IEEE Sensors Council

Consumer Grade EEG Measuring Sensors as Research Tools: A Review

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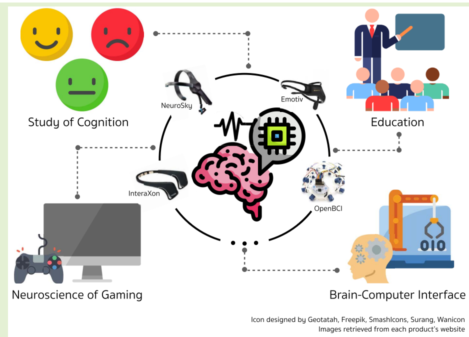
***Abstract*—Since the launch of the first consumer grade EEG measuring sensors 'NeuroSky Mindset' in 2007, the market has witnessed an introduction of at least one new product every year by competing manufacturers, which include NeuroSky, Emotiv, interaXon and OpenBCI. There are numerous variations in the make and versions, but these products clearly share the key selling points of affordability, portability, and ease of use. These features are patently well placed provided one of the main objectives for their development is to attract a new target group of commercial users. Nevertheless, with several decades of traditional EEG usage in clinical and experimental settings, the shift toward commercial and engineering sides has not been achieved without skepticism. With this in mind, researchers in related fields have been tirelessly working to ensure that these putatively novel features were not introduced at the expense of efficiency and accuracy by conducting validation studies to compare the performance of data derived from consumer grade EEG devices with ones from standard research grade counterparts. In this review, we seek to provide the detail of the products supplied by the major players, summarize studies that evaluate consumer product's performance against research grade devices, the key areas of applications that these consumer grade devices have been employed in over the past five years or so, and finally give our perspectives on the limitations and what these innovative tools could offer going forward in terms of research and commercial applications.**



***Index Terms*—Consumer grade EEG, EEG BCI, EEG cognitive study, EEG education, EEG gaming.**

I. Introduction

IN THE 21st century, electroencephalography (EEG), a non-invasive measurement of electrical activity across the scalp, has gradually gained precedence in clinical and research practices for its negligible health risk and minimal restriction on the users' age [1]. Researchers from diverse fields of study including neuroscience and engineering have made use of EEG devices in their experiments as a primary research tool to acquire relevant brain signals. Moreover, the method itself is routinely performed in conjunction with other neuroimaging techniques such as magnetic resonance imaging (MRI) in the clinic, for example, to diagnose neurological disorders such as epilepsy, sleep disorders, and attention deficit hyperactivity disorder (ADHD) [2] as well as to evaluate the patients with history of depression and other psychiatric disorders [3].

Mechanistically, when the resident neurons in the brain are successfully excited, spontaneous electrical current flows result which can be recorded by electrodes embedded in the EEG device [4], [5]. These electrical potentials principally reflect the sum of the postsynaptic activities caused by synchronous cortical neurons in the cerebral cortex [1], [3]. The oscillations of the EEG signals at varied frequencies represent the underlying rhythmic activity [4]. These frequency bands comprise of several waves: delta (<4 Hz), theta (4–7 Hz), alpha (8–12 Hz), beta (13–30 Hz), and gamma (>30 Hz) [6] [7]. The physiological signals exhibited by the brain are linked to a variety of functions including motor, sensory, and cognition [8].

The development of high-quality multi-channel EEG devices, often annotated medical or research grade as they are most commonly found in hospitals and laboratories, has enabled clinicians and researchers to assess neural signatures in the patients. However, these traditional EEG systems may necessitate a complex assembly and extensive application time, inadvertently inflicting discomfort and distress on the

Manuscript received November 10, 2019; accepted December 24, 2019. Date of publication December 30, 2019; date of current version March 17, 2020. This work was supported in part by the Robotics AI and Intelligent Solution Project, in part by the PTT Public Company Limited, in part by the Thailand Science Research and Innovation under Grant SRI62W1501, and in part by the Thailand Research Fund and Office of the Higher Education Commission under Grant MRG6180028. The associate editor coordinating the review of this article and approving it for publication was Prof. Aime Lay-Ekuakille. *(Corresponding author: Theerawit Wilaiprasitporn.)*

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Digital Object Identifier 10.1109/JSEN.2019.2962874

users [2]. Furthermore, most would agree that transitioning traditional EEG devices from the clinical environment into general usage is not free from difficulty and inconvenience. Recently emerging technology has supplied advanced hardware for the growing market of consumer grade wireless and wearable single-channel, and even more sophisticated multi-channel EEG devices. These virtual and effortless devices have been marketed for personal and everyday applications since the portable and affordable nature of the devices confers ease of access in settings such as at home or on the school's premise [9]. Even though the traditional research grade EEG devices remain preferable in the clinical establishments, numerous studies exploring the principal responses of the brain have been carried out using these consumer grade devices to curtail research cost and prolonged assembly time [2], [9]–[11]. Notably, the validation and repeatability of results obtained from these devices in research experiments are still an open question. A matter of contention also presides over the possibility of lower quality data the fewer sensors may yield.

The validity of currently available consumer grade EEG systems has been tested extensively by medical and research groups most commonly on accuracy, coverage, and data quality. This review covers research studies in the past five years that utilize consumer grade EEG devices as the primary equipment for data acquisition. Specifically, the literature search was performed on a number of renowned online publication databases including IEEE, Springer, and SCOPUS. The following search strings were entered in the search query: EEG, OpenBCI, EMOTIV, EPOC+, EMOTIV INSIGHT, Myndplay, Myndband, NeuroSky, MindWave, and interaxon MUSE. We handpicked published studies within the past five-year range among the initial search results. We then set a quality cut-off threshold based on the publishers, excluding studies that were not published in the First Quartile as stated in the inventory of Scimago Journal & Country Rank. As a result, the list was narrowed down to 91 titles. We presume that these papers likely represent cutting-edge research in terms of validation and usage of consumer grade EEG products. We then expanded our search using another search engine, Google Scholar, and retrieved more than 100 additional papers in the related fields. Figure 1 demonstrates the number of papers in each of these applications according to the devices employed. In this review, we describe the current status and the practical promises of implementing these devices in four different fields: cognition, Brain-Computer Interfaces (BCI), education research, and game development. We also address specific issues inherent to each device, and when appropriate, compare them to the medical grade devices.

Our four principal contributions can be summarized as follows:

- To the best of our knowledge, this is the first comprehensive review with up-to-date details on consumer grade EEG devices as research tools among the four major applications: cognition, Brain-Computer Interfaces (BCI), education, and neurosciences of gaming.

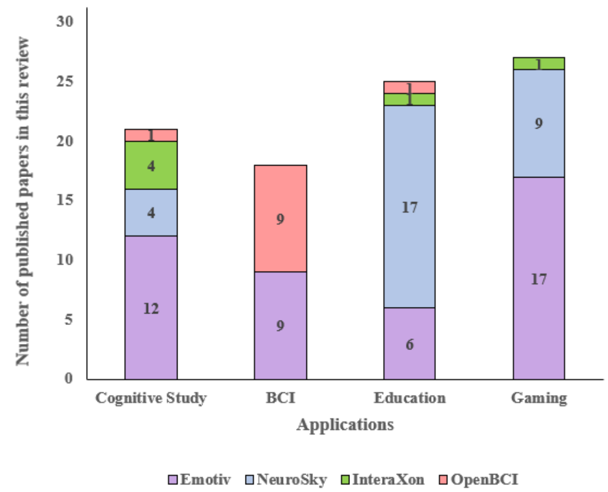

Fig. 1. Number of published journals as sorted by applications (cognitive study, BCI, education, and gaming) and products (Emotiv, NeuroSky, interaXon, OpenBCI). Emotiv products are popular in cognitive study as well as gaming while the products manufactured by NeuroSky dominate the educational field. BCI-focused research covered here exclusively make use of the products by Emotiv and the newcomer, OpenBCI.

- We position this review as a systematic guidance to the novice EEG-related researchers who are in need of an overview in the related research fields as well as those who intend to integrate these EEG devices to be utilized in an additional approach for the respective main research domain.
- We provide basic EEG knowledge and the limitation of its application under the boundary of the consumer grade EEG products.
- We identify the future usage trends on consumer grade EEG-based research applications and public repositories.

The review is separated into six sub-sections (see Figure 2 for schematic). Introduction is laid out in Section I, followed by Section II describing a comprehensive list of consumer grade EEG products by different manufacturers that are available in the market as well as those that have been used in actual scientific experiments. In Section III, we partition the embracing applications of consumer grade EEG into four categories, i.e., cognition, BCI, education, and neuroscience of gaming, respectively. Limitations of these products, future challenges, and their diverse utilities are elaborated in Discussion (see Section IV). Lastly, Section V provides the final Conclusion for this piece.

II. Consumer Grade Products

Over the past decade, the application of non-invasive functional neuroimaging techniques, such as EEG, has bled from chiefly academic into more commercial usage. Recorded brain signals from EEG are interpreted and linked to cognitive performances of all sorts by researchers in order to gain a better insight into the functionality of the human brain. Generally speaking, medical grade neuroimaging devices are most commonly adopted in academic research, necessitating high-fidelity performance and advanced functionality. In comparison, consumer grade devices are prized for their low cost, ease of set-up, and by and large acceptable performance,

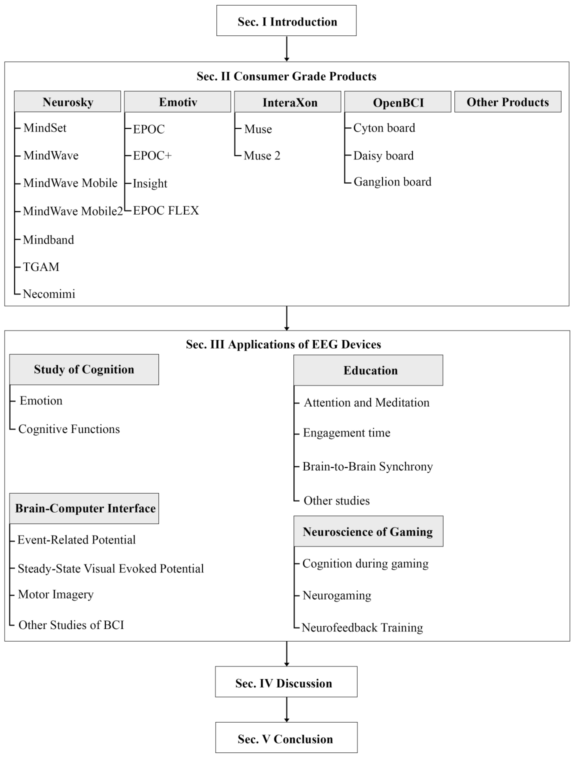

Fig. 2. The layout of this review: (I) Introduction, (II) Manufacturers and Products, (III) Applications, (IV) Discussion, and (V) Conclusion.

arguably making them a more appropriate system for commercial product development.

A. NeuroSky [12]

NeuroSky was one of the earliest players that took up the production and market distribution of consumer grade EEG devices. In 2007, NeuroSky MindSet, their very first product, was launched. It came as a headset with two electrodes, one to be placed on user's ear as a reference frame and the other on the forehead for signal reads. A protruding part sits on the user's forehead for the recording of EEG signals at the F_{p1} location. The success of MindSet launch was soon followed by the development and release of the second generation devices including MindWave, MindWave Mobile, MindWave Mobile plus, and MindWave Mobile 2. Whilst others have been discontinued over the years, MindWave Mobile 2 is still available to order. MindWave Mobile 2 was introduced as a device for education and gaming application, with the key functionality being the monitoring of attention and meditation. Interestingly, several studies have reported the use of made-to-order products by NeuroSky. In 2016, Wei and Ma [24] used a product called Mindband, a BCI device with single channel dry sensor, to study visual attention and reading performance in Taiwanese children and adults. Additionally, Lim and colleagues specifically ordered a customized mobile device with 2 dry electrodes instead of a default single channel electrode seen in other products from NeuroSky for their research on training program for children with ADHD [25]. It was reported that the additional sensor provided significantly higher quality performance.

For those interested in product development, NeuroSky also offers the ThinkGear ASIC Module (TGAM) [26] at the cost of $49 per piece. This module has been designed for the recording of EEG signals and computation of attention and meditation levels. However, this module is independently supplied and does not come in a package with a device, an electrode connection, nor a power supply, allowing users to develop their own hardware for the integration with this chip. Although the manufacturer has not revealed the information on the measurement algorithms, the number of usage is considerably high in the field of educational research. The product provides many measurement options including blink detection, mental effort, familiarity, appreciation, emotional spectrum, creativity, and alertness measurement [27]. Other than the academics as target users, NeuroSky also manufactured Mindflex [14] and NeccoMimi [16]. Mimicking a set of simple toy, Mindflex's EEG headset captures the user's brainwaves to steer a foam ball through the laid-out obstacles in the game setup. Another popular product, a Neurowear named NecoMimi, comes in the form of a head gadget equipped with brainwave sensor as well as a pair of movable plush cat ears which can be commanded by the change in the wearer's brainwave activity.

The products from NeuroSky have been tested in many validation studies. The main algorithms for attention and meditation monitoring developed by NeuroSky along with the blinking recognition were validated in a 2016 study by Maskeliunas *et al.* [9]. For the team to evaluate attention and meditation, the subjects were instructed to concentrate or relax while the experimenters recorded their attention- and meditation-associated brainwaves using the MindWave devices. Each of the metrics was verified; the measure was considered an attention value if the attention level was higher than that of meditation when the subjects were instructed to focus and vice versa. MindWave achieved only 22% accuracy in these tasks. The number is extremely low and showing the lack of consistency for separating relaxing and focusing people. In comparison to the study mentioned earlier that NeuroSky algorithm evidently failed to separate the relaxing and focusing subjects, the attention level measured by NeuroSky might probably be sufficient for determining the level of difficulty or thinking requirement for on-going tasks, which can be beneficial in certain tasks [28]–[30]. Maskeliunas *et al.* also investigated the blinking recognition algorithm provided by NeuroSky in the study [9]. The algorithm only achieved approximately 49.6% accuracy for blinking recognition, leading to the suggestion of using a gaze tracker such as Eyetribe instead. This has been shown to be consistent with a previous study in which Roesler *et al.* argued that MindWave performed with a high error rate of 43.52% accuracy for classifying different conditions of the eyes (open and close) [31]. Another study also reported a low accuracy of 40% for NeuroSky's blinking detection algorithm [32]. Although the blinking detection algorithm may not provide a practical usage, the hardware is per se plausibly viable. This has been successfully validated by Abo-Zahhad and colleagues using raw eye blinking waveform from MindWave for person identification amomg 25 subjects

TABLE I
SUMMARY OF CONSUMER GRADE EEG PRODUCTS AND BUILT-IN FUNCTIONALITY, ARRANGED CHRONOLOGICALLY ACCORDING TO LAUNCH YEAR

Product	Sensor	Channel	Sampling rate [Hz]	Wireless connection	Raw data access	Battery Life [Hours]	Price [USD]	Released Year
NeuroSky MindSet* [12]	Dry	1	512	Bluetooth	Yes	-	-	2007
Neural Impulse Actuator*	Dry	-	-	-	No	-	-	2008
Emotiv EPOC* [13]	Wet	14	128	Bluetooth	Yes	-	-	2009
Mindflex** [14]	Dry	1	512	No	No	***	99	2009
MindWave* [12]	Dry	1	512	Bluetooth	Yes	-	-	2011
XWave headset [15]	Dry	1	512	No	No	***	-	2011
Necomimi** [16]	Dry	1	512	No	No	***	69	2012
Emotiv EPOC+ [13]	Wet	14	128/256	BLE	Yes	12	799	2013
Melon HeadBand* [17]	Dry	3	-	Bluetooth	-	-	-	2014
MyndPlay Myndband [18]	Dry	1	512	BLE	Yes	10	299	2014
Muse [19]	Dry	4	220/500	BLE	Yes	5	199	2014
OpenBCI [20]	Dry/Wet	8/16	250	BLE and Wifi****	Yes	26	750/1800	2014
Aurora DreamBand [21]	Dry	1	-	BLE	Yes	-	299	2015
Emotiv INSIGHT [13]	Semi-dry	5	128	BLE	Yes	8	299	2015
Muse 2 [19]	Dry	4	256	BLE	Yes	5	249	2016
FocusBand [22]	Dry	2	128	BLE	No	12	600	2016
SenzeBand [23]	Dry	4	250	BLE	Yes	4	299	2016
MindWave Mobile 2 [12]	Dry	1	512	BLE	Yes	8	199	2018

*Not available for sale, **For entertainment, ***Require triple-A batteries,****Require additional WiFi Shield board

with a 97.3% accuracy by applying the team's own algorithm [33].

Moreover, resting states of the frontal area measured using EEG embedded in MindWave during eyes opened (EO) and eyes closed (EC) conditions were compared with two medical grade devices; B-Alert and Enobio [2]. The power spectra of MindWave are similar to both of these devices. Only a slightly wider broadband has been found. However, due to unavoidable blinking during EO, eye blink artifacts are presented, leading to an inferior quality when it comes to EO as compared to EC. The concern over electrode misplacement is also prominent as MindWave consists of dry electrodes and doesn't require an electrode cap, unlike medical grade devices. Notwithstanding, the results generated from MindWave have been shown to be reliable and reproducible. Of note, having only one channel could insinuate a double-edge sword for NeuroSky. The ease of use, affordability, and fast data processing may be compromised by a decrease in the overall performance including ambient noises in signals and less versatility. However, they are demonstrably capable of monitoring the changes or comparing the level of attention while the ability is somewhat limited when it comes to determining whether the user is in the state of concentration or relaxation.

B. Emotiv [13]

Emotiv is another manufacturer of consumer grade EEG devices that managed to carve out a substantial market share for themselves (see Figure 1). In comparison to other consumer grade EEG devices, the products from Emotiv are boasted with a higher number of channels, with the electrodes being wet. These features enable the Emotiv products to achieve better performance and wider scalp coverage in exchange for a more complicated set-up and higher price tag. The Emotiv system provides channels within the 10-20 system, i.e., AF_3, F_7, F_3, FC_5, T_7, P_7, O_1, O_2, P_8, T_8, FC_6, F_4, F_8, and AF_4. From our research, among the available consumer grade devices, Emotiv is the most prevalent choice for scientists in the field (Figure 1). Emotiv offers the users various performance metrics [34] (5 basic measures of mental performance), the capability to create and execute a number of mental commands [35], and a built-in facial expression detection [36]. The classification of facial expression is also provided by the Emotiv system based on the muscle noise that is routinely filtered out of the EEG recordings to classify which muscles the noise originates from. Furthermore, 3D functional brain map for data visualization can also be purchased for research use [37].

Presently, there are three Emotive products in the market, namely, EPOC+, INSIGHT, and EPOC FLEX [38]. EPOC+ is a device designed for academic research, distributing the electrode placements across the scalp, covering as wide an area as possible and offering a quick and easy-to-use setup. The device is an upgraded version of Emotiv EPOC which is no longer manufactured. On top of the standard EEG sensor, EPOC+ has nine built-in motion sensors (3x gyro, 3x accelerometer, 3x magnetometer). INSIGHT is lower in cost, consists of fewer numbers of channels, and uses semi-dry polymer as an electrode which can still detect the signals. INSIGHT has been designed to be adapted into everyday use rather than for academic research. In comparison to the aforementioned products, EPOC FLEX is the only medical grade product that is furnished with higher number of sensors and other features including 34 saline soaked sensors and a control box for wireless customization [38]. It is probably fair to say that most research studies opt for EPOC/EPOC+.

Consumer grade products from Emotiv have been used to conduct numerous studies. Take for instance, in 2013, Badcock *et al.* used Emotiv EPOC to investigate auditory Event-Related Potentials (ERP) in 21 subjects [39]. In short, the subjects were stimulated with 566 non-target (1000 Hz) and 100 target (1200 Hz) tones in the attended and non-attended condition. Neuroscan Synamps[2] [40], a medical grade EEG amplifer, was used as the standard for comparison. Intraclass correlations (ICC) were applied to test the similarity of the signals acquired by these two devices and it seemed that there was no statistically significant difference between the auditory ERP waveforms obtained. However, the mismatch negativity (MMN) waveforms were found to exhibit lower signal-to-noise ratio and these waveforms from half of the subjects appeared to be dissimilar to the medical grade device. The MMN waveform is one of the ERP components which can be calculated from subtracting the ERP of the target tone from the ER of the non-target tone. To substantiate previous findings, peak measurement was also performed. P1, N1, P2, P3, and MMN peak amplitudes and latency displayed no statistically significant difference. However, if we include the noisy signal, the difference between Emotiv EPOC and Synamps^2 has been shown to be significantly higher in terms of MMN amplitude. In a later study, Badcock *et al.* used Emotiv EPOC to look at auditory ERPs in children [41]. The exact same procedure as the one applied in adults was adopted. One major difference lied in the implementation of a wireless system for event triggers and marks. The experiment was performed in a shielded room and more epochs were rejected when compared to the original procedure which might have attributed to the higher ICCs reported, yet by and large, the results were comparable to their previous investigation. These studies illustrate the Emotiv EPOC device to be a reliable tool for auditory ERPs measurement. Importantly, these products have been validated extensively by independent groups of researchers, e.g., in studies that focused on ERPs [39], [41], [42] as well as medical application testing [43].

In 2012, Debener *et al* introduced some modifications to the Emotiv system and merged the hardware with the EEG electrode cap [44]. In 2017, Barham *et al* duplicated the method by integrating similar alterations into Emotiv EPOC. The study used the modified tool to obtain ERPs, then afterwards later compared the measurements with a medical grade system [42]. The hardware and bluetooth transmitter were removed from the device's original case and connected to a research grade electrodes cap. Saline soaked felt pads were replaced by Ag/AgCl electrodes, allowing the electrodes to be positioned more accurately and lowering the impedance. An auditory oddball paradigm was adopted during which the subjects were presented with a non-target tone (500 Hz) interspersed with a target tone (1200 Hz). Both the ERP and MMN waveforms obtained from the Emotiv system were found to be similar to the medical grade device, similar to what was observed in the study by Badcock *et al.* [39]. The overall data quality obtained from the modified device was higher than the one from the default-make reported by Badcock *et al.*, likely owing to a more accurate electrode placement and better electrode quality. In summary, modifications to the Emotiv EPOC system evidently led to a significant increase in the signal-to-noise ratio, although a trade-off was required by the removal of the wireless elements.

Emotiv EPOC has likewise been tested in medical applications. Schiff *et al.* examined the system's ability to diagnose hepatic encephalopathy (HE), a condition where liver failure leads to abnormalities in the brain function [43]. The total of 72 consecutive outpatients with cirrhosis diagnosed by medical doctors at the Department of Medicine, University of Padua, Padua, Italy, were selected for the study. The team observed the results obtained from Emotiv EPOC to be on par with the ones acquired by the medical grade system, both displaying a significant correlation with the HE index. Included in their report was a Bland and Altman diagram showing the average median frequencies of both systems where the standard deviation was approximately 3 Hz in each direction ($\pm$1.96 standard deviation). These results confirmed the reliability of the consumer grade EEG system in one instance of medical application. One may claim that neuropsychological and psychophysical tests are sufficiently effective for the purpose of patient assessment, but for these tests to work properly, the patients are required to be cooperative. Relying on EEG-based data overlooks this concern and apparently is feasible for HE diagnosis, though it is still not widely used due to higher operational cost. That said, Emotiv EPOC has been validated for at least one particular case of diagnosis. Furthermore, the price of Emotiv EPOC is also significantly lower, costing only $750 compared to the price range of $30,000-$50,000 for medical grade devices [45].

In opposition to the positive evaluation results outlined thus far, there have also been reports on low quality EEG data and poor performance with regard to Emotiv EPOC. Duvinage *et al.* explored the performance of Emotiv EPOC for P300-based applications [45], [46]. Emotiv EPOC was compared to the Advanced Neuro Technology (ANT) acquisition system, a medical grade EEG system developed by a company from the Netherlands [47]. Specifically when observed during walking, the performance by Emotiv EPOC was worse than the benchmark and the signal-to-noise ratio obtained was inferior to ANT. Despite the acceptable results with respect to applications in entertainment and communication, the studies did not recommend the Emotiv EPOC system as an option for rehabilitation and medical usage. Similar to MindWave, attention and meditation evaluation as well as the blinking recognition were also validated using the Emotiv system in the same study [9]. Emotiv achieved around 75.6% accuracy for blinking recognition and 60.5% accuracy for focusing/relaxing classification. The discomfort after a long period of device usage has been remarked on by some subjects; this was previously mentioned in another study [48].

Albeit having more channels than NeuroSky and Muse (next to be discussed), data quality, sensor location, and electrode number pose considerable challenges for Emotiv EPOC application in scientific research compared to medical grade devices. It is possible that with a longer period of experiences and the subject screening may facilitate and ameliorate the issues as Emotiv EPOC does not require a flexible EEG cap, resulting in less adjustability for different head shape, size, and hair style. The previously mentioned modified Emotiv EPOC [42], [44] also has been proven to be useful and improved in terms of performance to compete against its competitors.

C. Interaxon [19]

Manufactured by interaXon, Muse is a wearable headband with built-in brainwave sensors, particularly advertised as a meditation facilitating device. The device comprises of four sensors located at $AF_7, AF_8, TP_9,$ and TP_{10}. Unlike the products from NeuroSky and Emotiv, Muse's electrodes can be adjusted for a better fit on the user's head.

Both TP_9, and TP_{10} are the most sensitive areas of electrode placement to obtain the emotion-specific signals compared to other positions [49]. Other than measuring and monitoring the meditative state of the user, Muse also supplies a mobile application for meditation training [50]. Two years after the successful launch of Muse, interaXon seized the opportunity to expand their product range in the market and officially released Muse 2 along with update ther Muse. The new product offers more features with emphasis on the physique of the user for higher quality of meditation monitoring including body movement, heart rate, and respiratory rate. For the raw data access, the company announced that they are stop supporting Muse software development kit (SDK) [51] so the only official methods for accessing raw data from Muse is to use there Muse direct application via iOS. However, there are developers providing codes on GitHub for connecting Muse to your computer and accessing the raw data [52]–[54].

One study tested Muse's performance in measuring ERPs [55] by using the product to obtain N200 and P300 ERP components during a visual oddball task and reward positivity during a reward-learning task. The EEG signals acquired from Muse were compared to the signals obtained from Brain Vision ActiChamp System, a standard EEG system with a 10-10 electrode configuration. They specifically addressed three major concerns pertaining to the use of Muse headband for ERP researches, namely data quality, event markers, and usage of non-standard electrode locations.

First of all, the concern regarding data quality comes from the facts that Muse's configuration may not meet the criteria for requisite specifications in high quality ERP research according to the guidelines for ERPs to study cognition [56]. The guideline suggests a non-polarized Ag/AgCl electrode for measuring the slow changes in potential, multiple electrodes reference to note overlapping ERP components, and an adequate rejection ratio of the amplifier. However, Muse headband is armed with conductive silicon-rubber (dry) electrodes for placement on only four different locations. This accessibility, especially to the frontal region, ensures its advantage over the other consumer grade EEG systems. Krigolson and colleagues [55] were determined to validate the data produced by Muse despite these configurations. The product was selected due to its ease of use and portability, although some adjustments for higher quality signals may be necessary. The removal of data due to data loss during the experiments has also been discussed. However, in contrast to the initial presumption of ease of use, Muse's flexible electrodes were found to be difficult to adjust and required prolonged training for experimenters to place efficiently on a subject, hence, the ensued loss of data. Different head shapes, head sizes, and hair styles might have contributed to the most optimized electrode placement and lower signal-to-noise ratio which lead to the removal of data from the experiments. A large number of trials was obliged before the data lost problem was solved. Tutorial videos on Muse adjustment are highly recommended by the authors. It has been released by the manufacturer in order to curb such issues.

The method to accurately label the time of experimental stimuli has been a major concern for researchers as the event markers are often needed to be created separately, in contrast to the medical grade devices. Random time lag is often experienced upon Bluetooth data transfer [57], [58] since Bluetooth connection generally lacks the stability that the wire connection exhibits. This problem has commonly appeared and is also applied to the others wireless EEG devices. In order to counter this problem, Krigolson and colleagues instead chose to rely on the event markers and forego full-range EEG data [55]. Only the segment of time after the stimuli have been initiated was recorded. However, N200, P300, and reward positively ERP components have been shown clearly in the results.

Generally, brain signals during an oddball task are prominently captured by the P_z electrode, whereas those during a reward learning task can be obtained from FC_z [55]. However, only four electrodes supposedly located at TP_9, AF_7, AF_8, and TP_{10} were equipped on Muse. Therefore, they have to use the signals that come from a pooled average of electrodes TP_9 and TP_{10} during the oddball task and a pooled average of electrodes AF_7 and AF_8 during the reward-learning task.

Similar to MindWave, resting states EEG data acquisition by Muse was compared to several medical grade devices [2]. The overall power spectra measured from MindWave's frontal electrodes have been shown to be comparable to the medical grade devices. However, the data acquired from Muse displayed an increase in the broadband power and a higher variation of signals, performance, and electrode placements, suggesting lower reliability. Additionally, Muse data exhibited poor consistency between Visit 1 and Visit 2 by the same subjects compared to B-Alert, Enobio, and MindWave where the alpha peak in Visit 1 was absent. It could be speculated that poor adjustment of the mobile headband may have caused the inconsistent data as the electrodes could have been misplaced. Krigolson and the team have also shown similar difficulty in adjusting the headband, resulting in a loss of data collection [55].

D. OpenBCI [20]

In keeping with the rapidly progressing BCI industry, OpenBCI was introduced to the market as an open source hardware and firmware together with an open source graphical user interface (GUI). It has been launched in the late 2013 after a successful Kickstarter campaign, a public-benefit corporation. Distinctive from other consumer grade EEG products, OpenBCI's products, i.e., cyton, ganglion, and daisy board, merely serve as an amplifier. Electrical activities detected in the brain (EEG), muscles (EMG), and heart (EKG) can be measured by the sensors equipped on the schematic OpenBCI printed circuit boards (PCB). The device offers compatibility with the standard EEG electrodes as well as other attributes. Its informative open source application can be written with the program Processing [59]. Furthermore, computer-aided drafting (CAD) of the EEG headset that can be augmented by 3D printing and the circuit design for connecting with Arduino, a microcontroller, also provided. However, OpenBCI's impact on the market is still limited and more suitable for users with background in engineering as it requires further customization and additional accessories when compared to other ready-to-wear products. Although the apparatus comes with designed electrode placement and noise reduction feature, the operating system must be tailored by the users.

Several studies have made an effort to validate OpenBCI against traditional EEG systems. At the 6th International BCI Meeting in California, USA, in 2016, Frey presented a comparison between EEG signals obtained from OpenBCI's board and g.tec g.USBamp, a medical grade EEG amplifier [11]. Both of the devices are equipped with 16 electrodes at similar locations. The results suggested that OpenBCI could perform almost identical to the traditional EEG amplifier from g.tec for both P300 speller and EEG-based workload monitoring using the n-back task [60]. Another study evaluated the performance of Texas Instruments ADS1299, a system on chip (SOC) amplifier used by OpenBCI [61]. In this study, the subjects were instructed to execute two tasks, i.e., right foot ballistic dorsiflexions while sitting and stepping on-and-off a step-stool. Movement-related cortical potentials (MRCPs) for the signal-to-noise ratio, amplitude and time of the negative peak, cosine similarity, grand average of participants, and topographic map were extracted from EEG data. These measurements were compared to Compumedics Neuroscan NuAmps [62], a medical grade EEG system from Germany which resulted in comparable data quality. No significant difference between the average power of each band was found. The signal-to-noise ratio from ADS1299 has been shown to be similar to NuAmps. However, MRCPs are not normally applied with the EEG applications, as most of these applications are designed solely to assist people with muscular disability in order to improve their quality of life. MRCPs require a lot of movements which may lead to the incidents of cable swaying and undesirable head movements. Generally, a sizable amount of motion artifacts may be detected compared to ERP or Steady-State Visual Evoked Potential (SSVEP). The two major issues in using OpenBCI also have been noted: the prototype data consisting of large value artifacts and the missing data. It has been postulated that the large value artifacts are created as a result of data storage in SD card which can be removed by averaging of the values. The missing data in one of the prototype files have been speculated to be ascribed to the disconnection of the Daisy board from the main OpenBCI's board and the reconnection has been unsuccessful during data recording.

E. Other Products

In the face of a growing demand and rapid advance in technology, many products developed by different manufacturers have been launched into the market and diverted further from research-oriented goals. Neural Impulse Actuator was promoted as a BCI-based game controlling device in the hope to replace the use of a keyboard and mouse. However, the device was no longer being manufactured since May 2011. Two developers, X wave [15] and Melon [17], directed their products toward attention monitoring. Notwithstanding being accepted as one of the Kickstarter's investment projects, Melon terminated its product development in 2016. Different devices have also been introduced to the wellness industry. MyndPlay used TGAM from NeuroSky to develop their headband; the company mainly sells its application. The application is mostly focused on entertainment purpose but also touches upon brain training and education. Designed as a headband with built-in sensors, Aurora Dreamband [21] comes with the ability to detect the user's motion and track their sleep pattern. The development of FocusBand [22] was initiated in 2009 and fully launched in 2016. The headset and application were first pioneered with the goal of assisting golfers to monitor and inspect their mental state and physical performance from the prompted neurofeedback. Expanding its targeted market of wearable headsets, Focusband thereupon launched NeuroSelf Care Business and NeuroSleep, allowing the users to observe their performance in the working environment and sleeping condition, respectively. SenzeBand is a EEG headband with four channels and two reference sensors that can track the attention, focus, mental workload, and relaxation levels. The company also provides apps/games for mental training, managing stress, and keeping track of brain activities. Chief Scientist of Neeuro, the manufacturer of SenzeBand, is an IEEE fellow as well as a professor at Nanyang Technological University who has been publishing numerous papers on neurofeedback/brain training game [25], [63]–[65].

It could be said that these low-cost devices are the tangible outcome of the advancement in medical technology and BCI, which has taken a big leap into the consumer market. The cheaper price means increased affordability and accessibility, which together makes it easier for researchers to study attention and subjects' mental state without the need for prior knowledge in electronics and engineering. Furthermore, the applicability of these BCI devices has extended into education and gaming industries. In comparison to the expensive medical grade devices, these products are publicly available for purchase, lower in price, and more user friendly. Although these devices may have unlocked several opportunities for public usage, it is clear that their functionality is more limited when compared to the medical grade counterparts. Some major disadvantages associated with the products from NeuroSky include low sensitivity, owing to the presence of a single channel as well as inflexible location and electrode type. Its EEG sensors for attention and meditation perform less favorably and with greater limitation compared to other products. However, they are easily adapted for evaluating student's attention study in a classroom or triggering specific events in application. NeuroSky may be validated in a small amount of studies but the products have been used in many high ranking publications, especially in educational research. On the other hand, Emotiv equips its products with 14 channels, resulting in a more available usage of signals while retaining favourable portability. It is involved in far more validation studies and usage in research compared to the others. Muse is quite new but has a significant number of usage in research. Muse is advertised as a meditation friendly device. However, the product provides raw data as well as more channels than NeuroSky's products. On another level, despite its high adaptability in the form of a circuit board, OpenBCI demands prior knowledge in electronics, bio-signal processing, and brain anatomy/physiology. However, its full capability and open source materials allow the users to develop and apply to other industries, expanding its applications further in the near future. Since it can be used with standard Ag/AgCl electrodes and can accommodate up to 16 channels, the highest quality signals amongst the consumer grade devices can arguably be acquired using OpenBCI.

III. Applications of Consumer Grade EEG Devices

Investigation into the functionality of the human brain has drastically diversified from psycho-physiological procedures to engineering practices in the past decades. Over the years, advances in technology have enabled augmentations of EEG to diverge from traditional research to consumer derived applications in order to attain the market demands. In this section, we explore and summarize different fields of study that have adopted EEG-based approaches, including its applications in the study of cognition, BCI, education, and neuroscience of gaming.

A. Study of Cognition

EEG has made considerable headway in terms of technical advancement and adaptability for usage since its conception by Richard Caton in 1870s and the first recordings in human by Hans Berger in 1924 [1], [155]. At the outset, the idea of electrical firings in the brain mostly attracted the attention of neurologists and cognitive psychologists who were interested in deciphering how the brain functions in a normal setting and what goes wrong in neuropathological conditions [4], [156]. Data on different wave characteristics and their relevance to distinct regional or behavioural features, for instance, gamma waves (30–70 Hz) and the involvement in conscious perception have gradually accumulated over the years [8]. Nonetheless, one should note that despite the substantial progress made, controversies are still rife regarding the exact functions of different brain waves and neural mechanisms that underpin specific cognitive functions. Numerous, sometimes contradictory, postulations have been put forward but to this day there remains many unresolved questions [157].

Fundamental research in the field of cognitive psychology persists given the existing knowledge void, and the field continues to work toward unlocking the mystery of the brain. Furthermore, brain machine interface is on the rise, setting out to create a machine capable of emulating human as closely as possible. As such, applied psychology for translational use has emerged as an investigative niche. In the context of this review, a number of research groups have made use of consumer grade EEG devices in their studies and this section seeks to cover the latest psychology-related research on emotion and cognitive functions that utilized consumer grade EEG products, supplied by Emotiv, NeuroSky, interaXon, and OpenBCI.

1) Emotion: Various facets of emotional processing have been studied by scientists: one angle being how emotion is recognized and evoked in individuals, and more recently the applicability of this information for the construction of emotion recognition software. It could be said that consumer grade EEG is a relatively new invention compared to medical grade EEG devices that have been around for some time. Hence, it is crucial that the devices are properly validated for respective studies. To this end, our team carried out an intensive investigation into the capability of OpenBCI in emotion recognition research [71]. To our knowledge, the study was the first to report evidence for comparable performance of OpenBCI to high-end EEG derived data for emotion recognition algorithms. We recruited 43 participants to watch prelabelled emotionally-charged video clips and recorded EEG signals elicited during the viewing. Peripheral physiological signals were simultaneously collected using Empatica4 (E4) wristband [158]. The participants were also asked to give each video a rating on a 1-9 scale under five headings, namely, valence, arousal, happiness, fear, and excitement. With these self-report scores, we conducted a straightforward analysis to assign ground truth labels. Subsequently, recordings from OpenBCI and E4 were applied to training and testing a classification model based on K-means clustering. We found that the model exhibits the best prediction accuracy (67% in the case of valence and 70% for arousal based on K-means method) for affective tagging given the fusion data. We proposed that OpenBCI application could most certainly be extended to future studies.

Two other groups similarly described the use of classification algorithms for affective tagging of audio-visual stimuli [69], [70], albeit drawing EEG data from another brand of consumer grade device. Both groups recorded EEG signals during the participants' viewing of emotional clips with the Emotiv EPOC system. Katsigiannis and Ramzan [69] collected EEG and ECG signals from 23 participants along with self-assessment ratings on valence, arousal, and dominance. Their classification tool was built upon support vector machine (SVM) method and applied to either EEG-based features, ECG-based features, or a combination of both. Regarding affective recognition, these datasets have been found to be as effective a training group as those obtained from the more expensive medical grade devices. Liu *et al.* [70] presented a real-time EEG-based emotion detection system that works on data being live-fed from the Emotiv EPOC headset. The stream gets wired to an EGGLAB toolbox in the Matlab environment for brief storage which facilitates signal processing, feature extraction, and machine learning implementation. On top of the standard monitoring of arousal and valence levels, the group formulated a 3-tier SVM-variant classification scheme. The first level separates neutral from non-neutral emotions. Secondly, non-neutral emotions are further categorized as positive or negative. Lastly positive emotions are divided into joy, amusement, and tenderness whereas negative emotions are broken down into anger, sadness, fear, and disgust. The reported accuracy varies in relation to different tiers, ranging from approximately 65% to 92%.

In addition to emotion classification, a slightly different line of investigation explores anxiety and stress quantification [66], [67]. Again, both capitalize on EEG data and machine learning techniques. Zheng *et al.* [66] measured EEG and photoplethysmogram (PPG) responses in 20 participants with the NeuroSky MindWave Mobile headset and PPG-fitted glasses,

TABLE II
SUMMARY OF CONSUMER GRADE EEG MEASURING DEVICES UTILIZED IN DIFFERENT RESEARCH APPLICATIONS

Application	Research area		Product	Number of subject**	Year**	Reference
Study of Cognition	Emotion classification/regulation		NeuroSky MindWave Mobile	15 and 20	2016 and 2018	[66], [67]
			Emotiv EPOC	23, 27, and 30	2015 and 2018	[68]–[70]
			OpenBCI	43	2019	[71]
	Cognitive Function	Attention (with/without other cognition)	Emotiv EPOC	6 and 86	2018 and 2019	[72], [73]
			Emotiv EPOC+	10	2017	[74]
			Muse	6029	2016	[75]
		Mental workload/fatigue	NeuroSky MindWave Mobile	20	2017	[76]
			NeuroSky's chip (TGAM)	15	2017	[77]
			Emotiv EPOC	22	2017	[78]
		Other studies	Emotiv*	18	2016	[79]
			Emotiv EPOC	9, 16, 19, and 24	2016, 2017, and 2018	[7], [80]–[82]
			Muse	28, 50, and 209	2017 and 2019	[83]–[85]
Brain-Computer Interface	Event-related potential		Emotiv EPOC	6 and 10	2017 and 2018	[86], [87]
			Emotiv EPOC+	14	2017	[88]
			OpenBCI	4, 7, and 10	2015, 2016, and 2018	[89]–[91]
	Steady state visual evoked potential		Emotiv EPOC	5, 10	2018	[92], [93]
			OpenBCI	4	2018	[94]
	Motor imagery		Emotiv EPOC	30	2017 and 2018	[95], [96]
			OpenBCI	1 and 7	2018	[97], [98]
	Other studies		Emotiv EPOC+	60	2018	[99], [100]
			OpenBCI	3, 10, and 20	2017 and 2019	[101]–[103]
Education	Attention (with/without meditataion)		NeuroSky*	42, 44, and 148	2016, 2017, and 2018	[104]–[106]
			NeuroSky MindSet	5, 10, 20, 32, 96, and 126	2014, 2015, 2016, and 2017	[107]–[114]
			NeuroSky MindWave	10 and 60	2017	[115]–[117]
			NeuroSky MindWave Mobile	30 and 80	2016 and 2017	[118], [119]
			NeuroSky MindBand**	78	2017	[24]
	Engagement time		Emotiv EPOC	48 and 50	2014 and 2016	[120], [121]
	Brain synchrony		Emotiv EPOC	12	2017 and 2019	[122], [123]
	Other studies		Emotiv EPOC	10 and 40	2011 and 2015	[124], [125]
			Muse	26	2019	[126]
			OpenBCI	22	2018	[127]
Neuroscience of gaming	Cognition during gaming		NeuroSky MindWave Mobile	8 and 20	2016 and 2018	[128], [129]
			Emotiv*	10 and 60	2016 and 2018	[130], [131]
			Emotiv EPOC	8, 15, 20, and 30	2015 and 2018	[132]–[135]
			Emotiv EPOC+	10, 12,and 20	2016	[136]–[138]
	Neurogaming		NeuroSky MindWave Mobile	9 and 16	2016 and 2019	[139], [140]
			Emotiv Insight	2	2018	[141]
	Neurofeedback training		NeuroSky*	43, 160, and 174	2015 and 2018	[142]–[144]
			NeuroSky Brainlink	12	2018	[145]
			NeuroSky Mindwave	9	2016	[146]
			Emotiv*	5 and 119	2016 and 2019	[147], [148]
			Emotiv EPOC	3, 8, 9, and 107	2013 and 2017	[149]–[152]
			Emotiv EPOC+	5	2018	[153]
			Muse	577	2015	[154]

*Only the manufacturers are presented, **Sorted from minimum to maximum.

respectively. The participants were positioned on a stationary bike and instructed to pedal first at a leisure speed, then a competing speed while imagining their competitor to be going at 80 km/h. The rationale for the latter instruction was to elicit anxiety. At the beginning of each session, individual's baseline anxiety score was evaluated with a Competitive State Anxiety Inventory-2 (CSAI-2) questionnaire. In order to determine if EEG and PPG features offered useful pointers for anxiety evaluation, the group put together classification algorithms based on the principles of k-nearest neighbours (kNN) and SVM with radial basis function. On average, the classification accuracy achieved was only 63%, clearly leaving some room for improvement. Betti *et al.* [67] tested an SVM algorithm on 15 extracted features from physiological measurements during the Maastrict Acute Stress Test, including heart rate, electrodermal, and EEG signals (MindWave Mobile), and noted an 86% accuracy in disentangling a stressed from relaxed state.

One recent study utilized the system for the more traditional enquiry into regional brain activation [68]. 27 participants were exposed to a virtual reality simulation (park navigation) designed to induce sadness (e.g., poignant music, upsetting statements, or images), during which the concomitant brain activities were garnered with the Emotiv EPOC gear. The team set out to evaluate and contrast brain activities in three groups of volunteers, one being the control group, the other two were told to employ an emotional regulation strategy (either cognitive reappraisal or expressive suppression) during the emotionally charged VR session. Frontal activation shown by earlier studies to be associated with sadness induction was identified in the control group. Furthermore, significant activation in the cingulate, occipital, and parietal region was observed in the cognitive reappraisal group, apparently in line with previous reports. Less conclusive findings, however, were observed with respect to the expressive suppression group. Another key observation was that the results obtained pointed towards the usability of the Emotiv EPOC headset as an investigative tool capable of yielding equivalently pertinent data to those acquired from complex neuroimaging systems.

2) Cognitive Functions: 'Cognitive functions' is a group of an umbrella term that encompasses a whole array of mental processes, e.g., attention, memory, and perception [159]. These abilities are generally believed to be regulated by both bottom-up and top-down controls, and reinforced by feedforward and feedback mechanisms [160]. This section aims to give a broad-brush summary of consumer grade EEG studies on plentiful variants of cognitive functions, including sustained attention, working memory, decision making, to name a few.

Attention is unquestionably one of the most popular cognitive attributes that has received incessant dissection over the years. Most recent studies often link attention to learning performance; the detail of which you may find in the subsequent section. One study that made use of the Emotiv system employed a combination of visual attention task and EEG brainwaves to decode attentional state to faces and scenes [73]. In this study, the participants were instructed to respond to images that belong under a pre-defined subcategory and to withhold their response to task-irrelevant images. Afterwards, a linear SVM classification was applied on the recorded signals and was shown that, on average, the prediction accuracy of behavioural performance was 77%, apparently on a par with the previous fMRI study [161]. Further, attention was addressed in combination with mental exercise by Hashemi and colleagues from InteraXon in a large-scale investigation that gathered EEG recordings from 6,029 subjects of all ages using the Muse headband [75]. The volunteers had to fit the headband by themselves by following visual and auditory instructions on the Muse mobile application, to collect their own EEG data while undertaking a category exemplar task and a subsequent neurofeedback session at their convenience. Notably, the investigation identified discernible age-related changes in brainwave characteristics, depending on sex and frequency band. Another study in 2017 reports the monitoring of construction workers' attention and vigilance with a wireless Emotiv device during an on-site object relocation task [74]. In brief, recruited construction workers (n = 10) were asked to move an object from the original to the assigned location. Along the path were four items that had been strategically placed as obstacles. Vigilance was tagged with each obstacle encountered. Event related information including frequency, power spectrum density, and spatial distribution were statistically analyzed, and found to closely reflect each participant's perceived risk.

Aside from attention, working memory is another vital aspect of cognitive functions. By employing the Emotiv EPOC wireless headset, a group of researchers monitored focused attention and working memory of the participants while they were completing a battery of cognitive assessment tests associated with 23 basic cognitive skills and 5 compound skills [72]. Focused attention and working memory are classified as basic skills according to this series of tests, and respective scores on these skills could be directly measured. The team applied extracted features from the collected EEG signals to train an extensive array of classifiers and reported that the built models were able to distinguish three levels (i.e., low, intermediate, and high) of focused attention and working memory with 84% and 81% accuracy, respectively. In a similar vein, another research team deployed a well-known dual N-back task, which was originally designed to tap into a person's working memory capacity [7]. In short, a series of stimuli were sequentially presented to the participants, and they were required to identify if the current stimulus was the same as the one that came up 'n' trials ago. It was observed that different memory workload levels corresponded to participants' reaction time and accuracy, and manifested as disparate EEG patterns. Specifically, the power in the theta band was significantly distinctive between the lowest (0-back) and higher workload levels. Finer distinction could be seen in the alpha and low gamma band (30-40 Hz), allowing differentiation between 1-, 2-, and 3-back levels. These features in turn lent themselves to classification of workload levels based on EEG recordings.

An alternative method for assessing working memory is to administer the Pearson Automated Working Memory Assessment, from which two memory constituents are extracted, i.e., counting recall (verbal working memory) and spatial recall (visuo-spatial working memory). This test was adopted by Buszard *et al.* in their experiment to investigate the relationship between working memory capacity, EEG coherence, and performance under pressure [79]. The team hypothesized that the verbal component score would be positively correlated with brain activity coherence between the left temporal (verbal-analytical processing) and premotor areas (T3-F3) while participants were carrying out a novel motor task, based on earlier studies that confirmed the association between verbal-analytical processes and motor performance. To test this hypothesis, Beta1 (13–20 Hz) and Alpha2 (10–12 Hz) frequencies were recorded between T3-F3 and T4-F4 during a tennis hitting task in unpressured and pressured conditions. They found that the scores on verbal and visuo-spatial working memory were predictive of Beta1 and Alpha2 coherence between T3-F3 and T4-F4 regions. In summary, individuals with larger verbal working memory capacity exhibited greater verbal involvement (explicit motor learning) during motor performance, whereas larger visuo-spatial capacity was linked to decreased verbal involvement (implicit motor learning).

Recent work on other domains of cognitive functions include studies of relevance judgement (Emotiv) [81], decision making (Emotiv) [82], mental workload (NeuroSky) [76], mental fatigue and stress (NeuroSky, Muse, and Emotiv) [77], [78], [84], subconscious face recognition (Emotiv) [80], and aesthetic preference (Muse) [83]. Regarding relevance judgement, EEG measurements and eye movement data acquired during 3-epoch news reading task with requisite relevance decision were used to train proximal SVM classification models. The group found that particularly for shorter epochs, texts of varied relevance could be distinguished based on EEG and eye-tracking features. Turning to a study of a person's willingness to pay, Ramsoy *et al.* [82] had the participants view a set of products and prompted them to estimate the amount they were willing to pay for each of the products. EEG signals recorded using Emotiv revealed that gamma and beta band asymmetry in the prefrontal areas was significantly congruent with the participants' willingness to pay. Interestingly, there was no significant correlation between frontal alpha asymmetry and the payment decision, contradictory to previous research that has demonstrated this trait as having cognitive and emotional translatability. Frontal EEG was also harnessed for mental workload evaluation during four cognitive and motor tasks, i.e., calculation, finger tapping, mental rotation, and lexical decision [76]. Theta activity displayed a concomitant increase with task difficulty, and an SVM-based model was 65% to 75% accurate in its prediction of mental workload associated with different activities.

In a study by Morales *et al.*, prefrontal brain activity was recorded with the ThinkGear ASIC module (TGAM) headset (NeuroSky) along with saccadic velocity sampled with infrared oculography (JAZZ-*novo*) [77]. The recordings were taken while the participants undertook simulated driving for two hours; they were asked before and after to reflect and submit their ratings on the Standford Sleepiness Scale and an adapted version of the Borg rating of perceived exertion. For analysis, two established indices of fatigue were examined, i.e., EEG power spectral density and saccadic peak velocity. An inverted U-shaped quadratic trend was observed in the case of the delta EEG power spectra, whereas a linear increase was detected for the beta spectra. These observations were reported to be in agreement with corresponding saccadic eye movements (decreased velocity) and driving performance (increased speeding time). The authors suggest that these results can be taken as evidence for the applicability of the TGAM headset as a detection system for mental state changes that occur during day-to-day task execution such as driving. Another recent study employed Muse for detecting drowsiness and demonstrated the benefit of having multiple sensors equipped in the consumer grade EEG device [84]. Mehreen and colleagues also included other features to predict drowsiness such as the data from accelerometer and gyroscope, which were also provided by Muse. By combining the EEG spectral analysis, blinking detection from EOG, and head movement from gyroscope and accelerometer, the team used SVM as a classifier and achieved 92% accuracy for predicting whether the participants were alert or drowsy.

On a marginally different note, it is clear that EEG recordings are highly correlated with individual's mental state. Through intricately entangled connections, the state of the mind can also influence the body and manifest as physiological responses. This point was addressed by Muhlbacher-Karrer *et al.* in their experiment which was more of a proof of concept for the usability of their capacitive hand detection sensor [78]. Nonetheless, Muhlbacher-Karrer *et al.* did include the use of an Emotiv device to collect EEG data as one of the many domains related to driver's state; others being electrodermal activity, electrocardiogram, and capacitive hand detection sensor. Five levels Daubechies wavelet of order 4 (db4) were employed to extract the sub-bands delta, theta, alpha, beta, and gamma. Further analysis was conducted to obtain an average of 25 features per channel, which were used as an input for Cellular Neural Network classifiers (CNN). They reported that EEG data were particularly informative for stress detection and combined features from all available sensors, which drove detection accuracy to an impressive 92%. In an investigation of mental stress, another research group used Muse to record EEG data from 28 participants pre- and post- activity [85]. These data were labelled either as a binary stressed vs non-stressed, or three classes (stressed, mildly stressed, and non-stressed), based on participants' self-report perceived stress on a standard perceived stress scale questionnaire (PSS). The team showed that binary classification (stressed vs non-stressed) yielded a better prediction accuracy compared to the three-class alternative (93% and 64% respectively). These accuracy numbers were derived from five feature groups selected by their novel feature selection algorithm claimed to outperform existing algorithms.

Let us now turn to two more psychology-based studies which delved into less common investigative tracks. Martin *et al.* questioned if it would be possible to tap into the subconscious mind behind facial recognition [80]. They devised a visual recognition task that consists of a series of photographs of well-known people from various fields, and captured visual ERPs of the participants with the Emotiv EPOC headset. An exit questionnaire was included after the task to allow labelling of conscious recognition (CR), false recognition (FR), conscious no recognition (NR), and subconscious recognition (SR). A number of ERPs beside P300 were used to train SVM classifiers to distinguish between NR and SR, which reportedly yielded an average accuracy of 65%. Lastly, portable Muse headbands were deployed to measure EEG correlates of individual's artistic preference in a group of volunteers while being given a tour of the art exhibition [83]. The researchers found that subject's favorite piece of art elicited a bespoke suppression of the beta band which was not present in the baseline condition or during the viewing of other paintings. Interestingly, this observed suppression occurs regardless of whether the subject is aware of the original interpretation of the artwork.

To conclude, the evolving picture on psychology-related consumer grade EEG application seems to suggest that in the case of psychological studies, the usage of consumer grade devices is somewhat evenly distributed in the investigation of emotion, attention, and mental processing. Moreover in terms of the prevalent product brand, Emotiv takes the lead. What is also interesting is that most research attempts heavily focus on the utility of brainwave signals as a proxy for interpretation by classification algorithms, more specifically supervised machine learning techniques. Whilst there is noticeably less usage in fundamental research to further elucidate the underlying biological mechanisms of human cognitive processing. This is possibly due in part to the technical limitations that the devices themselves pose. Nonetheless, it is worth pointing out that the applicability of existing devices has largely been validated against medical grade counterparts, and in certain cases, other more sophisticated (and more costly) neuroimaging apparatus.

B. Brain-Computer Interface

The development of brain computer interface (BCI) has been on the rise since 1970s [162], with EEG being the most widely used technique for the application of BCI systems [163]. EEG represents the functional brain information in terms of the electrical activity across the scalp. Most of the research using EEG-based BCIs has been developed with the aim to to provide aide for individuals with difficulties in motor control functions difficulties or neuromuscular disorders [164]. These real-time BCI systems allow users to command the computer directly via their brain activities. Consumer grade EEG devices, mostly designed as headsets, have been introduced to the market since 2007 following the growing interest for lower cost and simpler to wear products [165]. In the fundamental state of the BCI domain, recent reports explored the consumer grade EEG-based BCI research according to the three types of brain responses typically used in BCIs; ERP, SSVEP, and Motor Imagery (MI).

1) Event-Related Potential: Visual, auditory, and tactile stimulation are commonly used to evoke event related potential (ERP). P300 wave is one of the major components in ERP [166], typically appearing 300 ms following stimulus onset. P300 speller was regarded as the state-of-the-art P300-based BCI (P300-BCI) application in 1988 [167]. With P300 speller, individuals with motor disabilities are able to select alphabets on a computer screen via visual perception and brain responses. Most of the pioneering research groups have been developing P300-BCI using medical grade EEG amplifiers. However, the majority of the public cannot afford to obtain those P300-BCI for personal and practical uses. In 2014, an open-source consumer grade EEG entitled OpenBCI was launched in the Kickstarter Campaign [168]. Our team is one of the first generation users who have been conducting research using OpenBCI. We designed a type of visual stimulation to enhance the P300 wave for BCI. The proposed visual stimulation was generated from orientation and motion modulated stimulus. We then proposed the use of P300-BCI as an alternative input channel for personal identification number (PIN) application [89]. By having PIN as a test bed application, we went on to report an adaptive P300 detected algorithm [90]. Over the last two years, we picked up five P300-BCI related studies. Two of them supported OpenBCI [91], [169] while the other three demonstrated the applications of Emotiv [86]–[88]. All studies were commonly gearing toward more user-friendly practical applications.

Early in the 21st century, portable or headset EEG devices were scarce. Hence, at the time most P300-BCI researchers had to make do with a stationary BCI system. The researchers were able to use high computational resources via their personal computers. In the present day, the use of BCI systems has been steering toward more practical applications in daily routine. Recently, two research groups reported similar investigation on the development of P300-BCI in a mobile device to track physical activities such as running. The monitoring of the system on the mobile device requires mobile applications (m-apps), where one common concern was computationally inexpensive algorithm. One group proposed *MindEdit* application which allows individuals to select the alphabets on an android-based smartphone screen using visually evoked P300 response (brain response) [86]. P300 detecting algorithm for *MindEdit* is based on novel ensemble classifiers that utilize the principle component analysis (PCA) algorithm. This algorithm allows *MindEdit* to perform with acceptable accuracy and information transfer rate on an android smartphone. In another study, six well-known P300 detected algorithms (Fisher's Linear Discriminant Analysis (LDA), Stepwise Linear Discriminant Analysis (SWLDA), Bayesian Linear Discriminant Analysis (BLDA), SVM, Multilayer Feed-forward Neural Network (NN) and Boosting) were compared in order to investigate their impact and accuracy on a speller application [88]. The results suggested that BLDA was the most suitable for P300-BCI m-apps. The configuration on the number and the channel of electrodes were also considered in both studies mentioned. In 2015, Pérez-Vidal and colleagues proposed the usage of the Stockwell Transform with LDA for a similar application with only two electrode channels placed on occipital lobe [87]. The visually evoked P300 as well as oscillatory evoked P300 were used in the development of m-apps. Expanding the applications to iOS devices, tactile-based P300-BCI for a similar m-app was introduced in 2018 [91]. The system proposed was shown to detect P300 via EEG variations in the beta frequency band. However, this tactile-based system was a preliminary work, undoubtedly requiring further investigation.

To support m-app and web-app developers in the BCI field, *WebBCI* JavaScript toolkit was published as an open-source resource [169]. *WebBCI* offers specific tools for BCI such as application programming interfaces (APIs) for the calculation of EEG featured extraction of the power spectral density (PSD), common spatial pattern (CSP), and linear-discriminant analysis (LDA). *WebBCI* currently supports the consumer grade EEG devices that are open-source, such as Muse and OpenBCI. Together with the aforementioned research studies and direction, the consumer grade EEG products have certainly inspired both researchers and engineers in moving toward robust applications in daily life.

2) Steady-State Visual Evoked Potential: In addition to P300, SSVEP-BCI is another type of visually evoked brain response. The pioneering SSVEP-BCI system was introduced in 2000 by the Air Force Researcher, USA [170]. To generate steady state brain signal that is detectable by an EEG amplifier, human visual perception has to be synchronized to a specific visual stimulus frequency. For example, while an individual is watching a steady flickering stimulus on a monitor screen, the signal detected in the occipital lobe is oscillated at a near exact frequency as the flickering stimulus. Using the fundamental knowledge in generated SSVEP, researchers have developed SSVEP-BCI, creating multiple flickering stimuli on-screen. Once the user moves their gaze to a target stimulus (choice selection), the synchronized EEG signals can be detected as a result of the target frequency. Canonical Correlation Analysis (CCA) is the state-of-the-art algorithm for recognizing the frequency for SSVEP-BCI [171]. CCA can recognize oscillated EEG frequency synced to the visual stimulus.

In 2018, only a few publications using consumer grade EEG are related to SSVEP-BCI. A combination of Emotiv and a head-mounted device (HMD) named HTC VIVE, have been applied in a study of visual feedback and is used to familiarize disabled people with brain-machine interaction on a 3-D space [92]. Brain interaction in the 3-D scenario is widely regarded by researchers as a challenging issue. The participants were asked to perform quadcopter controlled/navigated tasks. SSVEP stimuli were presented on HMD for four directional controlled commands. The proposed SSVEP-BCI system was asynchronous; an advantage from HMD as the head movement and pose data could be observed at all times. Thus, the system could determine whether the participant's gaze was in a steady or transitional state. SSVEP frequency recognition during the steady state provides higher accuracy. If the participant was in a transitional state, the system would not be synchronized and would not be ready for the commanding. Moreover, the head pose data supported the system in generating a visual guide as a feedback on the target SSVEP stimulus. The feedback facilitated the participant in attending to the target. This work evidently demonstrates the advantages of low-cost and portable EEG when integrated into a wearable device.

Similarly, Lamti and colleagues developed EEG and gaze data fusing framework for wheelchair navigation [93]. Emotiv and Tobii eye tracker (EyeX model [172]) were used to capture brain and eye activities, respectively. Three major modules were back-ended of their proposed system. The first module involved a selection module concentrating on gaze to select a command and activate SSVEP stimulus. The second module acted as a distraction module which considered both brain and eye features to determine user's intention in wheelchair navigation. Taking together the outputs from the selection module, the distraction module, and PSD from SSVEP response as the final input features of the validation module (the last module), the final output was the command in the wheelchair navigation. The novelty of this work was the distraction module, playing an important role in making the navigation robust and stable by taking the user's intention into account.

Another type of steady-state EEG responses called Auditory Steady-State Responses (ASSR) is stimulated by steady auditory stimulation (steady tone) [173]. While an individual listens to a speaker-generated steady sound, that individual's EEG will be oscillated at the same tone or frequency (especially in the temporal region [174]). Recently, OpenBCI-based ASSR-BCI was proposed for a home automation system where the user was shown to control the devices exclusively with the auditory signals [94]. The study neatly demonstrates the advantages in using portable EEG in day-to-day activities. The benefits of the framework have branched out from healthy individuals to elderly and handicapped people. Moreover, a hybrid system, combining the measurement of both ASSR and P300, has been introduced by Kaongoen and colleagues which is able to put OpenBCI to use for BCI applications [101]. The system is visual independent, as user wears a pair of earphones. The team generated two ASSR stimulus patterns with different carrier and target frequencies. Each stimulus was fed to each side of the earphones simultaneously. Meanwhile, a beep sound was generated and presented randomly between the two earphones. The beep sound was expected to elicit P300 when the user was paying attention. The study demonstrated that using both ASSR and P300 stimuli simultaneously could lead to an improvement in the performance classification of a selective attention task.

3) Motor Imagery: Early in the 21st century, a pioneering BCI research group proposed motor imagery-based BCI (MI-BCI) as a novel BCI avenue [175]. MI response can be generated by activating the neural correlates of motor functions without actual motor execution. An algorithm is then initiated to translate the response into the format that machine can read and execute subsequent command. The imagery of the left/right upper and lower limbs as well as their functional performance are the most common tasks for MI-BCI studies. Many previous studies have utilized state-of-the-art experimental protocols with the datasets in order to conduct and analyze different imagery tasks [176]–[179]. Despite the similar aim toward direct interpretation of the brainwaves, MI-BCI is widely known as the least robust system when compared to P300- and SSVEP-BCI.

Many studies have applied MI-BCI to facilitate the rehabilitation of sensorimotor functions. Athanasiou and his colleagues in collaboration with the Department of Neurosurgery at Aristotle University of Thessaloniki, demonstrated feasibility regarding the use of an off-the-shelf EEG (Emotiv) for MI-BCI system in comparison to the medical grade EEG

(128 electrode channels) from Nihon-Kohden, Japan [95]. The team reported the learning curves in using MCI-BCI on two different feedback systems: Kinesthetic (real robotic arm) and Visual Motor Imagery (human hand movement on a computer screen). The performance of the system with Kinesthetic Motor Imagery as the feedback was found to be superior in assistive training for MI-BCI's users.

The adaptation of the consumer grade EEG device was reported by a study that used a model trained by large MI-EEG datasets obtained from the medical grade device as the operating model for unseen data recorded from Emotiv in 2018 [96]. The operating model yielded acceptable results as a wheelchair controller. This study emphatically demonstrates the benefits of large-scale public datasets generated from the medical grade device in improving the performance of those from the consumer grade device.

An advantage of consumer grade (OpenBCI) has been demonstrated by collecting a large volume of MI-EEG contained imagining right/left hand moving and resting tasks [97]. Using recorded data, a dynamic feature extraction was proposed on the basis of wavelet package decomposition. The proposed method covered both time and frequency information. The extracted features were then incorporated to construct a classifier based on quadratic discriminant analysis (QDA) with dynamic time warping (DTW) as a non-typical constraint. Because EEG produces time series or sequential data, DTW benefits QDA in comparing similarity of the input features by dealing with the issue of time delay or offset. Moreover, a group of researchers from the International Business Machines Corporation (IBM) based in Melbourne, Australia, recently launched a robust OpenBCI-based MI-BCI system [98]. Medical grade EEG was convinced to be excessive for practical situation. The experiments were based on binary tasks of right-hand imagery and resting state. Simple deep neural network structure was built to recognize EEG from the two tasks. The study concludes that the proposed system would be incorporated with low-power processing chip provided by IBM's TrueNorth neurosynaptic chip [180]. A combination of consumer grade EEG such as OpenBCI and low power consumption processing chip might be a breakthrough in the deployment of everyday applications.

4) Other Studies of BCI: Over the century, advanced technology has gradually revolutionized the controlled conditions and protocols in various research experiments which have been practiced and implemented globally into wireless and mobile applications for daily use. A criterial review was recommended for EEG-BCI in 2017 [181]. The criteria outline three major concerns, including hardware (such as portable/wearable, wireless, dry electrodes, electrode montage etc.), software (such as online, single channel, artifact removal especially eye blink [182], etc.) and environmental element (such as performed outdoors, performance of daily-life tasks, etc.).

Additionally to the aforementioned BCI-based works which were categorized into the studies of ERP, SSVEP, and MI, we reviewed three recent research directions using consumer grade EEG devices for both daily and medical usages. In 2018, age and gender prediction using EEG-BCI was the matter of the moment topic. The outcomes can be contributed to various applications including biometric, healthcare, entertainment, and targeted advertisements. Kaur et al. had gathered the data on EO, or resting state, from 60 healthy participants (age ranged from 6-55 years old) using Emotiv EPOC+ [99]. EC is considered one of the most simplest tasks to extract EEG signals from an individual. Using random forest algorithm, Kaur et al. achieved 88% accuracy for age and 96% for gender classification. These results required less EEG data compared to the state-of-the-art methods. However, Kaushik et al. implemented a deep learning approach named BLSTM-LSTM on the same datasets as Kaur et al. and reached up to 94% and 98% for age and gender classification [100]. In this perspective, BLSTM-LSTM performed with the advantages of data-driven approaches in BCI research fields. A collaborative research between the Department of Electronics and Telecommunications and Ophthalmic Hospital in Italy utilized and validated OpenBCI for clinical examination in early 2019 [102]. The exam included the pattern reversal visual evoked potential (PR-VEP) testing using a commercial device. In contrast to ERP for BCI (P300-BCI), early onset components of VEP (N75, P100, N135) plays an important role in many cognitive studies. Not only was the medical grade EEG replaced in their research, a monitor screen used to generate a visual stimulation was also replaced by a part of smart glasses. The results from the investigation suggested reproducibility and efficacy among 20 healthy participants with no history of ophthalmologic diseases. In the same year, a multi-person brain communication architecture was introduced to examine problem solving ability through an online Tetris-like game [103]. Two of the three participants were designated as senders and wore OpenBCIs in front of their personal computers which incorporated both gaming screen and SSVEP stimulation. Through the stimulation, the senders could send an information to the central computer which was connected to transcranial magnetic stimulation (TMS). TMS device is typically used to stimulate specific brain regions for therapeutic purposes. Here, TMS was used as a message generator, relaying the feedback (both beneficial and bias in this study) to the third person (receiver) after the central computer received SSVEP responses from the senders. The receiver was stimulated directly at the occipital cortex, creating a flash of light for the receiver to perceive without any input through the retina. Over repeated trials, the receiver learned to recognize the stimuli from TMS and interpret the messages that were sent by the senders. With the experimental set up blocking half of the gaming screen, the receiver could only rely on the information transmitted by the senders in order to complete the game. The proposed architecture and scenario firmly established a proof of concept for brain-to-brain communication.

Currently, BCI research has moved along the data-driven computational intelligence such as deep learning (DL). Recently, our team published the works related to a data-driven DL algorithm which would be beneficial to BCI applications [183], [184]. Furthermore, the proposed algorithm with the large-scale datasets could be advantageous for the consumer grade P300-BCI applications [183]. In our perspective, the consumer grade EEG amplifiers are major components of the world of data-driven BCI technologies. Novel adaptation of the advanced technologies can break the cost and mobility barrier where the scale of EEG-based datasets can be rapidly produced. The cycle of data feeding into the DL algorithm can lead to further development of applications to improve and sustain our quality of life.

C. Education

Because most EEG related educational research studies rely on experiments that mimic the real-world scenarios, consumer grade EEG devices are deemed to be more appropriate than medical grade devices. Educational researchers favor lightweight easy-to-use devices due to their low price, wearability, single channel, and the usage of dry electrodes. These advantages, therefore, reduce stress and/or nervousness of participants in the study and provide better setup while still deliver reliable results. These devices offer easier solution for monitoring brain activity while the participants perform in different learning tasks. Here, we divide different fields of research that have been conducted on real classroom or those that have compared the different types of teaching/learning methods into four subgroups: attention & meditation, engagement time, brain-to-brain synchrony, and other studies.

1) Attention and Meditation: The method of EEG has been proven to be capable of capturing and measuring the level of attention for many decades [185]–[187]. Since then, researchers have been proposing novel methods for attention recognition and evaluation [188]–[194]. The methods are varied in different feature extractions or de-nosing algorithms such as using spectral features, PCA, and multi-wavelet transform. Recent research studies are leaning towards machine learning as a classifier with a combination of SVM, Bayesian classifiers, hidden Markov models, k-nearest neighbors, and neural networks. The accuracy of the classification is typically more than 75%, depending on the tasks and experimental set up. The number of EEG channels provided by research grade devices used in the experiments ranges from 16 channels (BIOPAC system, Inc) [193] to 256 channels (BioSemi system) [189]. With only 1 or a few channels, the quality of the data captured by the consumer grade EEG devices and their achievable performance become questionable.

However, a study asserts that one of the consumer grade EEG devices is capable of recognizing the attention level of the subjects by analyzing the raw EEG signals they could detect [195]. Liu *et al.* collected raw EEG signals from 24 subjects with NeuroSky MindSet to assess the level of attentiveness [195]. The subjects were tasked with completing an English test under 2 different scenarios in which both the experimenters and the subjects were to label whether the subjects were attentive or not. Five features were extracted including the energy value of each frequency (alpha, beta, theta, and delta bands) along with the ratio of alpha and beta activities. The inclusion of the ratio was based on a previous study in which it has been suggested that the alpha activity is related to relaxed state and the increasing of the beta activity indicates an increase in attention [196]. These features were employed to train the SVM classifiers. As a result, the study achieved up to 76.82% classification accuracy. Although the algorithm may not perform flawlessly, the hardware is deemed reliable for capturing valid EEG signals. NeuroSky, the manufacturer of MindSet, MindBand, MindWave, and MindWave Mobile, provides the customers with a pre-built algorithm designed to capture and detect attention and meditation states [27]. The attention level will be increased when a user is focusing on performing cognitive tasks such as imagining images of animals, numbers, or specific objects. However, the level will be decreased if the user is distracted. This algorithm has largely been developed for the measurement of effectiveness of different teaching methods in educational research. Meanwhile, the meditation level will be increased when the user is relaxed and will be decreased if the user encounters stress. As we previously discuss in Section II, we believe that these algorithms may not correctly represent the actual attention of the user. However, the increasing/decreasing trends are reliable for monitoring purpose [9], [28]–[30].

The changes in attention level have been used as one of the evaluation methods by researchers. Since 2014, many educational research studies are only relying on the EEG devices as a validation tool. These studies have been applying NeuroSky's algorithm for monitoring the subjects' attention level while they are performing the learning-related tasks. For example, studies such as the comparison of mobile polling [107], effects of different types of mobile text display on the user's attention [113], and the effect of different kinds of book (conventional, picture, pop-up, talking, and e-book) on the individuals from different age groups (elementary school students and adults) [24], [112] have been explored. Mobile polling is an interactive learning method where many students answer the question on their mobile phones simultaneously. The attention level when using mobile polling may be lower than traditional clicker but it can be seen elevated during the activity. In a text display experiment, Chen and Lin have demonstrated that different types of text display, namely static, dynamic, and mixed, do not exhibit any significant effects on the users' attention [113]. In a comparative study, the multi-sensory stimulating talking books or e-books [112] are suggested to be suitable for elementary school boys whereas conventional books are recommended for higher grade elementary school girls.

Although attention level that has been interpreted from the EEG signals is a great indicator in educational research, many research groups have combined its property with other physiological factors. In addition to measuring the sustained attention level, Chen and Wu [111] have employed emWave system [197] to detect emotion, cognitive load, and learning performance in subjects. emWave provides a software for monitoring heart rhythm and heart rate variability-based emotion recognition algorithm. The procedure for measuring the cognitive load was based on the cognitive load scale [198] while using paper-based tests to evaluate the subjects' learning performance. Lai *et al.* and Huang *et al.* have applied FaceReader [199], a facial expression detection software, to indicate the emotional states along with EEG-based attention level of the subjects [104], [105]. Therefore, the purpose of these studies aims to search for the changes in EEG signal and facial expression when the subjects received reward for correctly answering the questions. The results have suggested that the students, who received the rewards for the correct answers, paid more attention than those who did not receive any rewards. However, no correlation has been found between the positive stimuli and the learning performance. Although most of the researchers are focusing only on attention, some also include meditation into their studies as NeuroSky also equips its pride meditation detector on to the products [104], [107], [116], [117]. However, meditation may not play an essential role when compared to attention during an active classroom and can only be incorporated with other factors for performance evaluation.

Despite the popularity of the software provided by NeuroSky amongst the researchers in the educational domain to monitor the participants' attention, many methods have been developed in order to evaluate attention. For instance, the frequency bands could be extracted using the discrete wavelet transform (DWT) [200]. Genetic algorithm [201] for feature selection along with SVM classifier can then be further applied [115].

Beside using the consumer grade EEG devices for evaluating the teaching/learning methods, there are also researchers who took one more step further and created different systems for sustaining the students' attention and improving their learning performance. These systems generally monitor a user's attention level and trigger a set of acoustic alarm when their attention drops below a certain threshold [106], [114], [119]. They can also create an interactive agent that is capable of giving a proper feedback, based on the user's emotion and attention levels [118]. These interactive agent has the capability of focusing not only on attention (from brainwaves), but it also includes the emotional aspects of the users by using Chinese semantic analysis, facial expression based on EmguCV [202], and skin conductance detected by Q sensor a wearable emotion detector from MIT.

2) Engagement Time: Assessing the engagement of an individual is far more complex than evaluating attention as it involves the overall experience of the tasks that the individual comes across. The engagement time may depend on the individual's attention, satisfaction, and the feeling of novelty or usability [203]–[205]. Therefore, the engagement of the students with the teacher in a classroom or an online lesson is essential for their learning progress. One of the metrics that the Emotiv system provides is the measurement of the engagement time which is characterized by the increase in physiological arousal and beta bands along with the decrease in the alpha bands [34]. In 2014, a novel sensor-based method for analyzing the user's motivation was established [120]. A unique equation was created for calculating the user's motivation based on the engagement time provided by Affectiv Suite's EmoEngine. Affectiv Suite was the former name of an algorithm provided by Emotiv. Affectiv along with Cognitiv and Expressiv have been combined and the names were changed to Performance metrics at the moment. The method is capable of outperforming the traditional questionnaire-based methodology due to the interruption between the game's sequences in the questionnaire-based method. Therefore, this approach is more suitable for analyzing the user's motivation in a long game's sequence. Additionally, it is real-time and can provide further insight of the change in the motivation level. In 2016, Ghergulescu and Muntean proposed a mechanism called ToTCompute: TimeonTask Threshold Computation [121]. This novel mechanism aims to help educational game creators to monitor the participant's engagement during their interactive lessons. The system is designed to collect the engagement level, which is calculated by Affectiv Suite, and feeds the information into the database along with the timestamp of the events. The system then automatically computes the appropriate values (when a student's engagement value drops to 5%, 10%, or 15% of an initial value) for triggering specific events to motivate them.

3) Brain-to-Brain Synchrony: Brain-to-brain synchrony is defined as a relationship among the brainwaves of multiple individuals associated with each others in which many studies [122], [123] calculated it with a method called total interdependence [206], [207]. The synchorny has been adapted to study social dynamics including the interaction among students as well as teachers in the actual classroom over the course of two full semesters (fall and spring) [123]. Dikker *et al.* and Bevilacqua *et al.* collected EEG signals from the students and their teachers in an archetypal classroom environment and computed a synchrony [122], [123]. The brain-to-brain synchrony of the student-to-group, student-to-student, and student-to-teacher interactions were being monitored. Dikker *et al.* explored a potential usage of the brain-to-brain synchrony as a bio-marker to study the student's engagement and social dynamics [122]. It was found that brain-to-brain synchrony was related to teaching techniques, individual differences, and social dynamics. Student-to-group synchrony was higher in some students depending on the teaching techniques (video or lecture). The students showed higher student-to-student synchrony with their classmates. Bevilacqua *et al.* focused mainly on the synchrony between the students and the teacher [123]. The EEG data were analyzed along with the students' quiz scores, self-reported engagement, and student-teacher closeness. The results suggested that the overall synchrony of the group of students studying with videos was higher than with lectures. The student-to-teacher synchrony was correlated with their closeness. Furthermore, the students' test scores were also correlated with the closeness, though not brain-to-brain synchrony. The findings showed how cognitive outcome, such as the student's academic performance, can be predicted by social dynamics, such as perceived closeness.

4) Other Studies: Other than the popular applications of consumer grade EEG devices aforementioned in this section, there are other unrelated, yet interesting, studies that focused on the simultaneous EEG&eye-tracking during a second language learning database, the classification of cognitive loads, predicting the user's frustration, the possibility that the user will fail the test, and .

Language and communication are parts of the most important aspects in our every day life. EEG have been applied to the studies of neurolinguistics to investigate various neurophysiological mechanisms including language processing, language transition, language comprehension [208]–[210]. However, most of these studies have not yet explored the possibility of the application of consumer grade EEG devices for language research. Notaro and Diamond [127] established a system of simultaneous EEG, eye-tracking, behavioral, and screen-capture dataset featuring an online German language course via web-based duolingo interface [211]. EEG signals were collected with a 32-bit OpenBCI board (Cthon Biosensing) at 250 Hz sampling rate. 8 electrode placements were at standard 10-20 system EEG locations [212]: F_3, F_z, FC_z, C_z, P_z, O_1, and O_2. Eye-tracking data was collected using Gazepoint GP3 at 60 Hz. The cursor movement, clinking, and screen-capture were also recorded. Participants were instructed to complete four language lessons including "Basic 1", "Basic 2", "The", and "Phrases". The data have been suggested to provide an insight regarding learning a second language from a neuroscience perspective or help developing a better web-based language learning course. The data are available at [213].

In order to classify the difficulty of intelligible textual contents, Sinha *et al.* performed an analysis using Muse and EyeTribe for eye tracking to determine the cognitive load during reading [126]. The experiments were segregated into two parts; global and detailed analyses. In global analysis, only Muse was employed to determine whether the content is easy or hard to understand for the participants. It was found that the entropy of the left temporal region was significantly higher when the participants were reading more difficult contents and the entropy of the left frontal lobe was higher when the participants engaged in the easier contents. This has suggested the impact of the difficulty of the textual contents on the language processing associated with the left temporal region. The eye movement and its pattern were analyzed and found to be accelerated when the easier contents were scanned, affecting the brain activity of the left frontal lobe. The reading behavior was also inspected in the detailed analysis. With these individual patterns and the localized brain activity, new insights using EEG device could pave the into the cultivation of academic assessments.

In the study of emotion using EEG, the sentiment of frustration and excitement may cause a significant impact on the students' learning ability. Inventado *et al.*, employing Emotiv EPOC, attempted to predict students' emotion, specifically frustration and excitement, after receiving feedback from the Intelligent Tutoring Systems (ITS), a computer system capable of providing feedback for cognitive assistance [124]. The frustration and excitement values along with the standard deviation and mean, age, gender, 5 values of the elements from the Big Five personality test [214], and types of feedback (activity transition, solution evaluation, and hint) as features were calculated. The study also compared several types of machine learning algorithms; linear regression, kNN, and SVM for predicting the user's emotion level. The results suggested that linear regression performs with higher quality than the other algorithms with R^2 of 0.462, 0.560, 0.627, and 0.484 for predicting frustration, excitement, change in frustration, and change in excitement respectively.

The use of games for educational purpose has become widespread and recognized as marketable for researchers and developers. For instance, LewiSpace is developed in 2015 as an educational game in a 3D environment with the aim to teach the construction of Lewis diagrams for different chemical compounds [125]. The game is programmed to detect whether the participant is struggling with the game systems and provide different examples or hints for better understanding. The authors collected features including the EEG signals from Emotiv EPOC (short/long-term excitement, mediation, frustration, and boredom from Affectiv suite), pupil diameter from an eye tracker to calculate the participant's workload, valence, and arousal, and facial expression from FaceReader software. Self-reports using the Big 5 personality questionnaire were also gathered from the participants. The features were combined to predict the possibility of success or failure in each of the tasks in the game. The study achieved 66% accuracy with logistic regression, a machine learning model. Further application of consumer grade EEG devices in gaming is discussed in the Gaming Section.

To our best knowledge, the most prominent issue that has been recognized evinces the prevalence of the study of attention in the field. However, there are more cognitive aspects to be explored in order to improve the educational environment. To better assist the users, Emotiv now provides the performance metrics validation which composed of stress/frustration, engagement, interest/valence, excitement, focus/attention, and relaxation/meditation [34]. These are significant factors and directly related to education. These factors can provide more insight, higher quality validation, and more accurate prediction in different research fields. Another issue is that there are very few studies conducting in actual traditional classrooms and no sport learning study is found. Most of the works have been directed towards online learning. We are interested to see not only how computer/online learning system can act as a substitute for a teacher but also how they can help providing sufficient assistance. More works are crucial on traditional classrooms or those that assist the teacher/lecturer to provide an additional suitable learning environment to increase the efficiency in learning and academic performance. The EEG based educational research is still in an early stage in terms of both technology and knowledge. In the near future, these devices will expectantly provide a simple manner to implement, lower assembly time, lower cost, and capable of monitoring other advanced cognitive aspects. This will undoubtedly lead to a drastic increase in the number of consumer grade EEG-based educational research studies.

D. Neuroscience of Gaming

In another application perspective, consumer grade EEG devices also draw attention of the researchers who are inspired by entertainment and media, especially in gaming. Various works have been conducted using the EEG devices to determine and capture the feelings [131] and emotions [133] of the players during the gameplay by analyzing the activity of the brain. The recording of the brain activity has also been employed for the classification of the level of expertise as the players engage in the gameplay [134]. Therefore, EEG devices have served as a game console. This presents options for game players to choose, whether they would prefer a traditional choice of gadgets, e.g., a keyboard, a mouse, or a joystick, or indulge in a novel experience to control the game with their very own brainwave [140], [215]. Other than for entertainment, the purposes of creating games have diverged to include many other assistive techniques such as extra instructions in the classroom and even being used by medical personnel for assessing the cognitive function of the patients with neurological and neurodevelopmental disorders for treatment [142]. Furthermore, clinical researchers have developed functional training in the form of gaming [216].

The following section touches upon the usage of consumer grade EEG devices to determine the effects of game playing on the cognitive functions of the players. We also discuss the utility of these devices in brain-controlled games and go on to briefly explore the work that have incorporated consumer grade EEG devices into video games for the improvement of emotional process experienced by the patients with neurological and neurodevelopmental disorders.

1) Cognition During Gaming: Recently, psychologists and researchers in related fields have started adopting consumer grade EEG devices as a medium to assess the cognitive functions of the users as they are playing games. There are many game types including mobile games, video games, and computer games; and the games that have been designed specifically for educational and training purposes are referred to as serious games [217]. It has been established that games can help entertain and relax players, relieving them from stress and anxiety, improving problem solving skills, managing resources, and enhancing hand-eye coordination [131], [218]. However, there is no denying that certain aspects of games can be harmful and destructive to the players' health and wellbeing. Here, we discuss the effects of game playing on human cognitive system, specifically looking at online brain responses.

Various methods on identifying how the brain functions while playing games have been introduced using consumer grade EEG devices [131], [133], [137]. The effects of gaming can be partitioned into two groups, namely, effects on emotions, and experience. For instance, to study the effects of games on emotion, Aliyari and colleagues [131] have suggested to record the variations of the brain waves using a 14-channel Emotiv device along with saliva samples from the players to determine the level of stress on the players created by the video games. The study discussed four types of stress regarding different types of games: logic stress (puzzle game), limit stress (runner game), fear stress (fear game), and interactive stress (excitement game). After playing the four types of games, the results of brain wave analysis and salivary test revealed that the level of cortisol, a stress hormone, increased significantly while the players were playing the fear and violent excitement game. This implies that these games must have induced a higher level of stress, and consequently both could prove destructive to the players' health. On the other hand, the level of cortisol decreased after playing the puzzle game and increased slightly after playing the runner game. These important changes from the logic and limit stress were suggested to be beneficial to the players in strengthening the cognitive elements and capabilities. However, for this method, specialized tests and involvement of the biomedical laboratory were mandatory for the assessment of the players' hormonal level.

Electrical signals recorded by the consumer grade EEG devices have been used to analyze the activation of the cognitive processes during and following gameplay. A method proposed by Mondjar and colleagues [138] presents the analysis of the recorded EEG signals which have been shown to be correlated with specific mechanics of playing video games, affecting the cognitive function of a player. Beta [219], alpha [220], and theta [221] frequency bands were recorded and the relationships between brainwaves and cognitive processes were determined. The results indicate that serious game can be used to stimulate players under many circumstances to exercise the cortical areas responsible for memory, attention, and concentration. These cognitive activities were found to be stimulated by five different mechanics: accurate action, timely action, pattern learning, logical puzzle, and mimic sequences.

Gaming became a tool for the study of players' emotions as they are engaged in computer games [132], [133], [136]. An approach to record emotions, analyze them, and determine the correlations to the signals was evaluated using the Emotiv EPOC headset by Kosiski and colleagues [133]. In the study, the players were presented with three pre-selected games, each with its unique characteristics, while the EEG signals were recorded to determine the relationship of the brain activity during emotion elicitation and the elements of each game. Consistent with previous studies, the recorded brainwaves exhibit the changes in brain activity during the gameplay. As the human brain is sensitive to the constantly changing events in video games, different scenes during the gameplay are found to be causing different types and intensities of emotion in each player, e.g., excitement from accurately hitting the target and frustration from missing the goal [136], or . To visualize the brain activity, many brain visualization settings have designated the area of the brain that performs high activity using red color and the area with low activity using green color in the presence of emotions during gaming [137], [222]. Furthermore, many neurogaming approaches have grounded the study of affective states on the task engagement and the 2-Dimensional valence/arousal plane [132]. Valence can be calculated by taking the ratio of alpha to beta EEG bands between the right and left cortices. The alpha power has been shown to be associated with positive and negative valence states. On the other hand, the arousal levels, indicator of arousal state, are represented by the ratio of average beta to alpha EEG bands. This also implies the adaptation of different types of games for patients with neurological and neurodevelopmental disorders for clinical assessments of emotion.

Several attempts have been commenced to classify the expertise level of a player during gameplay based on brain activity recorded from consumer grade EEG devices [130], [134], [135]. Two studies recorded EEG data of the players and analyzed them to predict how well each player performs and the ranks of difficulty level the players belong to using

Naive Bayes and SVM Classifier [130], [134] as well as 17 morphological features in the time domain of EEG data for pattern recognition [223]. The regions of the brain which play a crucial role in gameplay have also been studied. Certain predefined threshold is a key indicator for identifying whether the player is classified as an expert or novice, calculated from an equation which, mainly, takes the gameplay score into account. Very frequently, the players state that boredom and frustration can be experienced in online games when they are playing against incompatible players, with lower or higher expertise level respectively, leading to felt dissatisfaction for the games. One utilization of a classical game, Tetris, was introduced in 2013 in order to evaluate the emotion induced by different levels of game difficulty [28]. Recorded using NeuroSky MindWave, 14 participants reported the levels of game difficulty in association with boredom and stress. Recently, Stein and colleagues [135] conducted a study on the classification of players' abilities and dynamic difficulty adjustment (DDA) using the Emotiv system. The EEG signal measurements recorded by the headset were analyzed to identify the excitement level experienced by the players. DDA was found to be triggered if the excitement level of a player dropped below a specific personal threshold. This technique helps adjusting the gameplay to suit the players accordingly by reducing difficulty for weaker players and increasing difficulty for stronger players. Moreover, a method of using the EEG signals as a base for an adaptive game-based learning has been introduced [129], [224]. The brain activity was constantly monitored, and the game mode was rapidly adjusted when the decrease in the excitement level was detected to be below a predefined threshold. This DDA system portrays a crucial role to modify a game to better suit the player's preference and maintains the player's engagement in the game, contributing to further enjoyment. Stein and colleagues [135] have conducted experiments only on shooting games (excitement games) however, hence it is still uncertain whether DDA can efficiently operate for the other types of games.

2) Neurogaming: Numerous work have been proposed on the use of consumer grade EEG devices for exclusively brain-controlled gameplay. This idea offers a novel paradigm such that it can be considered a transformative change in the gaming industry. Comparing to the traditional method where the players physically control the game avatar by hands using keyboard, mouse, joystick, or even foot paddle, brain-controlled games present an unconventional method for players. These revolutionized consumer grade headsets which are able to detect the changes in brainwaves allow the players to be entertained by merely concentrating on the game to issue and execute a command. Although this presents a groundbreaking method to gamers, it can also be equally positioned to provide a choice of entertainment for patients with motor disabilities.

The concept of attention-based mind-controlled games has been gaining attention from game manufacturers and research groups alike [139]–[141]. These work have contributed to the development of human brain-computer communication technique to offer a choice for people with disabilities to overcome their motor hindrance, allowing them to enjoy gameplay. In 2018, Queiroz and colleagues [141] introduced a BCI-based game in which player controls a wheeled robot via the Emotiv INSIGHT headset to reach a target. This experimental game was adopted from a classic Hot and Cold game; the main player's key goal is to locate a hidden object with a hinted guide from the other players whether the person is heading toward (Hot) or moving away (Cold) from the object. The study observed and analyzed the triggered brain signals detected by the headset as the subjects concentrated on the game. The headset was attuned to a software, enabling the conversion of the commands as *hot* or *cold* via computer interface to control the movements of the robot such as spinning around or changing direction. Similarly, Vasiljevic and colleagues [139], [140] introduced an attention-based BCI game called Mental War, presented as a tug-of-war game. The idea was adopted from a rope pulling sport match in which the players form two teams and pull a rope against each other in a test of strength. The attention value of the players represents a force applied against the opponent's avatar in the game. The average of attention values read over time, captured by the NeuroSky MindWave headset, were calculated for both players. Higher attention value detected by the headset denotes the amount of force pulled by the avatar passing the threshold in order to win against the opponent. This paradigm aims to beneficially assist those who suffer from disabilities or paralysis by providing entertainment options that could improve their quality of life and promote happiness.

Although this can be served as one of the options for entertainment, it still lacks the confirmation of the efficiency of using these consumer grade EEG devices in gaming. It should be extensively tested by players requiring special assistance compared to the healthy individuals to determine that playing games using these devices would provide equivalent or higher value of entertainment to players similar to the traditional methods.

3) Neurofeedback Training: Disorders on neurofunction can greatly affect the patients' daily life especially in terms of mental stability. Patients suffering from these groups of disorders are subject to all kinds of issues related to health, academic, social relation, and occupation throughout their lives [142]. Although medications are mainly prescribed to intervene and control the symptoms, they are not the absolute choice for permanent solution. It is important for the patients to understand the disorders and learn to control and manage the problematic symptoms [225]. Numerous studies have reported the side effects of medications that induce negative effects on patients [226]–[228]. Detection and treatment are often time-consuming and costly, which may lead to delay, obstruction, and hindrance in the administration of appropriate and deserved care and intervention [229].

The approach of neurofeedback training using games along with consumer grade EEG devices as an alternative for the treatment of neurological and neurodevelopmental disorders, has been presented by many studies [142]–[144], [146], [147], [150], [151], [153], [154]. Neurofeedback training, one of the behavioral, non-pharmacological treatments, has started to gain more popularity due to its promising effectiveness in disorder treatment and the improvement of the patient's health [230]. Studies have reported that neurofeedback training provides a treatment option for patients that do not want to undergo traditional pharmacological treatments, showing decreases in the fundamental symptoms as in the cases of amnestic mild cognitive impairment [148], cerebral palsy [152], stroke [149], and ADHD [231]–[234]. The treatment is essentially performed by requesting the patient to wear a BCI headset and perform specific tasks defined by a trainer. The headset records the brain signals resulted from the neural activity of the patient and converts to visual signals for real-time feedback. For any successful trials, such as performing assigned task correctly, a reward is given as a motivation to encourage the patient. BCI has been incorporated into different types of video games, especially in the serious games, as one of the means to provide disease monitoring, treatment, and physical functions [229].

Serious games, a type of video games with special characteristics involving objectives beyond just entertainment purpose, are introduced in combination with consumer grade EEG headsets, worn during the gameplay by patients, for detecting any abnormalities and improving attentional problems [153], [222]. The headsets are used to measure the subjects' brain activities and oscillatory rhythms while performing different assigned tasks. The different frequency bands are associated with the unique brain functions, such as alpha band in relaxation, beta band in fast activities, and gamma band for problem solving and memory, and have been used to assist clinical diagnosis and improvement method. Showing the patients their brainwave patterns could raise awareness of the specific changes in their physique that, in general, are not consciously controllable. Different mind-controlled games, "Exergame" [148], "RehabNet" [149], "Harvest Challenge" [146], "Shooting" [147], "Magic Carpet" [151], "FOCUS" [153], and "MindLight" [143], [144], are examples of video games and serious games, serving as neurofeedback training for patients with cognitive issues, in which the characters are controlled by the changes in brain signals and their patterns [229]. These games promote the same goal, i.e., to improve cognitive function of the patients with mental problems and serve as a type of training therapy for the patients recovering from neuro-related disorders, such as ADHD, cerebral palsy, dementia, paralysis, stroke, etc. As part of the training, patients are urged to concentrate in order to alter the brain signals to enjoy the game. Furthermore, to improve motor control of the patients with physical disabilities, they are advised to pay attention to arm and leg movement [152]. These work have been proven to be beneficial to the patients, helping to convalesce the controlling skills which may reflect in their behavior and general health.

In this section, various aspects of EEG applications in gaming domain have been discussed: emotion detection, gameplay media, and patient rehabilitation. Currently, the growing demand of BCI for different purposes in gaming has led to several developmental stages of the technology. It is important, however, for the studies in the future to validate the effectiveness of the gaming system in order to amplify the data processing and hardware development for the ultimate improvement in players' experience.

IV. Discussion

There is a considerable amount of studies employing consumer grade EEG devices for different applications. Many consumer grade products have been launched into the market, aiming to broaden the usage of these devices from the restricted barrier of research establishment into the public domain. However, the validity in terms of accuracy and practicality of the consumer grade EEG devices in comparison to the medical grade EEG devices, used in research facilities and hospitals, still remains in question. In this review, we have gathered and reviewed studies that attempted to validate these various consumer grade EEG devices in traditional and emerging approaches.

A. Available Products

Products from the four main manufacturers, namely, NeuroSky, Emotiv, interaXon, and OpenBCI, of the consumer grade EEG devices are readily available for purchase. Even though these products are similar in terms of wearability and lower cost, they all exhibit both advantages and disadvantages over one another. The products from NeuroSky (MindSet, MindWave, MindWave Mobile, and MindWave Mobile 2) are sold at lower costs in comparison to the products from the other manufacturers. Their design selling points are simplicity and ease of use. The products are equipped with only one single channel EEG sensor, which potentially reduces their usability, yet they are strong candidates for researchers interested studying attention/meditation monitoring and triggering events. Furthermore, the products from NeuroSky are particularly popular among educational researchers and are viable for other entertainment applications, especially gaming. In this review, the number of studies employing the Emotiv system, especially Emotiv EPOC, is the highest in the fields of cognition and gaming. The overall number of studies using the Emotiv system may have been higher than the use of OpenBCI in BCI research though it is significantly lower than NeuroSky in educational research. Not only does Emotiv EPOC provide 14 channels, which are significantly higher than NeuroSky and Muse, the products are ready to use, in contrast to OpenBCI. Having more channels is associated with the ability to simultaneously explore more brain regions, allowing the researchers to collect signals with more widespread coverage. The Emotiv system has been proven to be valid in ERP studies and medical usage. Muse, on the other hand, has been designed for meditation related usage. The first set of electrodes are located in the scalp area apposed to the frontal lobe where attention is mostly attributed to. The other half of electrode placement is located at the most sensitive scalp area where the signals can be obtained from the limbic networks in the temporal lobe, which are typically linked to memory and emotion. With the release of Muse 2 into the market, the manufacturer has added extra sensors for the detection of body movement (Accelerometer), heart rate (PPG and Pulse Oximeter), and respiratory rate (Gyroscope), making the product more attractive [19]. This allows the user to monitor more physiological factors. Although Muse is relatively new in the market, its relevant products have incrementally gained interest from researchers. The growing number of active users will surely contribute to the product becoming one of the most popular consumer grade EEG devices in the foreseeable future. In comparison to the other ready-to-wear devices, OpenBCI comes in a form of a circuit board. The device has been implemented predominantly in engineering related research studies, especially in the field of BCI. Its lower popularity among researchers in other fields may be due to the prerequisite for engineering knowledge in order to operate and construct other portions. However, OpenBCI provides an open source hardware, firmware, and GUI which are publicly accessible. The product is well accepted for its compatibility with any types of electrode, its mobility to be placed on any desirable location on the scalp, and its capability of connecting up to 16 channels. These attributes confer to the advantages of OpenBCI over the other available consumer grade products.

B. Study of Cognition

The evolving picture on psychology-related research seems to suggest that consumer grade EEG application is heavily focused on the utility of brainwave signals as a proxy for interpretation by classification algorithms, more specifically supervised machine learning techniques. Brainwave is often used in conjunction with other visceral signs to give researchers a more holistic picture of the body's response to extraneous stimuli. Interestingly, there is noticeably less usage of the consumer grade devices in fundamental research to further elucidate the underlying biological mechanisms of human cognitive processing, likely owing to the technical limitations that these devices are burdened with. What these devices apparently lack however appear to be compensated for by the portable nature and user friendliness. This means that they could be adopted in real world setting and distributed to a large number of users, instead of the confines of the lab and well-trained users only policy that are unavoidable considering the application of traditional, high-fidelity EEG devices. It should however be pointed out that, to the researchers' credits, the applicability of these relatively new consumer grade devices has largely been tested against the medical grade counterparts, and in certain cases, more sophisticated neuroimaging apparatus.Nevertheless, these tests could do with more numbers to establish repeatability, in essence to confirm that the performance of the low cost devices stand up to scrutiny and that the core functionality is not drastically compromised by their compact design and less complex setup.

C. Brain-Computer Interface

Although the concept of BCI has been around for many decades, the introduction of consumer grade EEG devices has inspired a new trend of seamless integration in everyday use. The attractive characteristics of these devices include their affordable price and portability. The utility of signals such as ERP and SSVEP has shifted from research focus to rehabilitation, such as wheelchair control, and software programming such as mobile and web applications. To our best knowledge, the products from interaXon and NeuroSky only play a small part in BCI. One probable reason is their few built-in channels which result in limited usage in research. Generally, the applications of ERP and SSVEP reply on visual stimulation during which the signals are captured from the occipital lobe. However, the electrodes in Muse and NeuroSky's products are positioned on the frontal region. In comparison, the Emotiv system are employed equally by different fields of research. Our major finding from literature search is that there is a significantly higher number of OpenBCI usage in BCI. We think that this notion is inevitable as OpenBCI requires considerable amount of prior knowledge in engineering, and in a way poses difficulty of usage for researchers in non-engineering fields. Distinct from the other products, OpenBCI only contains a circuit board, serving as an amplifier. However, this minimalistic circuit board could be integrated with virtually any developing system. It is clear that the growing popularity and quality will likely lead to further adaptation in the near future of ERP- and SSVEP-based applications from the existing state-of-the-art systems. Additionally, there are APIs for those interested in developing mobile/web based BCI application.

Unfortunately for MI, the current systems (both hardware and software) have not yet reached the stage that can be developed into everyday application. In order to solve this issue, researchers, including our team, have redirected the focus toward applying a large dataset, e.g., more than 40 subjects, collected as raw data from the combination of medical grade and consumer grade EEG devices, and applied machine learning/deep learning to assist, e.g., in developing an algorithm for online courses.

D. Education

The usage of EEG has been adapted for the field of educational research to evaluate and monitor the effectiveness of traditional and novel learning/teaching methods or developing feedback-based system to improve learner's performance. An attempt on meta-analyzing the studies on education using portable EEG devices was hitherto presented in 2017 [235]. However, with the increased popularity, more researchers since 2017 have been conducting experiments using these devices as research tools for further analysis of educational research. The number of studies toward the evaluation and promotion of attention is still exceptionally high in comparison to the other aspects of education, similar to the suggestions by Xu and Zhong [235]. Other cognitive features such as emotion and mental fatigue are evidently no less important and should not be neglected. Presently, the consumer grade EEG devices have been validated to be capable of measuring and monitoring some of these cognitive performances. Furthermore, most of the experiments were developing the online learning platforms, testing only context reading ability, and using adults as test subjects instead of actual students in a conventional classroom. Only a few studies such as the study of brain synchrony were managed in a classroom environment for an entire semester [122], [123].

Recently, studies using online learning has gained popularity among researchers due to its simplified methodology. Anyhow, the presence of a teacher or supervisor in the classroom environment should not be disregarded. Studies have shown that communication between individuals may contribute to a better learning experience than interaction with non-living objects such as a computer. A well-trained and experienced teacher would be able to appraise and evaluate the students' attention while adjusting the person's teaching style as well as paying more attention to specific students who are having trouble. BrainCo Inc., a startup company supported by Harvard University, USA, advertises one of its products as an EEG headband for classroom monitoring [236]. The company has partnered up with a school in china, supplying its products to students and faculty members. Combining the EEG devices and big data might be helpful to the teachers and students. Notably, the products are still in a developing stage and the company has yet to fully launch them into the market.

One interesting direction might be steering towards the consumer grade EEG application during physical education. However, the technology at the moment might not be capable with sufficient efficiency to collect a set of artifact and noise free signals during different conditions without discomfort or the limitation of the subjects' movement.

E. Neuroscience of Gaming

Discovering the effects of gaming on the players' cognitive functions using EEG has attracted much interest from scientists and game manufacturers. Consumer grade EEG devices have been used to detect emotion, especially enjoyment, and even the expertise of the players with the aim to adjust the game mode to meet the satisfaction and the preference of the players. This allows the players to be more engaged and immersed in the gameplay. Furthermore, these newly developed consumer grade EEG devices offer great alternative options for the players to navigate and control the movement of the avatars handlessly. This, optimistically, would provide an option for disabled individuals to experience a novel method of entertainment. In the medical field, these EEG devices have been applied in various clinical treatments for detecting and improving the rehabilitation of patients who suffer from neurological disorders. This method serves as one of the non-pharmaceutical treatment options for the patients. However, there are some limitations that could impede the usage that potential users should be aware of.

Consumer grade EEG headset provides various benefits to the gaming industry. Due to the affordable cost for consumers, it presents a novel way of playing game, assisting the players while enjoying the game, measuring emotion of the players, determining whether the players would encounter a challenging situation when competing with their opponents, or even aiding patients to recover from the cognitive and psychomotor problems. However, there are some restrictions that must be carefully examined before selecting consumer grade EEG devices as tools for neurorehabilitation. The two main issues comprise of the users and the devices. Although the portable devices are designed to be easily donned, some users, especially patients in need of neurorehabilitation, may encounter difficulty in setting up these devices. Hence, skillful trainers are required as assistance to apply the devices correctly and appropriately. For instance, as in the case of neurofeedback treatment, most patients express concerns regarding the problems such as unfamiliarity with the devices, the fear of usage, anxiety of the head being touched, discomforts of the seated position, and personal impairments, leading to the lack of participation in the training session. Aside from the concerns on the patients, the physical design of the consumer grade EEG devices may cause problems during the mounting. Some users have found that these devices do not fit properly on the head due to specific head shape, size, and hair length, resulting in incorrect electrode positions and difficulty of signals detection. For some users that require special assistance, some specific designs of the headset, especially from the Emotiv system, cannot be used in conjunction with a head support on the wheelchair for head control, causing pain and discomfort. This may lead to unsolicited head movement, headset shifting, and loss of connection. Regarding the sensitivity, the EEG device is generally sensitive to noise and, most of the time, other unwanted artifacts often caused by different factors such as movements during the recording process, leading to inaccurate results. Occasionally, the concentration and attention are lost during the session due to unrelated factors, stimulants, conditions, etc. If the players are affected and distracted, typically by the environmental factors, the data retrieved from the signals detected by the headset would presumably contain error and noise. To prevent this, the players should be closely supervised and monitored by qualified trainers.

On the other hand, the devices may not be fully equipped with available underlying algorithms for monitoring, detecting, and analyzing the collected brainwaves. Since algorithm of the headset software is usually not provided, it is difficult to assume the accuracy of the readings from the headset [133]. Therefore, it is reasonably challenging to verify the accuracy and the performance of the software. Thus, it is important that experts are present to monitor and ensure that the devices used in the experiments and trials are functioning properly and accurately. As a result, the performance validation of the devices becomes one of the intricate issues that the researchers are aiming to resolve.

F. Frontier Research Using EEG Measuring Sensors: Opportunities and Challenges

Irrespective of the EEG amplifier grade, here, we describe substantial research achievements reflecting the real progress in four EEG-based applications reviewed in this paper (Cognition, BCI, education, and neuroscience of gaming). To point out the emerging opportunities and challenges in using consumer grade EEG devices as the research tools to bolster further research advancement, we selected four potential implementations to illustrate the possibilities in extending and developing the current research findings to be of higher impact and deliver practical use.

1) Emotion Recognition: Earlier in 2019, the combinations of EEG features from the activation and connection patterns, calculated from 23 electrodes of a medical grade EEG device, had been reported to be the powerful features for emotion recognition [237]. According to our survey, OpenBCI with

16 electrodes or Emotiv EPOC+ with 14 electrodes might be able to provide similar features. This is certainly a challenging topic for further investigation. It is possible that OpenBCI, a low-cost open source device, has the capacity to bring us many more affective EEG datasets [71]. Finally, it might not only confer higher performance in the emotion recognition, but also knowledge in brain activity and connectivity during emotion elicitation.

2) MI-BCI: The machine learning method of deep learning has been growing rapidly and constantly, becoming the center of attention in the past few years including recent achievements in the MI-BCI research fields [238]–[245]. One of the main functions involves the facilitation of extreme feature extraction for data-driven solutions which may manifest superiorly against the human's arithmetic ability. Despite all noteworthy artificial neural network models, one of the major limitations of deep learning is its requirement for a large amount of data. Since consumer grade EEG devices are low-cost and light-weight, they are favorable for developing into deep learning related applications. This denotes a substantial advantage over the medical grade counterparts, considering the high cost and low adaptability in comparison to the portable devices. Using the consumer grade EEG devices, the researchers are proficient to distribute many devices to subjects simultaneously and constantly monitor the brain signals throughout the entire experimental intervals. Deep learning allows many researchers, including our team, to improve our methods for the detection of anomalies, as well as for the classification tasks, leading to more applications for MI-based EEG.

3) Brain Synchrony: Hyperscanning techniques using EEG were first introduced in social neuroscience studies decades ago. The experiments generally aim to explore the brain mechanisms as subjects undergo different tasks such as the Prisoner's Dilemma [246]–[249], Chicken's Game [250], "Bridge-like" card game [246], [251], [252], music related study [253]–[255], and movement imitation/synchronization [256]–[259]. A large number of electrodes are required to be attached on the scalp as well as stringent experimental protocols in order to accurately monitor the changes in the neural activity detected in different cortical areas. However, recent hyperscanning studies have demonstrated a promising future for educational research using consumer grade EEG devices to explore brain synchronization in an actual classroom environment [122], [123]. Despite having lower numbers of electrodes, consumer grade EEG devices exhibit higher mobility and portability in which it is deemed more favorable in the real world-based environment. Brain synchronization between student-student and student-teacher has been attracted much attention and displays an interesting factor which could be useful in predicting how well students learn and the outcome in the form of their academic performance. For instance, many protocols shave been established using the data on brain synchronization such as an attempt to predict the memory attention [260] and a combination of different consumer grade EEG measuring sensors to monitor a large group of participants while they were listening to a speaker audibly reading a novel [261].

4) Neurofeedback Training: Since 2015, the research and development using EEG measuring device as part of post-stroke rehabilitation have been dramatically increasing [262]. Two major advantages in using EEG as the tools for the post-stroke training include non-invasive methodology and portability. The system cost is also getting cheaper to be affordable for household uses in the near future. In 2018, a review article in a field of clinical and translational neurology reported a meta-analysis in using EEG for the post-stroke motor rehabilitation in the recent years [263]. In summary, a quantification of the upper limb using a Fugl-Meyer Assessment (FMA-UE) described the performance of an EEG device with virtual hand-feedbacks with convincing scores. This is considered as one of the great candidates in the upper limb post-stoke rehabilitation. Later in 2019, an efficacy of EEG-based BCI with visual feedbacks for the upper limb stroke rehabilitation was reported [264]. Interestingly, although a medical grade EEG device with 23 electrode-channels was employed, 10 electrodes were registered to be sufficient for the assessment in the proposed neurofeedback training. Here, emerging opportunities are transpiring as an experimental effort to replace medical grade EEG with certain consumer grade products equipped with at least 10 electrodes to reduce the financial burden of the patients. This could confer as an ultimate goal in the development of the neurofeedback training application for the household usage.

V. Conclusion

Evidently, the recently implemented low cost, wireless, lightweight, and easy-to-use wearability has fashioned an impact on the ascending attractiveness of the non-invasive consumer grade EEG devices among the researchers from various fields of study. In this review, we summarize both the available consumer grade EEG devices in the market and its counterparts which have been employed in numerous research and medical studies as well as its usage and reliability. Both traditional applications, i.e., cognition and BCI, and emerging applications, encompassing the educational research and gaming, have been adopting the devices and demonstrating its validations in comparison to the medical grade EEG devices. Despite the acceptable capacity and performance of consumer grade devices, there are persisting concerns regarding the retrieved data quality from the lower number of equipped sensors as well as the possible incessant movement due to the portability of the devices, resulting in artifacts and impact on its consistency. Furthermore, it is imperative to report the products' veritable capacity and not over-claim the products' actual capability. However, the advanced technology accelerates the development of these consumer grade EEG devices, increasing its potential and performing competence. Future efforts could be devoted in order to further evaluate its execution through the multidisciplinary collaborative research studies, aiming at the promising prospective daily applications beyond hospitals and laboratories.

Acknowledgment

The authors would like to thank Stephen John Turner for his support and suggestions on the draft of this review paper.

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