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The New Science of Learning: Using the Power and Potential of the Brain to Inform Digital Learning

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ABSTRACT: Integrating education practices and measurements of brain activity has the potential to make learning more engaging and productive. Direct recordings of electrical activity in the brain provide important information about the complex dynamics of the cognitive processes and mental states that occur during learning, which can ultimately empower learners. In this article, electroencephalographic (EEG) methodologies, including the time-frequency and event-related potential techniques, are introduced, and the application of these techniques to studies of digital learning studies is discussed. Considerations of how to collect high quality data in both laboratory and real world settings are also presented, along with potential research directions. Finally, a general guideline for publishing results is offered. These issues are critical for producing useful applications of EEG studies to the digital learning research community.

Keywords: Digital learning, Electroencephalograph (EEG), Event-related potentials, Dry-wireless EEG

1. Digital learning with a cognitive neuroscience approach

The emerging interdisciplinary field of learning science applies empirical research to educational designs with the aim of improving learning processes and outcomes (Fischer, Hmelo-Silver, Goldman, & Reimann, 2018). There is a long history of the shaping of educational practices based on knowledge of how the human mind encapsulates information and interacts with learning contexts (Vygotsky, 1978). However, because the flow of information is mostly unidirectional when using traditional styles of learning with textbooks, understanding of the effects of individual differences among learners and of the interactions between learners and learning contexts during the knowledge acquisition process is limited. The recent emergence of evidence-based digital learning provides opportunities to improve the effectiveness of learning for a wide range of learners and promote positive interactions between learners and learning contexts (Lan, 2020; Wu, Lan, Huang, & Lin, 2019). However, most studies have been based on behavioral findings, and evidence from brain activity data is relatively limited. To produce high quality studies and useful applications with brain activity data, the theoretical underpinnings of cognitive neuroscience and educational psychology must be considered.

Among cognitive neuroscience methodologies, electroencephalography (EEG) has been used to assess learners' spontaneous brain electrical responses. In what follows, we briefly describe the methodology, introduce the time-frequency and event-related potential (ERP) techniques and review some examples of how they are applied in digital learning studies. We then offer considerations about how to collect high quality data, and we provide suggestions for potential research directions. Finally, a brief guideline for publishing results is presented.

1.1. Why is EEG useful for learning science?

The 100-year history of EEG affords a rich and diverse spectrum of applications and provided solid foundations for research in a wide variety of fields. However, EEG offers a particularly unique perspective for learning science that is distinct from most other neuroscience methodologies because it directly reflects neural activities and provides a temporally precise, continuous, and multidimensional view of the cognitive neural processing associated with learning. For example, the unobtrusive and continuous assessment of learners' mental states in real time based on the EEG data opens up the possibility for digital learning platforms to track learners' states and constantly adapt the learning materials to each learner's capacity. Below, we summarize the basic principles of the EEG technique and review how these techniques are advantageous for digital learning science.

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EEG is well known for its high temporal resolution, as it measures the instantaneous voltage changes from the scalp with no delay from the actual neural activity in the brain. EEG, typically recorded by electrodes placed on the scalp, mainly reflects the postsynaptic potentials (PSPs) summed from a large population of neurons that are radially oriented near the scalp and activated synchronously. Direct neural activity measures like EEG stand in contrast to the BOLD signals used in fMRI research, reflecting cerebral blood flow subsequent to neural activity, which change too slowly to permit most cognitive processes to be measured in real time. Thus, compared to a questionnaire-based methodology in reflecting learners' mental states where responses tend to reflect only the moments immediately before the questionnaire was taken, an EEG assessment captures changes in real-time mental states of learners (e.g., cognitive load, emotions, fatigue, or motivations), which can then provide immediate feedback or to individualize the learning materials in digital learning environments.

An EEG signal can be decomposed into multiple frequencies through time-frequency analysis, and EEG-based passive brain–computer interfaces (pBCI) which provides efficient real-time quantification of learners' brain activities that was difficult to achieve with manual coding have become an important tool in learning science research. Frequency components of an EEG signal are usually quantified in terms of power (amplitude squared) at each frequency over time. Different frequency bands have been identified and labeled in the literature, including delta (δ: ∼0.2–3.5 Hz), theta (θ: ∼4–7.5 Hz), alpha (α: ∼8–13 Hz), beta (β: ∼14–30 Hz), gamma (γ: ∼30–90 Hz), and (very) high frequencies (> 90 Hz) (Biasiucci, Franceschiello, & Murray, 2019). The frequency bands have significance in various cognitive processes. For example, delta is typically observed when a person is sleeping, theta is typical of nervousness, an attentive and relaxed state of mind is characterized by alpha, alertness is characterized by beta, and problem solving or higher cognitive functions are associated with gamma. One thing to note is that by decomposing the EEG signal into its constituent frequencies, some temporal resolution is sacrificed; as in signal processing, temporal precision is inversely related to frequency precision.

Continuous EEG data can also be used to derive event-related potentials (ERPs). By aligning and averaging point-by-point over multiple segments of EEG data that are time-locked to a particular sensory, cognitive, or motor event of interest, random fluctuations in the EEG signal are cancelled or attenuated, leaving voltage fluctuations that have a systematic temporal relation with event onset. Unlike the frequency approach which inevitably sacrificed some degrees of temporal resolution, ERPs reflect the moment-by-moment fluctuation of brain activity to the millisecond; thereby allowing for the continuous monitoring of processing and the measurement of temporally transient effects. ERP data are also multi-dimensional, with polarity, amplitude, latency, and scalp distribution potentially linked to different aspects of the brain functioning in question. ERP data thus offer the opportunity to tease apart cognitive sub-processes related to learning that are not distinguishable in behavioral measures and/or that may occur too quickly to be captured by most other methods.

ERP data are often discussed in terms of components, which are systematic patterns of voltage changes in magnitude, timing, or scalp region, that can be linked to certain neural and psychological processes and/or certain brain systems (Luck, 2014). The tremendous number of published studies using ERP components, especially in the field of learning and memory, have produced a great deal of knowledge about component properties and characterizations and the factors that may influence the magnitude and timing of these components (for comprehensive reviews on ERP components, see Luck & Kappenman, 2013). This knowledge is thus advantageous and essential for designing digital learning studies, as it provides a solid basis for hypothesis testing and meaningful data interpretation.

1.2. EEG and ERP research in digital learning environments

Below we reviewed some examples of EEG and ERP studies in recent digital learning research, highlighting two major types of applications—EEG studies that assessed student's online mental states to adjust learning environments and ERP studies that assessed brain responses time-locked to specific events to infer learner's progress and identities.

One emphasis of digital learning research is to probe into learners' real-time mental states in a less interruptive manner and use that information to provide more customized and dynamic digital learning environment. For example, cognitive theories of instructional design hold that the type and amount of working-memory load (WML) that learners experience is crucial for successful learning (e.g., Mayer, 2009; Sweller, van Merrienboer, & Paas, 1998). In addition, affect functions have also been thought to play a critical role in learning and learning motivation (Ge, Zhang, Li, & Su, 2019; Keller & Suzuki, 2004; Pentaraki & Burkholder, 2017). Direct and undisruptive evaluation of learner's cognitive load and affective states is therefore essential to provide learning conditions with the optimal level of challenge that can reduce boredom and off-task behavior. These learner states have traditionally been assessed with post hoc questionnaires. Some studies relied on spontaneous biophysical signals of learners, such as facial expression, eye gaze, voice, skin conductance, blood pressure, heart rate, and body language. However, data analysis usually required manual categorization of the states from trained coders which could be time consuming and prone to inter-rater variability.

The EEG technique is ideally suited to help address the above-mentioned difficulties. Continuous whole-head EEG recordings during learning sessions can be classified into different patterns by machine learning algorithms and signal processing techniques for subsequent analysis with a decent level of classification accuracy within or across individuals (Gerjets, Walter, Rosenstiel, Bogdan, & Zander, 2014; Spüler et al., 2016; Wang, Nie, & Lu, 2014). For example, Conrad and Bliemel (2016) found that the average EEG alpha (8–13 Hz) was higher for materials that were appropriately challenging, but EEG beta (13–30 Hz) was lower when the challenge and skill dimensions were low. EEG-assessed cognitive load during learning has also been shown to be indicative of learners' attention and performance (Gaume, Dreyfus, & Vialatte, 2019; Hu, Li, Sun, & Ratcliffe, 2018; Mills et al., 2017) as well as processing demand imposed by the learning materials (e.g., lower cognitive load for processing 3D visuals than 2D visuals in a virtual learning environment, Dan & Reiner, 2017). Furthermore, students' attention and emotion (valence and arousal) can be classified by the fine K-Nearest Neighbor (KNN) algorithm with the EEG features when they are involved in the virtual reality (VR) courses or real lectures (Alwedaie, Khabbaz, Hadi, & Al-Hakim, 2018). These results not only provide objective and immediate assessments for understanding whether students are engaged in the course materials and the style designs, but also offer neurophysiological evidence indicating why virtual learning is more effective than traditional lecturing (Moazami, Bahrampour, Azar, Jahedi, & Moattari, 2014).

EEG-assessed mental state information has also been used to improve learning materials and tailor them to students' needs (Santos, 2016). For example, taking the multi-modal approach of measuring EEG signals in conjunction with blood pressure and skin conductance, Shen and colleagues demonstrated the feasibility of using physiological data to detect learners' real-time emotional states and to feed these states into a digital learning model to automatically adjust the content (e.g., deliver examples or case studies for the current topic when confusion is detected, or deliver music to a student's taste when hopefulness is detected) (Shen, Wang, & Shen, 2009). EEG-assessed cognitive load during learning has been used to provide immediate feedback and to prompt an interactive online learning environment to automatically adjust the difficulty of the learning materials to place them in the optimal range for a particular learner (Mora-Sánchez, Pulini, Gaume, Dreyfus, & Vialatte, 2020; Walter, Rosenstiel, Bogdan, Gerjets, & Spüler, 2017).

In addition to using frequency decomposition to quantify and distinguish different mental states, another main application of EEG technique is to derive ERPs to investigate brain responses that are phase-locked and time-locked to specific events. As the ERP technique requires averaging over multiple second-long EEG observations time-locked to event onsets, research taking this approach is usually performed in a more controlled setting to ensure that the EEG segments averaged together are elicited by similar events. With knowledge of the functional characteristics of many ERP components (Luck & Kappenman, 2013), ERPs have been used to investigate difficulties or learning progress of students (Brown, Howardson, & Fisher, 2016). For example, Conrad and Newman (2019) used the oddball P300 to detect mind-wandering among learners. Huang and Liu (2012) discovered that high- and low-achieving students used different mental rotation strategies (indexed by the ERP rotation-related negativity) while learning chemical structural formulas. Furthermore, Osterhout and colleagues (2006) demonstrated changes in brain responses in L2 learners as their proficiency progressed: while novice learners initially treated morphosyntactic errors as lexical or semantic errors (as indexed by an N400 effect), these learners' brain responses changed over the course of learning to approximate brain responses to morphosyntactic errors in their native language (as indexed by a P600 effect).

As some ERP components can be used to represent personal idiosyncratic processing, the ERP technique has also been applied to provide reliable continuous authentication to ensure that the identity of the individual does not change after logging in. Prior research has shown that some ERP components have robust identifiable features that can be used to differentiate the brain responses of different individuals. For example, the N400 response is thought to reflect idiosyncratic semantic experiences (Coronel & Federmeier, 2016), and the P300 has been associated with attention-mediated processes that vary across individuals (Polich, 2012). Taking advantage of these component characteristics, Song and colleagues proposed that P300 in conjunction with eye tracking could be used as biometrics for continuous personal identification (Song, Lee, & Nam, 2013). Applying pattern classifiers on ERP responses to a stream of text designed to be idiosyncratically familiar to different individuals, Armstrong and colleagues also demonstrated decent accuracy in identifying the individuals responsible for particular ERP responses (Armstrong et al., 2015).

2. Experimental design suggestions

Applying measurements of brain responses to the learning science field has the potential to provide input into the development of learning materials and facilitate the design of individualized learning environments. However, this type of research involves digital learning system development, experimental design, and neurophysiological signal processing, and is thus highly interdisciplinary. Additionally, EEG and ERP data are complex and multifaceted, which is an advantage of the technique but also makes data analysis challenging. A further challenge is that EEG and ERP data are sensitive to the various types of stimuli, the age range of participants, and uncontrolled experimental factors. Thus, collaboration with experts to identify a suitable experimental design and potential confounding factors is advised to ensure better research quality and more accurate data interpretations when studying EEG/ERP responses. Some suggestions for conducting this type of research are provided below.

To successfully integrate and apply neurophysiological results, researchers must first state the research question concretely and provide clear operational definitions of the cognitive processes and/or mental states to be examined. For example, when examining an overarching concept of engagement during a task, this could be defined as focused attention on the task or as a high cognitive load being required for the task (Brouwer, Zander, van Erp, Korteling, & Bronkhorst, 2015). It is possible that researchers using the same term may indicate a different underlying cognition across research fields, and thus it is important to reduce confusion by providing clear definitions. Second, researchers should formulate a linking hypothesis of which EEG/ERP measures are expected to vary with the cognitive processes/mental states in the study design. Drawing conclusions about cognition from EEG/ERP data requires inferences, and it is therefore important to know what assumptions are being made to permit these inferences. In other words, a detailed literature review is necessary to establish what independent variables do and do not influence the EEG/ERP measures before conducting the research (Cacioppo & Tassinary 1990). All inferences are correlational in nature—even when a tight correlation is found indicating that the linking hypothesis is correct, only a correlate of cognitive processes/mental states has been discovered. The measured brain activity cannot be interpreted as the direct manifestation of the cognitive processes/mental states that it has been linked to (Handy, 2005). Third, researchers need to be aware of confounding factors. EEG/ERP data are very sensitive to various types of factors that may not be controlled for in the study design, such as the modality of the stimulus presentation (visual versus auditory), the characteristics of the stimuli, such as familiarity with the materials (Kutas & Federmeier, 2011) and the concreteness (Huang, Lee & Federmeier, 2010; Huang & Federmeier, 2015) or ambiguity of the words (Huang & Lee, 2018), and repetitions (Kutas & Federmeier, 2011). The syntactic word ordering effect may actually reflect the uncontrolled concreteness differences between words (Huang & Federmeier, 2012). Fourth, because only EEG/ERP data that are associated with the cognitive processes of interest and not contaminated by artifacts will be included in the data analysis, researchers should identify tasks that require minimal gross motor movement. Fifth, researchers must assess and evaluate whether their given set of assumptions is warranted based on how the brain signals are collected and analyzed.

In Figure 1, we summarize some important experimental design suggestions. At the beginning of conducting a research, investigators have to consider which EEG system would be more suitable for addressing their research questions, this issue will be elaborated in the next session again. In some of the digital learning studies, the different teaching methods (e.g., digital learning vs. lecture-based training) are composed of different groups of participants; in this case researchers have to make sure the characteristics of participants in different groups are matched (such as age range, gender, participants' intelligence). Another issue that needs to be taken into account in the experimental design is the total duration of a study, since the EEG signal quality would be substantially reduced when participants are tired. It would be ideal to split one study into multiple short blocks with about ten to fifteen minutes per block. Between blocks, the participants could take a short break. When having multiple blocks in a study, then it is not good to administer the blocks to all of the participants in the same sequence. That means, a randomized counterbalancing is suggested to reduce the order and carryover effects. On the other hand, if the duration of the whole study is longer than one hour, then the researchers could seek the possibility of asking participants to join a multi-session study. Otherwise, splitting one study into two shorter studies could be another option. As for how many participants are needed to test the hypothesis adequately, the decision is based on the study design, the variability of the data and the type of statistical procedure to be used.

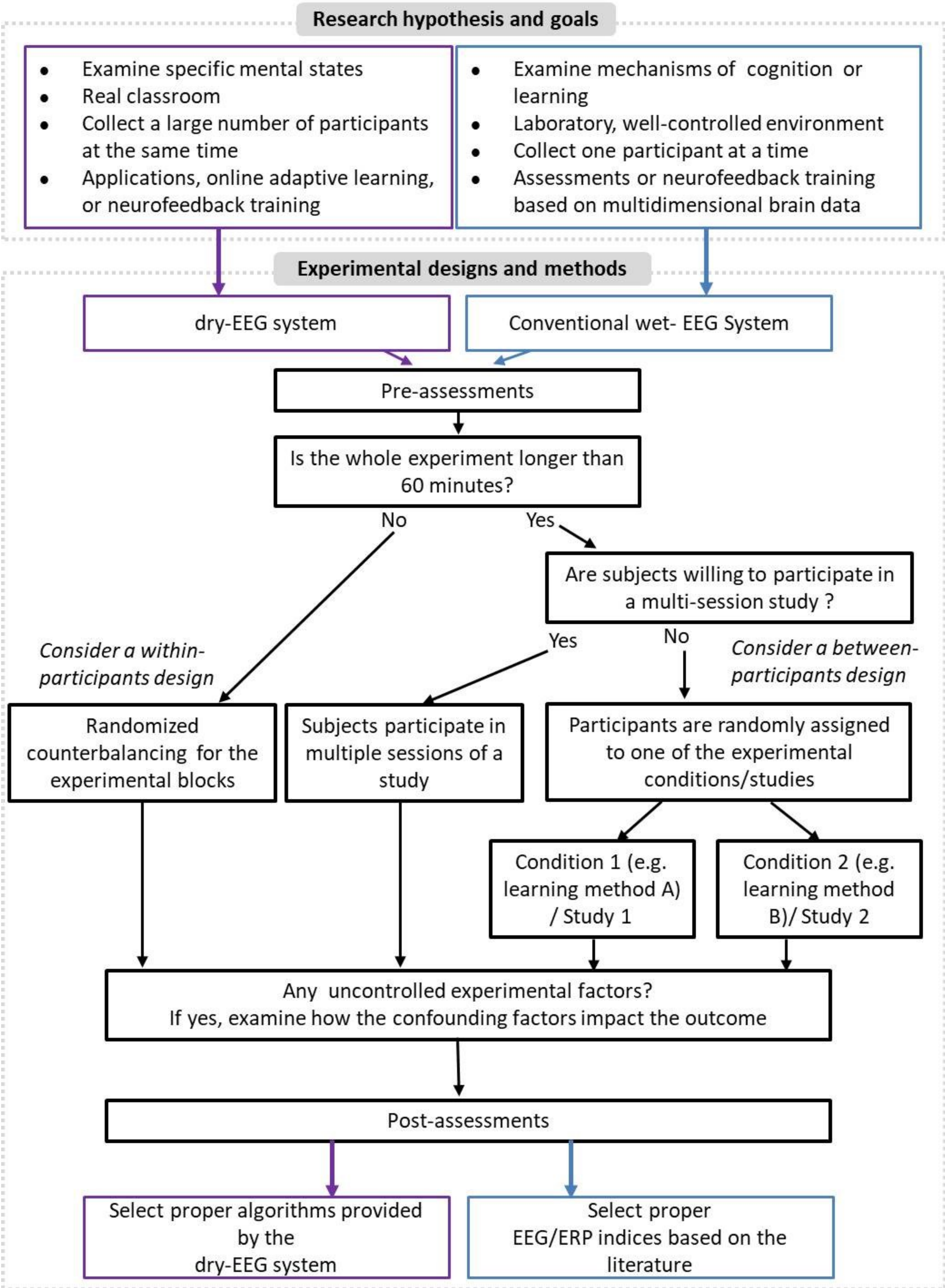

Figure 1. Summary of the experimental design suggestions

3. How to record publishable data from the lab to the field

In this session, we present major EEG/ERP data collection techniques and preprocessing methods that can be used beyond laboratory settings. Some suggestions are also offered for planning studies toward real-world measurements.

3.1. EEG data recording in the laboratory

Brain signals are small along the scalp surface, in the order of 10–100 microvolts, whereas non-EEG biological signals, such as skin potentials, muscle activities, blinks, and eye-movements, are in the order of 50–500 microvolts. To better read the brain signals, they need to be amplified and filtered by the recording system. When recording EEG signals, the most often used filtering ranges are within 0.01 to 30 Hz or, more conservatively, 0.01 to 100 Hz. It is important to keep most of the low frequency activity, but very high frequency activity can be safely discarded because it is unlikely to be biologically related. The continuous analog signal emitted from the amplifier must then be converted to a digital format (through A/D conversion), forming a discrete pairing of time points and voltages. Once the signal is represented as individual numbers in a time series, these numbers can be manipulated mathematically. Based on the Nyquist criterion, the minimum sampling rate recommended is at least twice as fast as the fastest frequency component in the signal. For example, to investigate an EEG signal of 40Hz, the sampling rate must be at least 80Hz. However, most researchers sample at four to eight times the highest frequency to ensure accurate detection of the EEG data and/or under the consideration that greater temporal resolution might be needed. Finally, EEG activity from the various sites on the scalp needs to be referenced to the mastoid(s) or earlobe(s), common locations that pick up minimal amounts of brain activity, to give the difference between each site and the reference electrode.

A system for presenting learning materials, pre- and/or post-testing, and receiving behavioral responses needs to communicate with the EEG data acquisition system in real time to send event codes whenever an event occurs (e.g., a stimulus being presented or a response generated by the subject). These event codes are used as the time-locking points for data processing or signal averaging, so the timing must be precise: the EEG acquisition system will not “know” what kind of event the subject is encountering nor at what time if no event codes are given.

Before data collection, researchers need to ensure that the areas under the EEG electrodes are free of dead skin, oil, and sweat, for low impedance. High electrode impedance increases noise and decreases statistical power, meaning that more trials are needed to reach statistical significance. Typically, impedance under 5 kΩ is suggested with the use of conductive gel (so called wet-EEG). The electrode positions should follow the standard International 10–20 system, because the relations between the 10–20 electrode system and the underlying cortical anatomy have been validated (Towle et al., 1993). A comfortable environment is also essential, and the experimental room should have an air conditioning system that can control the temperature, humidity, and air circulation for indoor air quality. Because sweat is one of the common causes of biological artifacts that can alter impedance, and high temperature also causes participants to become sleepier. Additionally, to minimize any muscle activities or body movements during the EEG/ ERP recording sessions, it is very important for the subject to be seated in a comfortable position.

3.2. EEG data recording in real-world settings

Compared with collecting EEG data in the laboratory, where recordings can be better controlled and monitored by the experimenters, collecting EEG data in the “real world” poses additional challenges. For example, gel application and post-recording cleanings are time-consuming. For real-world applications, dry-wireless EEG systems (dwEEGs), which are wireless systems using dry electrodes to collect EEG signals, have been developed over the past decade (Di Flumeri et al., 2019). Compared with the conventional wet-EEG devices, dwEEGs can shorten the time for preparation, remove the need to apply conductive gel, increase the convenience to new users, and enlarge the number of simultaneous participants for investigating their interactions. In Table 1, we contrasted features between wet-EEG and dry-EEG for studying digital learning topics. Although some limitations (e.g., the comfort of the sensor) are still being addressed (Di Flumeri et al., 2019; Lin, Yu, King, Liu, & Liao, 2020), dwEEGs already demonstrate their usefulness in many areas, including brain–computer interface (BCI) (Lin et al., 2018), sport science (Wang, Moreau, & Kao, 2019), clinical assessment (Lin et al., 2017; Ratti et al., 2017), and education (Xu & Zhong, 2018).

Table 1. Comparisons between the wet-EEG and dry-EEG devices for a digital learning research.

Device	wet-EEG	dry-EEG
Cost	High (USD 40,000 – 80,000)	Low (USD 100 – 15,600)
Channel number	32 to 256	1 to 64
Preparation	Experience required	Easy
Setting time	15–30 minutes	1–10 minutes
Wash hair	Yes	No
Comfortability	Average	Comfort to average
Signal stability	Very High	Very low to high
Weight	average	Depends on the channel number
Wireless	Yes	Yes
Scalable	Flexible	Fixed
Raw data	Available	Less available to available
Algorithm	Less available	Available
Artifact removal	Available	Less available to available
Analysis	All analysis, including brain connection, source, time and frequency domains	Time and frequency domain
Subjects at the same time	Most are one	Not limited
Research Topics	All topics and applications	Many are for applications (monitoring attention, emotion or meditation states)
Summary	Convectional and reliable tool for educational research, especially for collecting a single subject data at a time in the laboratory.	Convenient device to explore educational topics in the real environment, especially for evaluating specific processing/mental states of a larger population at the same time.

Some types of dwEEG (see Figure 2) have been used in real classroom environments to examine the relationships between dynamic changes in the brain and learning effects (Lau-Zhu, Lau, & McLoughlin, 2019). Although the first two systems (a and b) are designed for ordinary consumers and the others (c-f) are more for scientific research, all of these systems have been used in educational studies. Generally, these systems consist of a miniaturized light-weight amplifier with a Bluetooth module to transmit the signals, which increases the wireless and portability of each device (Bateson, Baseler, Paulson, Ahmed, & Asghar, 2017). The devices are light (under 269 grams), the sampling rate is reasonable (above 256 Hz), and the battery life of most dwEEGs is good (above 5 hours), supporting the criteria for standard EEG settings for regular experimental sessions. Each system has its own software to support the EEG signal collection, and most can save the raw data in text format for further signal processing using other software, such as EEGLAB (Delorme & Makeig, 2004). Most importantly, the signal quality and comfort of these systems have been validated following the traditional EEG paradigm with wet-EEG devices in the frequency domain (i.e., typically between 1–50 Hz, e.g., alpha band) and time domain (i.e., identifying time-locked brain electrical activity to a stimulus, e.g., P300) (Ruffini et al., 2006; Badcock et al., 2015; Oliveira, Schlink, Hairston, König, & Ferris, 2016; Williams, Norton, Hassall, & Colino, 2017; Rieiro et al., 2019; Kam et al, 2019; Lin et al., 2020). Although dwEEGs have been shown to benefit education studies (Xu & Zhong, 2018), the diversity of manufacturers still creates challenges for researchers in deciding which system to use and how many electrodes/channels are required for a study. Three challenges are described below for researchers to consider when planning their studies.

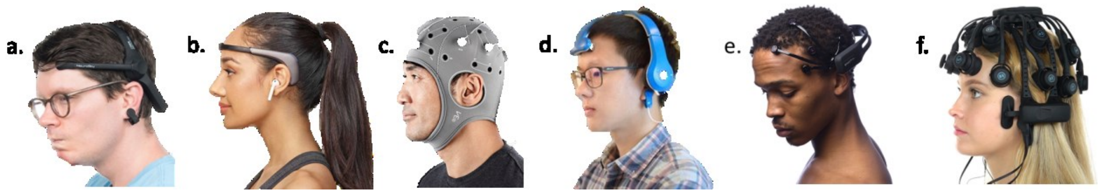

Figure 2. Examples of dry-wireless EEG systems. (a) MindWave 2 (NeuroSky); (b) Muse (InteraXon Inc.); (c) ENOBIO 8 (Neuroelectrics); (d) BR8 (BRI); (e) EPOC (Emotiv); (f) Quick (Cognionics)

First, measuring errors can occur due to low numbers of channels. Although fewer channels can reduce the cost and could be more comfortable for the participants due to a lighter weight, it will not only dramatically increase the application limitations but also the measuring errors (Xu & Zhong, 2018). For example, the frontal lobe is thought to be associated with emotions and motivation (Pessoa, 2009). However, this assumption is based on the asymmetry between two hemispheres and is most commonly computed by subtracting the natural log of the left side's alpha power (often using electrode F3) from the natural log of the right side's alpha power (electrode F4) (Coan & Allen, 2004). A single channel (e.g., the FP1 of NeuroSky) is not able to indicate frontal asymmetry--an effective index for emotion identification.

Second, measuring limitations can arise due to the layout of the channels. The final optimal design of dwEEGs is to cover the standard areas following the International 10–20 system used in the conventional wet-EEG. However, the layout of some dwEEGs is limited by the characteristics of the electrodes and cannot fit the 10–20 system. For example, although Emotiv possess 14 electrodes (wet), it does not cover the midline of the scalp, especially the central and parietal areas. These sites often evoke some unique components of ERPs that are associated with the motor and attention functions. For instance, a well-known P300 (P3b) is elicited over the parietal site (Pz electrode) when stimulus detection engages memory operation (Polich, 2012). The P300 latency and amplitude follow a maturational path from childhood to adolescence (van Dinteren, Arns, Jongsma, & Kessels, 2014) and are treated as an important index to investigate typical and atypical development. A lack of information on the parietal area places limitations on the use of P300 as an informative index for a study.

Third, the provided algorithms are short on validation. Some dwEEGs provide users with their own algorithms for monitoring the subject's attention level, emotions, and mediation states (e.g., Neurosky). Although most algorithms have corresponding technical support, the manufacturers do not provide clear statements on how the data are calculated. Moreover, the channel layout and channel numbers are still core problems for developing algorithms. Even for the few algorithms with high classification accuracy, cumulative samples are not enough to extend the usage range, especially for children (Xu & Zhong, 2018). Because developmental differences can influence the engagement of neural oscillations (Schneider, Abel, Ogiela, McCord, & Maguire, 2018), more evidence is required to validate the effectiveness of these algorithms before applying them in a real educational environment.

In sum, dwEEGs could provide good opportunities to study education/digital learning through measurements of brain activities. However, researchers need to consider the measuring limitations based on their research goal and budget before purchasing these devices. Researchers who hope to turn their research findings into practical achievements should be cautious in adopting the user-friendly interfaces and convenient algorithms provided by some dwEEGs. Three suggestions can be considered before deciding on the system of dwEEGs. First, if your study is an exploratory research, dwEEGs with more channels would be preferred, as more channels can cover more of the important scalp areas that provide critical information for further and diversity of analysis. Second, if you intend to use the same indexes as previous studies did, then exact corresponding channels should be involved in the layout of the selected dwEEGs. Third, if you focus on a particular application (e.g., attention monitoring of the digital learning process), you can use the algorithms provided by the device as they have been validated and published in peer-review journals with similar experiment designs and participants as yours.

3.3. Data preprocessing and writing-up

After data collection is completed, it is essential to remove the EEG signals that are contaminated by artifacts (both non-EEG biological and environmental electrical noises) prior to data analysis, as such artifacts may lead to misinterpretation of the EEG/ERP results. Eye movements and blinks can easily be identified on the electrodes attached to the supra-outer canthus of the left eye and infra-outer canthus of the right eye or on the frontal electrodes. A variety of techniques are available for removing these artifacts (see review in Urigüen, & Garcia-Zapirain, 2015; Jiang, Bian, & Tian, 2019) and can be primarily categorized into two approaches: estimation by reference channels and decomposing signals into different domains. The typical method of the first approach is the regression analysis which calculates the amplitude difference between reference channels (usually EOG/ECG) and other EEG channels, and then subtracts the estimated artifacts from EEG (Sweeney, Ward, & McLoone, 2012). This type of method is usually applied to remove eye movements. The second approach involves the independent component analysis (ICA) that can be used to remove all kinds of artifacts. This technique assumes that the EEG signal is a linear mixture of brain signals and artifacts which can be decomposed into independent components (ICs) (Makeig, Bell, Jung, & Sejnowski, 1996) to discard the artifacts and reconstruct the clean signals for further analysis. Recently, many researchers have developed different hybrid models to improve the accuracy and efficacy of the automatically processing (e.g., Icaeyeblinkmetrics toolbox; Pontifex, Miskovic, & Laszlo, 2017; artifact subspace reconstruction method; Chang, Hsu, Pion-Tonachini, & Jung, 2018). However, these must be applied with caution to ensure they do not distort the brain signals. Once the EEG signals are noise-free, further data analyses can be conducted.

The development of learning science depends on the validation of the results. Researchers therefore need to ensure that the details of the study are documented sufficiently so that others can evaluate and replicate published results. Specifically, other than the rationale for the proposed study and the discussion of the results, some details must be reported in writing up a paper with EEG/ERP results. First, detailed and clear descriptions are needed of the EEG measurements, such as the acquisition protocol, EEG data acquisition system, locations of the recording electrodes on the scalp, reference electrode(s), and methods and criteria that were used to remove the artifacts. Second, basic characteristics of the participants, such as mean age, age range, gender, and handedness must be reported. Third, the details of the materials used in the study and how the materials were presented to the subjects also need to be described. And finally, proper graphical representation of the EEG/ERP results on the paper is necessary. All these aspects are essential in a manuscript as suggested by the Society for Psychophysiological Research committee's guidelines (Keil et al., 2014; Picton et al., 2000). These guidelines not only provide a solid foundation for using or applying EEG technology in understanding human cognition but are also very helpful in communicating or comparing EEG/ERP results between studies.

4. Potential research directions and concluding remarks

We highlight three potential areas for new research. The first is to investigate interactions in the classroom setting. Researchers can use EEG as a more objective and naturalistic approach to investigate the effect of teaching materials on students or the interactions between a teacher and students or between students. For example, Dikker et al. (2017) used Emotiv to simultaneously record the brain activities of 12 high school students to identify neural markers of group engagement in a real-world classroom. Using brain-to-brain synchrony (BBS) as a neural marker, students with higher BBS showed greater engagement in the group. Moreover, students who showed higher BBS with the teacher reported greater social closeness to the teacher, especially when the teacher was giving a lecture (Bevilacqua et al., 2019). These findings suggest that BBS may reflect social interaction in real-world group settings and show dwEEGs to be useful tools for investigating the social relationships and interactions taking place in a real classroom setting.

The second research suggestion is to explore specific experiences with large-scale data collection. Educators are among those needing a way to naturalistically evaluate the specific experience elicited by a work of art, design product, or set of learning materials. Using a portable EEG device, a 400-person EEG dataset was collected to examine the neural basis of aesthetic experiences during visual exhibitions (Kontson et al., 2015). The connection strength in localized brain networks was significantly increased while subjects viewed the most aesthetically pleasing art compared to a blank wall. Moreover, the direction of EEG signal flow showed the early recruitment of broad posterior areas followed by focal anterior activation. This example shows that dwEEGs may be helpful in understanding how the brain integrates sensory input and ongoing internal states to produce specific phenomena, such as the aesthetic experience.

A third area of research potential is maximizing the efficiency of adaptive/online learning by real-time neuro-feedback. At the time of writing, the need for online courses has dramatically increased due to the COVID-19 pandemic. However, instructors are unable to immediately monitor whether students remain focused on their learning. With one advantage of dwEEGs being their capacity to provide convenient and real-time measures for monitoring participants' attention and emotional states, these devices can be used as a novel way to monitor online learning processes and elevate the efficiency of e-learning environments. To examine students' attention levels during digital learning, the Neurosky team has developed an attention aware system integrated with a video lecture tagging system (Chen, Wang, & Yu, 2017). Negative correlations were found between learning performance and low levels of attention to video lectures. In another study using Emotiv, some important features associated with the learning performance of Vietnamese language via video were extracted and used as indices to adjust the instructional methods and/or materials for adaptive learning (Hu & Kuo, 2017). Therefore, dwEEGs may provide a convenient approach to enhance the efficiency of online and adaptive learning for instructors or users within the digital learning environment.

Over the past half-century, EEG and ERP studies have opened up new avenues for understanding human cognitive processes as they occur in real time. Applying these techniques with competence, caution, and creativity can aid in the development of productive learning environments. Such advancements in learning science can ensure that everybody can learn effectively, both inside and outside of school.

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