are based on the assumption that brain signals measured with mobile devices can accurately be interpreted and translated into simple outputs that are relevant for teachers or employers, but the empirical evidence for this assumption is yet lacking (Williamson, 2019). Many other commercial applications claim to enhance or optimize brain

function or wellbeing (e.g., by electrical brain stimulation or neurofeedback training). Although such neuromodulation applications are beyond the scope of this paper, they too require careful ethical (Schuijer, de Jong, Kupper, & van Atteveldt, 2017; Williamson, 2019) and methodological consideration (Thibault & Raz, 2017), especially in more vulnerable populations (e.g., children with neurodevelopmental disorders). A recent effort by neurofeedback researchers led to a consensus on how to conduct neurofeedback research (CRED-nf checklist), advocating research standards, such as using (blinded) randomized controlled trial (RCT) designs, detailed reporting, and efforts to disentangle specific and nonspecific treatment effects (Ros et al., 2020). Educational neuroscience could build further on these initiatives and the long history of educational science with RCTs (Styles & Torgerson, 2018), to ensure rigorous evaluation of (commercial) neurotechnologies.

Direct-to-consumer marketing of neurotechnologies raises profound ethical concerns about unsubstantiated claims bringing risks for public trust as well as for safety (Coates McCall, Lau, Minielly, & Illes, 2019). Another issue is the potential "neuropower" (Williamson, 2019) provided by such EEG datasets (and optimization tools) to companies and governments. Emerging neurotechnologies increase the risk of using the brain as a "biopolitical resource," promoting optimization and thereby the competitiveness of a population (Rose & Abi-Rached, 2014). This means that the brain is increasingly viewed as an entity to optimize: to read and store its data and use this to optimize and "sculpt" in a way that companies and governments see fit. Even though the technology is currently not there to enable such power, it is important to anticipate such possible impacts in the future.

Conclusion and Future Directions

By bringing the lab into the real world, mobile neuroimaging technology extends the toolbox available to researchers to conduct real-world educational neuroscience. Research paradigms that are used alongside mobile neuroimaging vary considerably in how naturalistic they are: ranging from typical lab paradigms, in and outside the lab, to more naturalistic paradigms. As discussed throughout this article, there are trade-offs between ecological validity and experimental control, and finding the right balance between the two depends on the research question at hand. We suggest embedding mobile neuroimaging in a research cycle that involves lab-based and semi-naturalistic experiments. Another use case of mobile neuroimaging is to set up mobile labs that can help to include more representative samples, such as lower socioeconomic status students or beyond HICs. Due to the complexity of real-world learning environments, there are still limits to which research questions can be addressed with mobile neuroimaging. As it stands now,
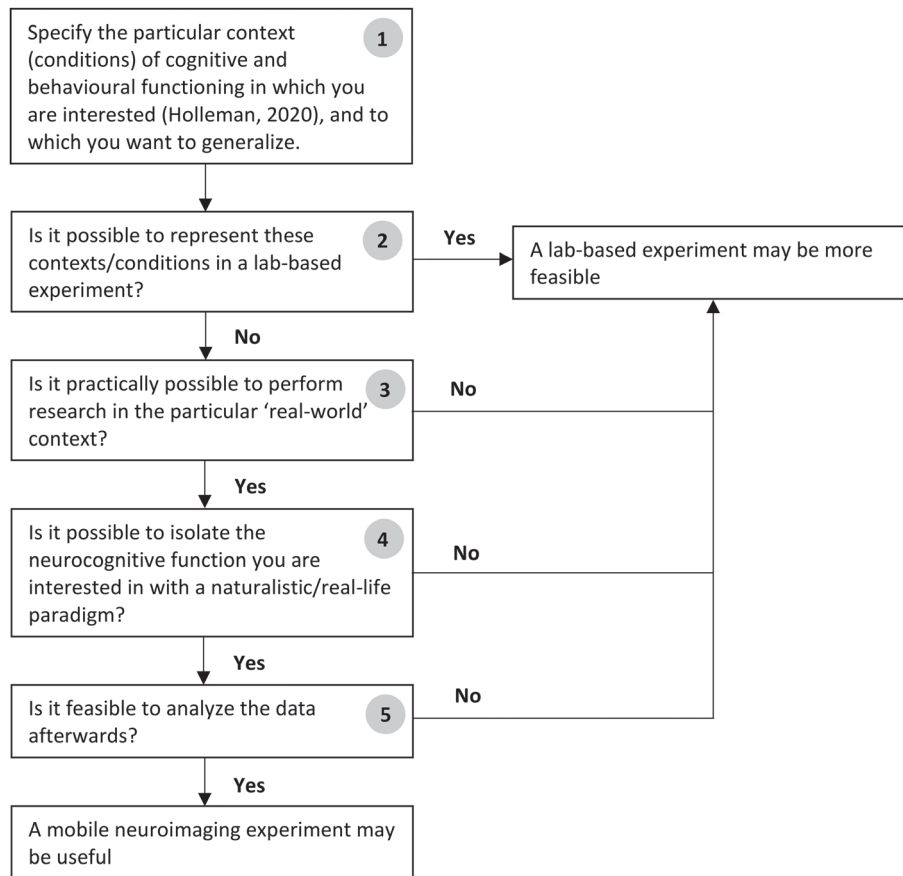
Fig. 2. Checklist for using neuroimaging technology in educational neuroscience. Before choosing mobile neuroimaging for a study, these steps/questions are useful to consider.

naturalistic paradigms are less suitable for event-related research into specific cognitive processes, while general cognitive "states" are more feasible to study.

Conducting mobile neuroimaging research in schools can be theoretically, methodologically, and technically challenging, which asks for new collaborations that cross disciplines. We see much value in creating a community of researchers who are interested in using mobile neuroimaging, to share best practices and discuss potential ethical issues. Our Emerging Field Group (https://earli.org/efg-01), supported by EARLI and the Jacobs Foundation, offers opportunities to create such a community. Mobile brain technologies can also be used as an educational tool and provide opportunities for teachers and students to gain hands-on experience in neuroscience research (Azeka, Carter, & Davidesco, 2020). Another overarching goal for educational neuroscience is to move toward *transdisciplinary* approaches, to have different disciplines jointly design studies from the outset (Youdell et al., 2020). In other words—this can truly integrate disciplines to create something new, rather than simply taking a neuroscience method and plug it into the classroom, without understanding this "target ecology."

Not all real-world educational neuroscience research should or can be conducted outside the lab; many research questions can be addressed by bringing the real world to the lab, using representative design principles. Figure 2 contains a decision tree, which may be helpful to decide whether a mobile neuroimaging study is actually needed and feasible. Additionally, preregistered studies and registered reports may help to enforce quality standards and prevent data collection without theoretical grounding, and the field would benefit from a better consensus on appropriate benchmarking criteria for establishing validity and reliability, which it is currently lacking (but see Oliveira, Schlink, Hairston, König, & Ferris, 2016). Open data needs to be ensured (i.e., that the researcher has access to the raw data of the mobile device), and the same holds true for any signal processing that is done in commercial devices.

We think it is important to safeguard that (commercial) applications should not outpace the evidence, and that ethical issues should be dealt with in advance and on the way, rather than waiting until ethically questionable applications are already in use. Therefore, reflexive practices should be used, such as responsible research and innovation (Van

Atteveldt, Tijsma, Janssen, & Kupper, 2019), where desirable and less desirable directions are discussed beforehand by researchers together with stakeholders, and importantly, researchers respond to these inclusive deliberations by adjusting the course of their research. This fits in the line of thought to take this new research field one step at a time.

REFERENCES

Van Atteveldt, N., Tijsma, G., Janssen, T., & Kupper, F. (2019). Responsible research and innovation as a novel approach to guide educational impact of mind, brain, and education research. *Mind, Brain, and Education*, *13*, 279–287. https://doi.org/10.1111/mbe.12213

Ayrolles, A., Brun, F., Chen, P., Djalovski, A., Beauxis, Y., Delorme, R., … Dumas, G. (2021). HyPyP: a Hyperscanning Python Pipeline for inter-brain connectivity analysis. *Social Cognitive and Affective Neuroscience*, *16*(1–2), 72–83. http://dx.doi.org/10.1093/scan/nsaa141

Azeka, S., Carter, S., & Davidesco, I. (2020). Neuroscientists in training. *Educational Leadership*, *77*(8), 66–69.

Balardin, J. B., Zimeo Morais, G. A., Furucho, R. A., Trambaiolli, L., Vanzella, P., Biazoli, C., & Sato, J. R. (2017). Imaging brain function with functional near-infrared spectroscopy in unconstrained environments. *Frontiers in Human Neuroscience*, *11*(May), 1–7. https://doi.org/10.3389/fnhum.2017.00258

Barreto, C., Bruneri, G., de A., Brockington, G., Ayaz, H., & Sato, J. R. (2021). New statistical approach for fnirs hyperscanning to predict brain activity of preschoolers' using teacher's. *Frontiers in Human Neuroscience*, 15(May). https://doi.org/10.3389/fnhum.2021.622146.

Bevilacqua, D., Davidesco, I., Wan, L., Chaloner, K., Rowland, J., Ding, M., … Dikker, S. (2019). Brain-to-brain synchrony and learning outcomes vary by student–teacher dynamics: Evidence from a real-world classroom electroencephalography study. *Journal of Cognitive Neuroscience*, *31*(3), 401–411. https://doi.org/10.1162/jocn_a_01274

Blasi, A., Lloyd-Fox, S., Katus, L., & Elwell, C. E. (2019). fNIRS for tracking brain development in the context of global health projects. *Photonics*, *6*(3), 1–10. https://doi.org/10.3390/photonics6030089

Blume, F., Quixal, M., Hudak, J., Dresler, T., Gawrilow, C., & Ehlis, A.-C. (2020). Development of reading abilities in children with ADHD following fNIRS-neurofeedback or EMG-biofeedback. *Lernen Und Lernstörungen*, *9*(3), 163–174. https://doi.org/10.1024/2235-0977/a000302

Bowers, J. S. (2016). The practical and principled problems with educational neuroscience. *Psychological Review*, *123*(5), 600–612. https://doi.org/10.1037/rev0000025

Brockington, G., Balardin, J. B., Zimeo Morais, G. A., Malheiros, A., Lent, R., Moura, L. M., & Sato, J. R. (2018). From the laboratory to the classroom: The potential of functional near-infrared spectroscopy in educational neuroscience. *Frontiers in Psychology*, *9*(October), 1–7. https://doi.org/10.3389/fpsyg.2018.01840

Brunswik, E. (1955). Representative design and probabilistic theory in a functional psychology. *Psychological Review*, *62*(3), 193–217. https://doi.org/10.1037/h0047470

Cantlon, J. F. (2020). The balance of rigor and reality in developmental neuroscience. *NeuroImage*, *216*(July 2019), 116464. https://doi.org/10.1016/j.neuroimage.2019.116464

Cantlon, J. F., Brannon, E. M., Carter, E. J., & Pelphrey, K. A. (2006). Functional imaging of numerical processing in adults and 4-y-old children. *PLoS Biology*, *4*(5), 844–854. https://doi.org/10.1371/journal.pbio.0040125

Cantlon, J. F., & Li, R. (2013). Neural activity during natural viewing of sesame street statistically predicts test scores in early childhood. *PLoS Biology*, *11*(1), e1001462. https://doi.org/10.1371/journal.pbio.1001462

Chen, C.-M., & Wang, J.-Y. (2018). Effects of online synchronous instruction with an attention monitoring and alarm mechanism on sustained attention and learning performance. *Interactive Learning Environments*, *26*(4), 427–443. https://doi.org/10.1080/10494820.2017.1341938

Coates McCall, I., Lau, C., Minielly, N., & Illes, J. (2019). Owning ethical innovation: Claims about commercial wearable brain technologies. *Neuron*, *102*(4), 728–731. https://doi.org/10.1016/j.neuron.2019.03.026

Cohen, S. S., Madsen, J., Touchan, G., Robles, D., Lima, S. F. A., Henin, S., & Parra, L. C. (2018). Neural engagement with online educational videos predicts learning performance for individual students. *Neurobiology of Learning and Memory*, *155*(January), 60–64. https://doi.org/10.1016/j.nlm.2018.06.011

Cohen, S. S., & Parra, L. C. (2016). Memorable audiovisual narratives synchronize sensory and supramodal neural responses. *eNeuro*, *3*(6), 1–11. https://doi.org/10.1523/ENEURO.0203-16.2016

Davidesco, I., Laurent, E., Valk, H., West, T., Dikker, S., Milne, C., & Poeppel, D. (2019). Brain-to-brain synchrony between students and teachers predicts learning outcomes. *BioRxiv*, 644047. https://doi.org/10.1101/644047

Di Lorenzo, R., Pirazzoli, L., Blasi, A., Bulgarelli, C., Hakuno, Y., Minagawa, Y., & Brigadoi, S. (2019). Recommendations for motion correction of infant fNIRS data applicable to multiple data sets and acquisition systems. *Neuroimage*, *200*, 511–527. https://doi.org/10.1016/j.neuroimage.2019.06.056.

De Vos, M., Gandras, K., & Debener, S. (2014). Towards a truly mobile auditory brain-computer interface: Exploring the P300 to take away. *International Journal of Psychophysiology*, *91*(1), 46–53. https://doi.org/10.1016/j.ijpsycho.2013.08.010

Debener, S., Emkes, R., De Vos, M., & Bleichner, M. (2015). Unobtrusive ambulatory EEG using a smartphone and flexible printed electrodes around the ear. *Scientific Reports*, *5*, 1–11. https://doi.org/10.1038/srep16743

Debener, S., Minow, F., Emkes, R., Gandras, K., & de Vos, M. (2012). How about taking a low-cost, small, and wireless EEG for a walk? *Psychophysiology*, *49*(11), 1617–1621. https://doi.org/10.1111/j.1469-8986.2012.01471.x

Dhawan, S. (2020). Online learning: A panacea in the time of COVID-19 crisis. *Journal of Educational Technology Systems*, *49*(1), 5–22. https://doi.org/10.1177/0047239520934018

Dikker, S., Haegens, S., Bevilacqua, D., Davidesco, I., Wan, L., Kaggen, L., … Poeppel, D. (2020). Morning brain: Real-world neural evidence that high school class times matter. *Social Cognitive and Affective Neuroscience*, *15*, 1193–1202. https://doi.org/10.1093/scan/nsaa142

Dikker, S., Wan, L., Davidesco, I., Kaggen, L., Oostrik, M., McClintock, J., … Poeppel, D. (2017). Brain-to-brain synchrony tracks real-world dynamic group interactions in the classroom. *Current Biology*, *27*(9), 1375–1380. https://doi.org/10.1016/j.cub.2017.04.002

Doi, T., Makizako, H., Shimada, H., Park, H., Tsutsumimoto, K., Uemura, K., & Suzuki, T. (2013). Brain activation during dual-task walking and executive function among older adults with mild cognitive impairment: A fNIRS study. *Aging Clinical and Experimental Research*, *25*(5), 539–544. https://doi.org/10.1007/s40520-013-0119-5

Eccles, J. S., & Roeser, R. W. (2011). Schools as developmental contexts during adolescence. *Journal of Research on Adolescence*, *21*(1), 225–241. https://doi.org/10.1111/j.1532-7795.2010.00725.x

Grammer, J. K., Xu, K., & Lenartowicz, A. (2021). Effects of context on the neural correlates of attention in a college classroom. *npj Science of Learning*, *6*(15), 15.

Grammer, J. K., Carrasco, M., Gehring, W. J., & Morrison, F. J. (2014). Age-related changes in error processing in young children: A school-based investigation. *Developmental Cognitive Neuroscience*, *9*, 93–105. https://doi.org/10.1016/j.dcn.2014.02.001

Hamilton, A. (2020). Hype, hyperscanning and embodied social neuroscience. *PsyArXiv*, 1–14. https://doi.org/10.31234/osf.io/rc9wp

Hammond, K. R. (1998). *Ecological validity: Then and now*. Retrieved from http://www.brunswik.org/notes/essay2.html

Henrich, J., Heine, S. J., & Norenzayan, A. (2010). Most people are not WEIRD. *Nature*, *466*(7302), 29–29. https://doi.org/10.1038/466029a

Hessels, R. S., Niehorster, D. C., Holleman, G. A., Benjamins, J. S., & Hooge, I. T. C. (2020). Wearable technology for "real-world research": Realistic or not? *Perception*, *49*(6), 611–615. https://doi.org/10.1177/0301006620928324

Hirsch, J., Noah, J. A., Zhang, X., Dravida, S., & Ono, Y. (2018). A cross-brain neural mechanism for human-to-human verbal communication. *Social Cognitive and Affective Neuroscience*, *13*(9), 907–920. https://doi.org/10.1093/scan/nsy070

Hirsch, J., Zhang, X., Noah, J. A., & Ono, Y. (2017). Frontal temporal and parietal systems synchronize within and across brains during live eye-to-eye contact. *NeuroImage*, *157*(June), 314–330. https://doi.org/10.1016/j.neuroimage.2017.06.018

Hölle, D., Meekes, J., & Bleichner, M. G. (2021). Mobile ear-EEG to study auditory attention in everyday life. *Behav Res*. https://doi-org.vu-nl.idm.oclc.org/10.3758/s13428-021-01538-0

Holleman, G. A., Hooge, I. T. C., Kemner, C., & Hessels, R. S. (2020). The 'real-world approach' and its problems: A critique of the term ecological validity. *Frontiers in Psychology*, *11*(April), 1–12. https://doi.org/10.3389/fpsyg.2020.00721

Jang, S., Choi, J. K., Oh, J., Yeom, J., Hong, N., Lee, N., … Kim, E. (2021). Use of virtual reality working memory task and functional near-infrared spectroscopy to assess brain hemodynamic responses to methylphenidate in ADHD children. *Frontiers in Psychiatry*, *11*(January), 1–12. https://doi.org/10.3389/fpsyt.2020.564618

Jasińska, K. K., & Guei, S. (2018). Neuroimaging field methods using functional near infrared spectroscopy (NIRS) neuroimaging to study global child development: Rural sub-Saharan Africa. *Journal of Visualized Experiments*, *2018*(132), 1–11. https://doi.org/10.3791/57165

Jiang, J., Zheng, L., & Lu, C. (2021). A hierarchical model for interpersonal verbal communication. *Social Cognitive and Affective Neuroscience*, *16*(1–2), 246–255. https://doi-org.vu-nl.idm.oclc.org/10.1093/scan/nsaa151

Kim, M. H., Grammer, J. K., Marulis, L. M., Carrasco, M., Morrison, F. J., & Gehring, W. J. (2016). Early math and reading achievement are associated with the error positivity. *Developmental Cognitive Neuroscience*, *22*, 18–26. https://doi.org/10.1016/j.dcn.2016.09.002

Ko, L. W., Komarov, O., Hairston, W. D., Jung, T. P., & Lin, C. T. (2017). Sustained attention in real classroom settings: An EEG study. *Frontiers in Human Neuroscience*, *11*(July), 1–10. https://doi.org/10.3389/fnhum.2017.00388

Ladouce, S., Donaldson, D. I., Dudchenko, P. A., & Ietswaart, M. (2019). Mobile EEG identifies the re-allocation of attention during real-world activity. *Scientific Reports*, *9*(1), 1–10. https://doi.org/10.1038/s41598-019-51996-y

Lau-Zhu, A., Lau, M. P. H., & McLoughlin, G. (2019). Mobile EEG in research on neurodevelopmental disorders: Opportunities and challenges. *Developmental Cognitive Neuroscience*, *36*(March), 100635. https://doi.org/10.1016/j.dcn.2019.100635

Lloyd-Fox, S., Papademetriou, M., Darboe, M. K., Everdell, N. L., Wegmuller, R., Prentice, A. M., … Elwell, C. E. (2015). Functional near infrared spectroscopy (fNIRS) to assess cognitive function in infants in rural Africa. *Scientific Reports*, *4*, http://dx.doi.org/10.1038/srep04740

Maidan, I., Nieuwhof, F., Bernad-Elazari, H., Reelick, M. F., Bloem, B. R., Giladi, N., … Mirelman, A. (2016). The role of the frontal lobe in complex walking among patients with Parkinson's disease and healthy older adults: An fNIRS study. *Neurorehabilitation and Neural Repair*, *30*(10), 963–971. https://doi.org/10.1177/1545968316650426

Matusz, P. J., Dikker, S., Huth, A. G., & Perrodin, C. (2019). Are we ready for real-world neuroscience? *Journal of Cognitive Neuroscience*, *31*(3), 327–338. https://doi.org/10.1162/jocn_e_01276

McKendrick, R., Mehta, R., Ayaz, H., Scheldrup, M., & Parasuraman, R. (2017). Prefrontal hemodynamics of physical activity and environmental complexity during cognitive work. *Human Factors*, *59*(1), 147–162. https://doi.org/10.1177/0018720816675053

Meshulam, M., Hasenfratz, L., Hillman, H., Liu, Y.-F., Nguyen, M., Norman, K. A., & Hasson, U. (2021). Neural alignment predicts learning outcomes in students taking an introduction to computer science course. *Nature Communications*, *12*(1), 1922. https://doi.org/10.1038/s41467-021-22202-3

Minielly, N., Hrincu, V., & Illes, J. (2020). Privacy challenges to the democratization of brain data. *iScience*, *23*(6), 101134. https://doi.org/10.1016/j.isci.2020.101134

Mirelman, A., Maidan, I., Bernad-Elazari, H., Nieuwhof, F., Reelick, M., Giladi, N., & Hausdorff, J. M. (2014). Increased frontal brain activation during walking while dual tasking: An fNIRS study in healthy young adults. *Journal of Neuroengineering and Rehabilitation*, *11*(1), 1–7. https://doi.org/10.1186/1743-0003-11-85

Moreau, Q., & Dumas, G. (2021). Beyond correlation versus causation: Multi-brain neuroscience needs explanation. *Trends in Cognitive Sciences*, *25*, 1–2. https://doi.org/10.1016/j.tics.2021.02.011

Nastase, S. A., Goldstein, A., & Hasson, U. (2020). Keep it real: Rethinking the primacy of experimental control in cognitive neuroscience. *NeuroImage*, *222*(December 2019), 117254. https://doi.org/10.1016/j.neuroimage.2020.117254

Nieuwenhuis, S., De Geus, E. J., & Aston-Jones, G. (2011, June 14). The anatomical and functional relationship between the P3 and autonomic components of the orienting response. *Psychophysiology*, *48*, 162–175. https://doi.org/10.1111/j.1469-8986.2010.01057.x

Nieuwhof, F., Reelick, M. F., Maidan, I., Mirelman, A., Hausdorff, J. M., Olde Rikkert, M. G. M., … Claassen, J. A. H. R. (2016). Measuring prefrontal cortical activity during dual task walking in patients with Parkinson's disease: Feasibility of using a new portable fNIRS device. *Pilot and Feasibility Studies*, *2*(1), 1–11. https://doi.org/10.1186/s40814-016-0099-2

Nordin, A. D., Hairston, W. D., & Ferris, D. P. (2018). Dual-electrode motion artifact cancellation for mobile electroencephalography. *Journal of Neural Engineering*, *15*(5), 056024. https://doi.org/10.1088/1741-2552/aad7d7

Novembre, G., & Iannetti, G. D. (2021). Hyperscanning alone cannot prove causality. Multibrain stimulation can. *Trends in Cognitive Sciences*, *25*(2), 96–99. https://doi.org/10.1016/j.tics.2020.11.003

Oku, A. Y. A., & Sato, J. R. (2021). Predicting student performance using machine learning in fNIRS data. *Frontiers in Human Neuroscience*, *15*(February), 1–12. https://doi.org/10.3389/fnhum.2021.622224

Oliveira, A. S., Schlink, B. R., Hairston, W. D., König, P., & Ferris, D. P. (2016). Proposing metrics for benchmarking novel EEG technologies towards real-world measurements. *Frontiers in Human Neuroscience*, *10*(May), 1–15. https://doi.org/10.3389/fnhum.2016.00188

Osborne-Crowley, K. (2020). Social cognition in the real world: Reconnecting the study of social cognition with social reality. *Review of General Psychology*, *24*(2), 144–158. https://doi.org/10.1177/1089268020906483

Pan, Y., Dikker, S., Goldstein, P., Zhu, Y., Yang, C., & Hu, Y. (2020). Instructor-learner brain coupling discriminates between instructional approaches and predicts learning. *NeuroImage*, *211*(August 2019). https://doi.org/10.1016/j.neuroimage.2020.116657.

Papademetriou, M. D., Lloyd Fox, S., Everdell, N. L., Darboe, M. K., Moore, S. E., Prentice, A. M., & Elwell, C. E. (2014). Optical imaging of brain activation in gambian infants. *Advances in Experimental Medicine and Biology*, *812*, 263–269. https://doi.org/10.1007/978-1-4939-0620-8_35

Parada, F. J., & Rossi, A. (2017). Commentary: Brain-to-brain synchrony tracks real-world dynamic group interactions in the classroom and cognitive neuroscience: Synchronizing brains in the classroom. *Frontiers in Human Neuroscience*, *11*(November), 10–12. https://doi.org/10.3389/fnhum.2017.00554

Perdue, K. L., Jensen, S. K. G., Kumar, S., Richards, J. E., Kakon, S. H., Haque, R., … Nelson, C. A. (2019). Using functional near-infrared spectroscopy to assess social information processing in poor urban Bangladeshi infants and toddlers. *Developmental Science*, *22*(5), 1–15. https://doi.org/10.1111/desc.12839

Pietto, M. L., Giovannetti, F., Segretin, M. S., Belloli, L. M. L., Lopez-Rosenfeld, M., Goldin, A. P., … Lipina, S. J. (2018). Enhancement of inhibitory control in a sample of preschoolers from poor homes after cognitive training in a kindergarten setting: Cognitive and ERP evidence. *Trends in Neuroscience and Education*, *13*(November), 34–42. https://doi.org/10.1016/j.tine.2018.11.004

Pinti, P., Aichelburg, C., Gilbert, S., Hamilton, A., Hirsch, J., Burgess, P., & Tachtsidis, I. (2018). A review on the use of wearable functional near-infrared spectroscopy in naturalistic environments. *Japanese Psychological Research*, *60*(4), 347–373. https://doi.org/10.1111/jpr.12206

Pinti, P., Aichelburg, C., Lind, F., Power, S., Swingler, E., Merla, A., … Tachtsidis, I. (2015). Using fiberless, wearable fnirs to monitor brain activity in real-world cognitive tasks. *Journal of Visualized Experiments*, *2015*(106), 1–13. https://doi.org/10.3791/53336

Pinti, P., Merla, A., Aichelburg, C., Lind, F., Power, S., Swingler, E., … Tachtsidis, I. (2017). A novel GLM-based method for the Automatic IDentification of functional Events (AIDE) in fNIRS data recorded in naturalistic environments. *NeuroImage*, *155*(May), 291–304. https://doi.org/10.1016/j.neuroimage.2017.05.001

Poulsen, A. T., Kamronn, S., Dmochowski, J., Parra, L. C., & Hansen, L. K. (2017). EEG in the classroom: Synchronised neural recordings during video presentation. *Scientific Reports*, *7*, 1–9. https://doi.org/10.1038/srep43916

Quaresima, V., & Ferrari, M. (2019). A mini-review on functional near-infrared spectroscopy (fNIRS): Where do we stand, and where should we go? *Photonics*, *6*(3), 87. https://doi.org/10.3390/photonics6030087

Rapanta, C., Botturi, L., Goodyear, P., Guàrdia, L., & Koole, M. (2020). Online university teaching during and after the Covid-19 crisis: Refocusing teacher presence and learning activity. *Postdigital Science and Education*, *2*, 1–23.

Reinero, D. A., Dikker, S., & Van Bavel, J. J. (2021). Inter-brain synchrony in teams predicts collective performance. *Social Cognitive and Affective Neuroscience*, *16*(1–2), 43–57. https://doi.org/10.1093/scan/nsaa135

Risko, E. F., Richardson, D. C., & Kingstone, A. (2016). Breaking the fourth wall of cognitive science. *Current Directions in Psychological Science*, *25*(1), 70–74. https://doi.org/10.1177/0963721415617806

Ros, T., Enriquez-Geppert, S., Zotev, V., Young, K. D., Wood, G., Whitfield-Gabrieli, S., … Thibault, R. T. (2020). Consensus on the reporting and experimental design of clinical and cognitive-behavioural neurofeedback studies (CRED-nf checklist). *Brain*, *143*(6), 1674–1685. https://doi.org/10.1093/brain/awaa009

Rose, N., & Abi-Rached, J. (2014). Governing through the brain: Neuropolitics, neuroscience and subjectivity. *The Cambridge*

Journal of Anthropology, *32*(1), 3–23. https://doi.org/10.3167/ca.2014.320102

Schilbach, L., Timmermans, B., Reddy, V., Costall, A., Bente, G., Schlicht, T., & Vogeley, K. (2013). A second-person neuroscience in interaction. *Behavioral and Brain Sciences*, *36*(4), 441–462. https://doi.org/10.1017/S0140525X12002452

Scholkmann, F., Kleiser, S., Metz, A. J., Zimmermann, R., Mata Pavia, J., Wolf, U., & Wolf, M. (2014). A review on continuous wave functional near-infrared spectroscopy and imaging instrumentation and methodology. *NeuroImage*, *85*, 6–27. https://doi.org/10.1016/j.neuroimage.2013.05.004

Schuijer, J. W., de Jong, I. M., Kupper, F., & van Atteveldt, N. M. (2017). Transcranial electrical stimulation to enhance cognitive performance of healthy minors: A complex governance challenge. *Frontiers in Human Neuroscience*, *11*(March), 1–15. https://doi.org/10.3389/fnhum.2017.00142

Shamay-Tsoory, S. G., & Mendelsohn, A. (2019). Real-life neuroscience: An ecological approach to brain and behavior research. *Perspectives on Psychological Science*, *14*(5), 841–859. https://doi.org/10.1177/1745691619856350

Storrs, C. (2017). How poverty affects the brain. *Nature*, *547*(7662), 150–152. https://doi.org/10.1038/547150a

Styles, B., & Torgerson, C. (2018). Randomised controlled trials (RCTs) in education research –methodological debates, questions, challenges. *Educational Research*, *60*(3), 255–264. https://doi.org/10.1080/00131881.2018.1500194

Su, K., Hairston, W. D., & Robbins, K. (2018). EEG-Annotate: Automated identification and labeling of events in continuous signals with applications to EEG. *Journal of Neuroscience Methods*, *293*, 359–374. https://doi.org/10.1016/j.jneumeth.2017.10.011

Thibault, R. T., & Raz, A. (2017). The psychology of neurofeedback: Clinical intervention even if applied placebo. *American Psychologist*, *72*(7), 679–688. https://doi.org/10.1037/amp0000118

Thomas, M. S. C., Ansari, D., & Knowland, V. C. P. (2019). Annual research review: Educational neuroscience: Progress and prospects. *Journal of Child Psychology and Psychiatry, and Allied Disciplines*, *60*(4), 477–492. https://doi.org/10.1111/jcpp.12973

Van Atteveldt, N., Van Kesteren, M. T. R., Braams, B., & Krabbendam, L. (2018). Neuroimaging of learning and development: Improving ecological validity. *Frontline Learning Research*, *6*(3), 186–203. https://doi.org/10.14786/flr.v6i3.366

Wijeakumar, S., Kumar, A., Delgado Reyes, L. M., Tiwari, M., & Spencer, J. P. (2019). Early adversity in rural India impacts the brain networks underlying visual working memory. *Developmental Science*, *22*(5), 1–15. https://doi.org/10.1111/desc.12822

Williamson, B. (2019). Brain data: Scanning, scraping and sculpting the plastic learning brain through neurotechnology. *Postdigital Science and Education*, *1*(1), 65–86. https://doi.org/10.1007/s42438-018-0008-5

Willingham, D. T., & Lloyd, J. W. (2007). How educational theories can use neuroscientific data. *Mind, Brain, and Education*, *1*(3), 140–149. https://doi.org/10.1111/j.1751-228X.2007.00014.x

Xu, J., & Zhong, B. (2018). Review on portable EEG technology in educational research. *Computers in Human Behavior*, *81*, 340–349. https://doi.org/10.1016/j.chb.2017.12.037

Youdell, D., Lindley, M., Shapiro, K., Sun, Y., & Leng, Y. (2020). From science wars to transdisciplinarity: The inescapability of the neuroscience, biology and sociology of learning. *British Journal of Sociology of Education*, *41*(6), 881–899. https://doi.org/10.1080/01425692.2020.1784709

Zink, R., Hunyadi, B., Van Huffel, S., & Vos, M. D. (2016). Mobile EEG on the bike: Disentangling attentional and physical contributions to auditory attention tasks. *Journal of Neural Engineering*, *13*(4), 046017. https://doi.org/10.1088/1741-2560/13/4/046017

Zion Golumbic, E. M., Poeppel, D., & Schroeder, C. E. (2012). Temporal context in speech processing and attentional stream selection: A behavioral and neural perspective. *Brain and Language*, *122*(3), 151–161. https://doi.org/10.1016/j.bandl.2011.12.010