Concerns in the Blurred Divisions Between Medical and Consumer Neurotechnology

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***Abstract*—Neurotechnology has traditionally been central to the diagnosis and treatment of neurological disorders. While these devices have initially been utilized in clinical and research settings, recent advancements in neurotechnology have yielded devices that are more portable, user friendly, and less expensive. These improvements allow laypeople to monitor their brain waves and interface their brains with external devices. Such improvements have led to the rise of wearable neurotechnology that is marketed to the consumer. While many of the consumer devices are marketed for innocuous applications, such as use in video games, there is potential for them to be repurposed for medical uses. How do we manage neurotechnologies that skirt the line between medical and consumer applications and what can be done to ensure consumer safety? Here, we characterize neurotechnology based on medical and consumer applications and summarize currently marketed uses of consumer-grade wearable headsets. We lay out concerns that may arise due to the similar claims associated with both medical and consumer devices, the possibility of consumer devices being repurposed for medical uses, and the potential for medical uses of neurotechnology to influence commercial markets related to employment and self-enhancement.**

***Index Terms*—Brain–computer interface (BCI), consumer products, data privacy, ethics, law, medical diagnosis, neurofeedback, neural prosthesis, patient rehabilitation.**

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I. Introduction

With the advent of wearable technology, individuals are readily able to monitor a wide array of characteristics of their bodies, ranging from movement patterns to heart rate. While these technologies have been predominately focused below the neck (e.g., watches, chest straps), a new variant of wearables have emerged that can monitor the brain. These devices have enormous implications for the health care industry, fitness and wellness communities, and possibly the most controversial area of application, the employment sector. Globally, neurological disorders were estimated to be the leading cause of disability (estimated as 276 million disability-adjusted-life years from 1990–2016) [1]. Neurotech Reports projects that neurotechnology will have a global market of $9.1 billion in 2020 [2]. These technologies have significant potential to reverse enormous financial losses due to neurological disorders and injuries, while enhancing the quality of life for affected individuals and their families. However, as this technology becomes more widespread, there is a potential for the technology to be repurposed for unintended medical purposes or to be misused for unethical purposes. As with any emerging technology, there are many ethical, economical, regulatory, and societal concerns regarding neurotechnology devices [3]–[7]. In this article, we discuss how these concerns may arise from the blurred line between medical and consumer applications.

Within the context of this article, neurotechnology is characterized into three distinct areas: 1) detection; 2) training; and 3) augmentation. While each of these terms has potential to invite confusion, they were specifically chosen to allow dual representation of each word within both medical and nonmedical contexts. For detection, neurotechnology can be used for applications needed to highlight the presence of a neural pattern. In the medical environment, these neural patterns can be associated with a disorder and lead to subsequent diagnosis. In the consumer environment, these patterns could be associated with abstract mental states such as a customer's interest in an advertised product, a driver's drowsiness during vehicle operation, or a student's loss of focus in a classroom setting. Training extends beyond detecting neural patterns and gives the user the ability to change or strengthen their brain through mental exercises. In the medical context, this may refer to rehabilitation paradigms that help patients recover from brain damage caused by a stroke. Nonmedical applications include exercises that improve mental skills related to focus, memory, or meditation. Finally, for augmentation, neurotechnology can be used to help individuals control devices through monitored brain activity.

The term augmentation, as used in this article, refers to the use of technology for the addition or enhancement of a particular human function. We wish to apply this term to encompass what traditional medical parlance would label as "restoration" or "rehabilitation" of a "normal" function that had been lost due to disease or injury. For spinal cord injury survivors, this could involve using a thought-controlled leg exoskeleton to help them walk. Traditionally, "augmentation" referred to using technology that aimed to enhance human function beyond what was "normal"—for example, an exoskeleton that could empower a person to do a 70-foot-high jump. Typically, the term "augmentation" carried a judgment that the enhanced function was frivolous or unnecessary from a "normal" medical perspective. This article rejects traditional distinctions between "normal" and "subnormal" and between traditional concepts of restoration or rehabilitation versus augmentation. We define augmentation in the medical context as measures that enhance human functions beyond the level a patient had when they entered the healthcare system, without demeaning patients by debating whether they were "normal" or lacking "normal" functions when they present themselves for treatment. Augmentation in the medical context simply focuses on extending or enhancing human functions in relation to which patients sought medical consultation. Augmentation in the nonmedical context refers to the extension or enhancement of human functions in ways that usually are not characterized as "medical" issues—for example, controlling an air drone or a room light's colors through a user's thoughts.

The goals of this article are as follows. First, we seek to characterize medical and consumer applications of neurotechnology. Second, we identify concerns that can arise when the boundaries between medical and consumer applications are crossed. Finally, we comment on how regulation can be used to address these concerns.

II. Medical Uses

Neurotechnology has traditionally been limited to hospitals and laboratories due to the size and costs of the systems. The complexity of these systems often requires a high degree of training to safely operate them and to accurately interpret their results. While neurotechnologies have mostly been used for diagnostics, they have recently entered the healthcare market with a strong focus on rehabilitation.

A. Detection

Neuroimaging methods provide clinicians and researchers the ability to image the structure and function of the brain. Detection, in the clinical sense, allows for the observation and diagnosis of disease or injury based on the brain images.

Structural imaging techniques are used to observe the structure of the brain and surrounding tissues (e.g., contrasting between white matter, gray matter, cerebrospinal fluid, etc.) and assist in the diagnosis of gross structural disease and injury. For example, magnetic resonance imaging (MRI) and computed tomography (CT)—an advanced X-ray technique—provide direct images of the brain and can be used to identify conditions associated with structural abnormalities such as swelling [8], tumors [9], or stroke [10]. However, the operating precautions (e.g., MRI magnet safety, CT radiation exposure), cost, and size make their purchase by the average consumer nearly unattainable, thus making them unlikely to enter the market as "wearable" technology.

Functional neuroimaging techniques are used to assess normal and pathological brain activity related to cognitive and motor function. Commonly used techniques include functional MRI (fMRI), positron emission tomography (PET), electroencephalography (EEG), and magnetoencephalography [11]. As it relates to the wearable market, a large number of these functional imaging techniques are unlikely to extend beyond medical applications (e.g., PET, fMRI) due to their cost, size, and risk factors—similar to challenges facing structural scanning methods. An additional consideration for the applicability of neuroimaging techniques as a deployable technology is the level of invasiveness of the recording modality. Noninvasive approaches include functional near-infrared spectroscopy (fNIRS) and EEG, which measure changes in brain activity through recording sensors affixed to the scalp [12]. Conversely, invasive sensors, such as electrocorticography (ECoG), stereotactic EEG (sEEG), and microelectrode arrays (e.g., Utah array), are surgically implanted on the surface of the brain (cortex) or within the brain volume [12], [13]. Techniques such as EEG, fNIRS, and ECoG measure the behavior of large populations of neurons, whereas implanted electrode arrays measure small populations or individual neurons in a particular region of the brain [12], [13].

To provide context for the application of these varying neuroimaging techniques as diagnostic tools in the clinic, we provide an example to illustrate their use. Epilepsy is a chronic disorder characterized by recurring, unprovoked seizures [14]. Approximately 30% of individuals with epilepsy are unable to control their seizures through medication and thus require advanced intervention, such as surgical removal of epileptic brain regions [14]. In this severe case, it is of utmost importance that the clinicians treating the patient are able to identify the source of epilepsy in the brain with high precision. Generally, noninvasive methods, such as EEG, fMRI, and PET are used to identify epileptic regions in the brain, while structural MRIs provide high resolution models of the individual's anatomy [15]–[17]. During a seizure, the responsible area of the brain can be characterized, for example, by increases in electrical activity (EEG) or blood flow (fMRI). Following initial localization of the epileptic source, clinicians can advance to surgically invasive approaches, such as ECoG or sEEG, to further identify the epileptic source. Finally, a surgical resection (removal of abnormal tissue) or other surgical interventions can be implemented to alleviate the epileptic symptoms.

Currently there is also research in utilizing neuroimaging devices to diagnose neurological disorders including Alzheimer's disease, attention deficit disorders, autism spectrum disorders, and depression [18]–[22]. A large focus is the identification of biomarkers, which are biological indicators for disease. They can potentially be used to diagnose diseases early, to identify optimal treatment routes for particular patients, and to predict the prognosis of the diseases. Recently, machine learning has been used with biomarkers to enhance diagnostic accuracy. These algorithms are likely to fit within the U.S. Food and Drug Administration's (FDA) definition of "Software as a Medical Device" (SaMD), which is subject to FDA regulation [23]. In

a recent draft guidance, the FDA discussed Clinical Decision Support (CDS) software, which incorporates an individual's medical information to provide patient-specific diagnostic or treatment recommendations in clinical settings [23]. Some (but not all) CDS software constitutes SaMD that the FDA would regulate as "Device CDS" software [23]. Based on the guidance, the FDA only intends to regulate CDS software as a device when the user (such as a healthcare provider) would be unable to independently review the basis of the software's diagnostic or treatment recommendations and if the software is intended for use in contexts where errors could carry serious risk to patients [23]. Thus, FDA regulation is likely to apply to diagnostic software in neural devices that use complicated machine learning algorithms. These algorithms can be so complex that the basis of their decisions would not be transparent even to medical professionals. However, there has been significant effort made in the field of explainable artificial intelligence (XAI), which can identify which features were critical in a predictive algorithm's decision [24], [25]. XAI may help improve algorithmic transparency and regulatory science.

B. Training

Clinicians and research scientists have begun to realize the brain's regenerative potential, resulting in a paradigm shift in the clinical treatment of neurological disorders and injuries [26], [27]. A *neurorehabilitation* approach for the treatment of cognitive and motor disorders includes any form of therapy or training that yields clinical benefits through the plasticity of neural networks in the human body. This term can be quite broad in that it includes therapies ranging from split-belt treadmill training [28] to the use of prisms for individuals with deficiencies in visual perception [26].

In the context of restoring motor function for stroke survivors, traditional rehabilitation therapies involve having the patient perform exercises with the impaired limb with the assistance of a therapist. For example, to treat upper limb impairment, a therapist may manually assist the individual during task-oriented training, such as picking up a small block and moving it to a container [29]. Similarly, motor training and motor adaptation, such as walking on a split-belt treadmill, can result in improvements in lower limb function [28]. However, in some cases, the individual may lack the required strength to perform the desired functional task such as moving the arm through a sufficient range of motion or walking on a treadmill. Robot-assisted therapy has become a popular approach for assisting the patient through the range of motion required to perform the prescribed functional task, and to alleviate the physical burden placed upon the therapist while assisting the patient through the task [30]. While robot-assisted devices may help facilitate neurorehabilitation, a contention about them is that they may only engage the limb without necessarily engaging the brain areas associated with movement. It is argued that Hebbian plasticity, or reinforcement of neural connections, only occurs when both the brain and limb are engaged simultaneously [31], thus raising the question of how to engage the brain. Recent efforts have explored activating assistive robots with motor commands detected from the patient's brain through neuroimaging modalities. Such systems are known as brain–machine interfaces (BMIs) [also known as brain–computer interfaces (BCIs)], which essentially allow users to control devices through their thoughts. The general notion driving BMI-based rehabilitation is the belief that direct engagement by the user will lead to better functional outcomes than traditional rehabilitation approaches [27], [32]–[38].

While stroke rehabilitation aims to restore neural connections between the brain and the limb, we note other training systems that aim to change a patient's inherent neural modulations. These *neurofeedback* (or *biofeedback* for biological signals in general) systems monitor neural modulations and display them back to the patient through visual or auditory cues. The patient is tasked to perform exercises which can reduce neural patterns associated with neurological disorders such as attention-deficit/hyperactivity disorder (ADHD) [39], [40]. The neurophysiological mechanisms and clinical efficacy of these interventions are still being studied.

C. Augmentation

BMIs can be used as a medical technology to augment individuals with severe impairment, paralysis, or limb loss as a means to restore lost motor function. For example, individuals with severe paralysis, such as high spinal cord injuries (SCI—tetra/quadriplegia) or advanced amyotrophic lateral sclerosis (ALS), may have limited or complete deficits in motor function and speech that can be partially restored with a BMI. BMIs have been used to control a computer cursor on a screen [41]; to achieve highly dexterous control of high degree-of-freedom anthropomorphic arms (e.g., Deka Arm System) [42]–[45]; for spelling words [46], [47]; and for decoding speech [48]–[50]—all capabilities that could significantly improve the lives of individuals with severe impairments. BMIs can also be helpful for amputees as a means of controlling their prosthesis [51]. The most advanced motorized prosthetic devices are controlled with peripheral sensors that monitor residual muscle activity or limb movements. While they help restore some motor function, they still do not match the dexterity that exists in an intact limb. BMIs can potentially enhance control by contributing complimentary neural signals with the peripheral sensor data.

We note that some studies in this field often involve participants who opt to be surgically implanted with electrodes that directly monitor the brain. The performance of these modalities is certainly greater than that of noninvasive alternatives, but there are risks associated with surgical complications, biocompatibility, infection, or signal degradation. To the participants with severe impairments, however, these risks are outweighed by the enhancement in the quality of life offered by these BMIs. We refer the reader to the following reviews, which compares various neural interfaces and comments on the risks with invasive neurotechnologies [12], [13].

D. From "Bench-to-Bedside"

The phrase "bench-to-bedside" is frequently used to describe the process of translating basic research into realizable clinical treatments. While the expression is often used within the context

of translating drugs into patient care, the same notion can be applied to neurotechnologies.

> How do we get neurotechnology A [e.g., a BMI for control of a hand prosthesis, a BMI-based speech prosthesis, a thought-controlled exoskeleton for stroke rehabilitation, etc.] into the care of end user, or patient, B [e.g., individual with SCI, ALS, stroke, limb loss, etc.]?

There is no doubt that all the previously described neurotechnologies will receive some form of regulatory oversight as medical devices. Indeed, the FDA is aware of the need to make these technologies available to clinicians and patients [52]. A draft guidance, entitled "Implanted BCI devices for patients with paralysis or amputation–nonclinical testing and clinical considerations" [53], is currently under revision after recently closing for comment before a final guidance is released. This guidance provides significant effort in outlining the FDA's view on BCIs. However, the guidance lacked some key points which were highlighted by some of the public comments [54]. The guidance lacks commentary on noninvasive systems, sequential use of BCIs in various phases of treatment (e.g., acute versus chronic phase of stroke), and neurotechnologies for neural recording or stimulation that are currently marketed as consumer devices. These concerns are valid for in-hospital care as well as for at-home rehabilitation or augmentation devices.

E. Who Is Going to Pay for It?

A significant concern for the translation of medical neurotechnology into the clinic, and ultimately for the care of the end user, is that of payment. For most BMI studies, the estimated cost to the end user is not reported, and, if so, it is usually based solely on the cost of the system (e.g., low-cost portable EEG systems, which provide the benefit of being low-cost at the potential sacrifice of data quality). These reported values neglect the overhead associated with BMIs as medical devices. A recent clinical study investigating an EEG-based speller for individuals with ALS estimated a total cost of $5000.00 for an at-home system [46], [55]. However, this system is designed to be low-cost, leading to the plausible subsequent conclusion that devices with more advanced neural recording methods, or those requiring surgical implantation, will come with a much higher price tag. It is important to note that neural recordings alone cannot be used as a BMI; software that utilize predictive machine learning algorithms are required to translate the brain signals for the desired functional task. Furthermore, when BMIs are coupled with external devices, the price of the end effector must be factored into the total cost to the user. While a tablet coupled with a BCI for cursor control may run in the hundreds of dollars, a take-home system that interfaces with high degree-of-freedom anthropomorphic arms (such as advanced prosthetic devices) may result in substantial costs for a complete system [56].

Because this article surveys a wide range of different neurotechnology devices, a detailed discussion of reimbursement issues is not possible. The demographics of the target patient population for a particular device influences which and how many payers are involved in making decisions on whether to cover the device, at what level of payment, and how the payments will be structured. For example, Medicare crucially affects the commercial fate of devices serving persons over 65; military payers are important for devices addressing veterans' health needs; and a multitude of private insurers and state Medicaid programs come into play for devices that serve patients of diverse ages and economic conditions. While different payers implement different policies, many are influenced by Medicare's coverage decisions [57].

By statute, Medicare covers technologies that are "reasonable and necessary" for diagnosis or treatment of illness or injury or to improve the functioning of a malformed body member [58]. This rules out preventive technologies unless Congress has specifically authorized coverage, but diagnostic neuroimaging technologies generally qualify for coverage. Medicare does not set separate reimbursement rates for most devices used or installed at hospitals and clinics, because payments for the devices are bundled into the fees for the healthcare services that utilize the devices [57]. Thus, healthcare providers receive a bundled fee for treating each patient, and providers recoup the costs of neuroimaging equipment they use and any neural devices they surgically implant via that bundled fee [57]. This incentivizes providers to choose low-cost devices that consume less of the bundled fee. However, it has the advantage that if a device manufacturer can persuade providers that its device is superior to alternatives and merits a higher price, the provider can agree to pay that price without seeking Medicare approval.

In contrast to the bundled fees Medicare uses for devices operated at healthcare facilities, Medicare separately reimburses durable medical equipment (DME) that patients use at home, which includes prostheses and other related equipment. In the past, these devices were reimbursed according to a fee schedule, but in 2009 Congress introduced competitive bidding to establish payment rates for many such devices [57]. This has reduced Medicare's costs, but some amputee advocacy groups urge policymakers to stop treating advanced prostheses as DME because this policy limits the choice and quality of devices available [59].

Still, governmental programs such as Medicare, Medicaid, and veterans' programs are considered more generous than many private insurers. Medicare covers prosthetics, subject to its usual 20% copay, and the Veteran's Affairs Department "provides the latest in technology without limits on cost" [60] and without a copay. In contrast, private insurers often set coverage limits or deem the latest technology to be "experimental" and thus ineligible for coverage [59], [60]. Private insurance plans generally commit to cover care that is "medically necessary," but there is no federal definition of this term and fewer than one third of the states have a regulatory definition. Whether a given type of device is covered depends on the terms of the particular insurance contract which the insurers define. This has the potential advantage of allowing device manufacturers to work out stand-alone fees that might reward superior devices with superior reimbursement levels. However, many private insurers set caps on reimbursement for prosthetic technology, thus severely limiting patients' access to advanced prostheses and neurotechnology devices [59], [60]. Since 2001, around 20 states have passed insurance fairness statutes to enhance amputees' access to modern prosthetic devices [59]. Advocates continue to press for reforms in other states, but a clear pathway for private insurance reimbursement for the most advanced BMI devices remains challenging [59].

III. Consumer Uses

Recently, a number of consumer-grade neural devices have entered the market that are targeted towards general wellness, entertainment, and educational uses. Most of these are comprised of noninvasive EEG headsets that are usually priced below $1000 [3]. These devices tend to employ an ergonomic design that facilitates the packaging of all the hardware (recording sensors, signal amplification, data storage, and wireless streaming) into a streamlined and wearable form factor. In general, the number of sensors on a consumer-grade system (1–16) tends to be lower than that of a research-grade system (32–128). Furthermore, consumer-grade EEG systems often employ dry electrodes—electrodes that do not rely on electrically conductive gel between the scalp and electrode tip—to facilitate faster and easier setup by the user. Finally, due to the more consumer-friendly form factor, the amplification hardware may limit the resolution of the data and the sampling rate at which the data can be recorded. Such limitations have garnered doubt on the capabilities of these devices in the neurotechnology space [61], [62]. Nonetheless, the portability and accessibility of these consumer-grade neuroimaging devices allow broad application beyond the clinic or laboratory.

A. Detection

1) Market Research: Market research involves gathering information related to how potential customers are attracted to products or advertising. While most market research is typically studied with interviews, self-reports, or focus groups, these methods are susceptible to subjective biases. This has garnered interest in using neuroimaging headsets for *neuromarketing*, which uses recorded brain activity to predict an individual's preferences. The rationale is that recorded brain rhythms could represent more objective and truthful measures about a customer's preferences [63], [64].

2) User Authentication: A major challenge in the security sector is the authentication of an individual's identity. Recent solutions utilize biometrics to identify individuals based on biological qualities such as their fingerprint, face, voice, etc. Neuroimaging headsets allow brain waves to be used as a biometric [65]. Users can respond to security queries through a personal mental task that would be monitored through a headset. This type of response offers advantages over other biometric methods: 1) it is confidential since the response is inherently covert; 2) it is difficult to mimic since it is expressed through brain waves unique to the individual; and 3) it is difficult to coerce from the individual since brain waves are sensitive to stress. [66].

3) Identifying Personality: There is also ongoing research in using brain activity to predict aspects of an individual's personality through EEG signals [67], some of which includes callousness [68], psychological resilience [69], and leadership qualities [70]. This is potentially attractive for the employment sector, where recruiters may seek individuals with particular personality traits for job positions. Given that candidates have incentives to present themselves in ways that are attractive to recruiters (such as acting confident or engaged), brain scans can allow recruiters to get a "true" reading of the candidate's personality.

4) Driver Drowsiness: Fatigue and drowsiness are significant factors that are responsible for vehicle crashes [71]. There is ongoing research in developing systems that can detect if a driver is drowsy, which could then prevent an accident either by alerting the driver or safely stopping the vehicle. Some conventional strategies include monitoring the driver's face orientation, eye gaze, or driving performance [72]. Since fatigue and drowsiness reflect a driver's state of mind, wearable brain scanning devices are proposed as a tool to detect these states. Ongoing research involves using machine learning algorithms to detect drowsiness from brain waves [73]–[76]. While this application does not have any clinical relevance, these devices are aimed at reducing risk of fatality or injury from vehicle crashes. How the failure of such devices should be handled in terms of liability concerns remains uncertain.

B. Training

1) Meditation: Meditation, being a skill that involves invoking a particular state of mind, can be difficult to learn due to its internal nature. Wearable neurotechnology can be particularly helpful in this area, as modulations in brain activity related to a proper meditative state can be displayed back to the user in real time as they practice the exercise. From such cues, the user can use this as feedback and augment their strategies to perform meditation more effectively [77]. Few studies have demonstrated that the use of such headsets with meditation exercises can yield changes in neural features related to attention during rest [78]. A note worth considering is that beyond helping users train for meditation, wearable neurotechnology can also validate if particular mental exercises cause lasting changes in neural activity. Such findings can help trainers augment their programs to help maximize benefits associated with meditation.

2) Focus and Attention: Consumer EEG headsets are also being marketed as a means to improve focus and attention. These devices are often coupled with mental exercises that are performed while the user wears the headset. While these are marketed as self-help tools for individuals to enhance their mental acuity, this type of technology has garnered interest by educators and parents to monitor how attentive children are during school classes [79]. The idea is that by monitoring the children's brain scans during a class lesson, parents and teachers can monitor when the students are focused or distracted [79]. With the feedback, coaching strategies can be adopted to help children focus, or teachers can augment their lessons to make them more engaging [79]. While many neuroimaging headsets are marketed as a means of improving one's own focus or attention, there is ongoing research in using such technology to detect and manage attention-related disorders such as ADHD [80], [81].

3) Sleep Aid: Sleep is crucial for an individual's mental and physical health. There are many ways for individuals to monitor their sleep habits at home, such as using smart watches that monitor motion, sounds, and heart rate. Neuroimaging headsets are also being sold as a means to monitor and improve the user's quality of sleep. Some products generate binaural beats in response to brain activity, which some studies claim can reduce stress and anxiety [82], [83]. While these claims of improved sleep may allow the technology to be classified as a general wellness device, manufacturers should be careful to omit mention of sleep-related disorders, such as insomnia or sleep apnea, if they wish to avoid oversight from the FDA as

a medical device. Few companies have directly marketed their wearable headsets as a medical device, making claims that they can detect sleep apnea and validating those claims via clinical trials [84], [85].

4) Working Memory: While the previous examples have discussed applications with headsets that monitor EEG, few companies are also marketing headsets that provide improvements in working memory through electrical or magnetic stimulation to the brain [86], [87]. While this can be marketed for healthy individuals, there is ongoing research on applying brain stimulation techniques to treat memory-related disorders such as disease Alzheimer's disease [88], [89].

C. Augmentation

1) Alternative Controller for Entertainment: The ability to control devices through the power of thought has its own intriguing novelty. EEG headsets are also offered as an alternate joystick controller for video games, or to control toys such as an air drone. Some headsets also allow users to control cosmetic wearables, such as cat ears on a headband or a tail that is worn at the waist. Based on how these products are marketed, it is clear they are targeted solely for entertainment.

While such products are meant for entertainment, there is ongoing research to add gaming elements to rehabilitation programs [79], [87], [90]. As mentioned previously, there are neural training programs that involve clinical patients using BMIs to engage cortical areas for rehabilitation. Implementing gaming elements can help increase the patient's motivation and compliance with the rehabilitation program [79], [87], [90]. As the products above are available for consumers, clinical populations seeking rehabilitation through neural training could seek out these products to augment their recovery.

2) Artistic Expression: Artists are actively exploring the use of EEG headsets as a component of artistic installations. The use of neural data can range from simply showing the brain waves directly or by transforming the signals into another form, such as visual effects or sounds [91]. For example, neural signals can modulate precomposed musical fragments or change the color and shape of a visually displayed flower-like pattern [91]. Furthermore, some artists have used the processed neural signals to control dynamic dresses [92] or motorized environmental installations [93]. Many artists are attracted to displaying brain waves in their raw form as it accentuates a very personal and unique aspect of the individual. This has led to research in using EEG signals as an alternate form of emotional and artistic expression [94].

D. Educational Do-It-Yourself Kits

Consumer-grade neurotechnologies can also provide opportunities for hobbyists and educators who wish to learn and teach bioinstrumentation technology. The construction of such neurotechnology often involves working with sensors that interact with the human body, designing and fabricating the hardware to make them wearable, and programming algorithms to detect different mental states. These concepts can be explored through accessible consumer neurotechnology.

To meet such a demand, there are a few neurotechnology companies that have adopted an open-source model to their products, where they provide schematics and a framework for developing a neuroimaging headset at home. For example, these companies may offer a storefront where users can buy electrodes for a customized headset, downloadable designs that allow users to create the physical hardware using three-dimensional printing (3D printing), and programming code that allows users to access the data recorded on the headsets—usually a software development kit, or SDK. A user is free to customize the hardware configuration, such as the number of electrodes and their locations on the scalp. A user can also choose how the raw neural data are processed and analyzed for their specific application. In general, these companies do not readily market their products for specific applications, but instead, simply offer the technical specifications of the hardware and general uses of the device.

While a few companies offer a very accessible environment for developers to modify neural imaging headsets, some companies have developed a unique strategy for layering access to various aspects of the systems. For example, to access raw data (which would allow greater flexibility for developers to add their own functionality), a developer would need to pay a monthly subscription fee. However, an important note is that there are fully open-source third-party software applications specifically designed to stream data from a large number of commercially available headsets, including research-grade and consumer-grade devices. These software packages allow for the streaming of data from devices that normally do not have publicly disclosed programming code or designs. This broadly expands a developer's ability to select a device among a large assortment of consumer systems, giving them more access to powerful devices for demanding projects. Such projects could involve clinical benefits, which present the potential for individuals to develop devices at home that might otherwise be considered medical devices by the FDA.

IV. Concerns When Consumer Devices may Be Repurposed for Medical Uses

We discuss how device manufacturers, software programmers, and consumers can play a role in repurposing consumer neurotechnology for medical purposes. A summary of the concerns can be found in Table I.

A. Careful Wording on Intended Use for General Wellness

Developers that market a neural device directly to consumers may feel incentivized to tout the device's health benefits to increase sales. This strategy must be approached with caution, however, because a developer's claims can affect whether the FDA will regulate the device and if so, which, if any, of the FDA's various premarket review pathways could apply. Devices—including components or accessories of devices—are subject to FDA regulation if they are "[i]ntended for use in the diagnosis of disease or other conditions, or in the cure, mitigation, treatment, or prevention of disease…" [95]. In 2016, the 21st Century Cures Act [96] clarified how the FDA's device regulations apply to medical software [97]. Software that encourages wellness or a healthy lifestyle is not FDA-regulated, unless it crosses the line into "diagnosis, cure, mitigation, prevention, or treatment of a disease or condition" [100]. Unregulated general wellness software includes products such as step counters and nutrition

TABLE I
SUMMARY OF CONCERNS RELATED TO THE REPURPOSING OF CONSUMER DEVICES FOR MEDICAL PURPOSES

Concern	Motivating Factors	Related Regulation
• Consumer device manufacturers may claim medical benefits.	• This can attract clinical patients as potential customers.	• Devices with clinical claims are subject to FDA oversight and must be cleared or approved by the FDA.
• Software companies may repurpose consumer headsets for medical uses.	• Software companies might enhance sales by associating their software with a consumer headset.	• The software company may fall under FDA regulation, requiring FDA clearance or approval of the software and its associated or bundled consumer device. • The FDA's Pre-Cert Program may ease regulatory burdens but is still in its preliminary phases. The FDA's Clinical Decision Support guidance may apply.
• Consumers may repurpose consumer headsets for medical purposes.	• FDA-regulated medical devices may be inaccessible due to high costs. • Open-source environments make it feasible to modify consumer devices. • Consumer and medical applications are similar.	• This may escape regulation because the FDA regulates developers rather than consumers, but the FDA can press companies to write explicit warnings against inappropriate medical uses.

calculators. Many consumer-facing neural devices may be able to fit within this category if developers word their product labeling and marketing materials carefully.

Late in 2019, the FDA issued a final guidance that clarifies the line between regulated and unregulated wellness devices [98]. Claiming that a device offers medical benefits or that it can diagnose or treat specific health conditions can cause the device to require FDA clearance or approval as a medical device. This might involve submitting a premarket notification, or 510(k), which typically involves submitting bench data to prove that the device is substantially equivalent to a predicate device already on the market with the same intended use. Devices that are novel or pose higher risk might be required to go through the premarket approval (PMA) pathway, which typically requires clinical trial data [99] and thus entails higher costs and a slower path to market. Another alternative is to seek a *de novo* classification, in which the developer asks the FDA to classify a novel device (which normally requires a PMA due to its novelty) as a lower-risk device by demonstrating that it is not very high risk, making the device eligible for 510(k) clearance [99].

Many of the consumer devices mentioned previously escape FDA regulation despite claims of reducing stress or improving focus or aiding sleep. While these may sound like clinical benefits, such products can qualify as "general wellness" devices provided they are of low risk and avoid claims about diagnosing or treating specific diseases or health conditions [98]. Devices may be found to be low risk if they are not implantable or invasive and would not pose serious risks if they malfunctioned [98]. Developers need to describe potential benefits very carefully to stay within the boundaries set in the FDA's recent guidance [98]. The FDA does permit references to specific diseases as long as the device merely promotes a "healthy lifestyle" to help mitigate the effects of having the disease. An example of a general wellness claim would be a device that "coaches breathing and relaxation skills, which, as part of a healthy lifestyle, may help in living well with migraine headaches," [98]. Such claims are permissible in a non-FDA-regulated consumer device. Even so, many consumer device manufacturers appear to avoid advertising in this way, perhaps to dispel any suggestion that they are marketing a medical device [98].

B. Managing Software That Can Add Medical Capabilities to Consumer Neurotechnology

Even when a device developer positions its device as a consumer product and scrupulously follows the FDA's guidance by avoiding any diagnostic or therapeutic claims, there is always a possibility that other parties might repurpose the device for inappropriate medical uses. This potential for repurposing and misuse arises because consumer-grade devices often produce data which resemble that of FDA-regulated medical-grade devices. Such data can be used with customized software that can be designed to draw clinical inferences. A related case has been reported, where it was found that machine learning algorithms can be used with fitness trackers to detect atrial fibrillation with an accuracy of 90% [100]. This raises the possibility that neurotechnology devices marketed by a manufacturer for general wellness, like fitness trackers, could be repurposed for medical uses by a third-party software developer.

When a software application (app) company writes code that encourages consumers to use a consumer-grade device for medical purposes, the legal analysis is a bit more complicated. In this case, the party who would be answerable to the FDA is the software app developer, rather than the consumer device developer. There are two ways to view the app developer's activities. The first is that the app developer is repurposing the consumer device by altering its intended use and thereby transforming it into a new medical device intended for diagnostic or therapeutic uses. According to the FDA's regulation, a party who alters the intended use of an existing device is responsible for demonstrating that the device is safe and effective in the new intended use [101]. The FDA could require the app developer to show that its algorithm draws clinically valid inferences and, moreover, could require it to show that its inputs—the data from consumers' devices—are sufficiently reliable to be repurposed for a medical use. The second view is that the software app is a "software as a medical device": in other words, the software is a medical device in its own right that is being sold as a separate accessory to the consumer-grade devices that consumers already own. The app itself is a medical device that the FDA can regulate [95].

While the hardware is central to any neural recording device, it is the software accompanying a neural recording device (and

the claims made about that software) that largely distinguish whether it is a consumer product or a medical device. Thus, regulators are developing strategies for overseeing the software itself as a medical device, alone or in combination with specific hardware. As of this writing, the FDA is currently working on the Digital Health Innovation Action Plan, which recognizes that such software has potential clinical benefits [102]. The agency is currently developing the "Pre-Cert" program which aims to regulate apps by evaluating the software developer with the app and by monitoring the app's performance while it is in the market [103].

C. Unintended Medical Uses of Consumer Devices by Consumers

While there are ongoing developments in place to regulate software companies, we also note that consumer hobbyists and "do-it-yourself biotech" enthusiasts who are not affiliated with companies can publish software in this space. This is possible if such participants have access to the following:

1) software packages that allow a consumer to access data from a consumer headset;
2) machine learning algorithms that have powerful potential to make medical inferences;
3) research or other data relating neural signals to clinical conditions.

While clinical expertise was traditionally needed to draw medical inferences from neural data, machine learning algorithms can empower laypeople to draw clinically relevant information from available data. The necessary inputs are increasingly available through open-source platforms to create a headset with medical applications. For example, to develop a BMI that helps with hand impairment, a hobbyist can download a machine learning algorithm, access public neural data related to hand movements, and build a smartphone app that interfaces a consumer headset with a 3D-printed orthosis. A hobbyist can then share the app with other clinical patients for free. This environment of shared knowledge and distribution of medical devices has been seen with 3D-printed prostheses, which have allowed amputees to obtain low-cost devices from hobbyist communities and nonprofit organizations [104]. Although these devices bypass purchase from a commercial manufacturer, they still fall under FDA regulation as a Class I exempt medical device.

When reimbursement issues constrain patients' access to FDA-regulated medical devices, as is the case in the United States, consumers can grow desperate and take matters into their own hands by repurposing consumer-grade devices to meet their unmet medical needs. The Institute of Medicine observed this pattern in a 2016 report that found widespread reliance on consumer-grade personal sound amplification products by patients who were unable to afford needed hearing aids [105]. As neurotechnology is enhanced through research and development, the public becomes increasingly aware of the potential to use these devices to detect and manage a wide variety of mental disorders and to restore motor capabilities in individuals with disabilities. It seems likely that consumers might seek consumer-grade neurotechnology for do-it-yourself medical applications, even if technology manufacturers make no medical claims. The FDA regulates manufacturers and suppliers of products, not consumers. The agency can stop developers from marketing a device for inappropriate medical uses and from supplying "how-to" instructions that promote misuse, but the FDA cannot impose sanctions on consumers who nevertheless figure out ways to repurpose a product for their own use.

Finally, consumers may wrongly extrapolate medical concerns from consumer devices. This might occur when a consumer headset does not work for the end user, or if the detected patterns are biased. For example, a user failing to yield improvements in exercises related to enhancing focus or working memory might draw inappropriate conclusions that they have an attention or memory-related disorder. This is especially pertinent for headsets used to monitor students' engagement in classrooms, where a child displaying repeatedly low focus measures might cause parents and teachers to wrongly assume the child has an ADHD-related disorder. Consumers can be overly trusting of these consumer devices due to the manufacturer's optimistic advertising and news media that regularly report enticing neuroscience findings [4], [5]. Laypeople may be unaware of factors that would make these headsets unreliable. First, even with state-of-the-art hardware and knowledge, applications can still vary in performance across individuals. For example, BMIs have been found to not function in many healthy individuals due to their idiosyncratic brain patterns [106]. Second, consumer-grade headsets are likely to perform worse than medical devices due to the tradeoff in hardware performance for lower costs [61].

D. Legal Liability of a Consumer Neurotechnology Device Manufacturer When Misuse Occurs

If a developer of a consumer device becomes aware that other parties are misusing its product, will this fact cause its product to fall under FDA regulation? The short answer is that this potential exists in theory, but is rather unlikely in practice, and there are steps developers can take to lessen the legal risks they might face because of other people's misuse of a device.

Device developers and manufacturers naturally will be concerned about the impact of such misuses. Legally speaking, the distinction between a consumer device and a medical device depends on the device's intended use [95]. Generally, a device's intended use refers to the objective intent of "the persons legally responsible for the labeling" [101] of the device, which usually means the device developer/manufacturer. The FDA can consider direct and/or circumstantial evidence of the developer's intent [101]. Direct evidence would include claims the developer or its representatives—such as its sales force—made about the device, whether in labeling, advertising, or oral and written statements [101]. Permissible circumstantial evidence includes facts showing that the developer knew that the device was being misused for purposes other than those for which the developer labeled and advertised [101].

This last point creates a theoretical risk that a developer could be held responsible if it knew others were misusing its device for unintended purposes. In reality, this risk is small. A leading treatise on FDA law notes that the "FDA has rarely attempted to classify a product as a drug or device in the absence of relevant representations by the manufacturer or distributor" [107]. In other words, the agency generally bases its decisions on the direct evidence: what the developer/manufacturer said about the

TABLE II
SUMMARY OF CONCERNS RELATED TO WIDESPREAD USE OF NEUROTECHNOLOGY

Concern	Motivating Factors	Related Regulation
• Wide-scale collection of neural data could be used to discriminate against individuals in employment and insurance.	• The broad collection of data can be galvanized by the push for health screenings and scientific knowledge.	• Regulation is in place to protect individuals from genetic information discrimination (GINA). Similar protections have been proposed for neural data.
• Consumer devices used for training may cause harm associated with maladaptive plasticity.	• Clinical training interventions usually report mild side effects. • Consumers could modify and use their devices with unintended parameters.	• Similar concerns surround biohackers and at-home gene manipulation. While the FDA does have some oversight powers, they have exercised restraint thus far.

device's intended use. It is rare for the FDA to assert the authority to base decisions on known misuses, and even rarer for the FDA to prevail in court when it tries to do so (but see [108]). The recent FDA guidance on general wellness devices treats claims by the developer/manufacturer as the main source of evidence the agency will rely on when deciding whether a device is a general wellness device or an FDA-regulated medical device [98].

Even if a manufacturer knows consumers are misusing its consumer device, it is unlikely that the FDA will deem it to be a medical device and force the device's developer to seek a 510(k) clearance or PMA to establish that the device is safe and effective in the unintended new use. The agency might, however, press the developer to add a warning in the product labeling to clarify that the device has not been proved safe and effective in the new use. Besides FDA regulatory matters, device developers also may face liability from state tort lawsuits. Here again, it is prudent for a device developer who learns of an inappropriate medical use of its device to warn against this use and to take steps, including enlisting help from the FDA, to discourage it.

V. MEDICAL INFLUENCES ON NONMEDICAL NEUROTECHNOLOGY

We discuss how previous medical studies with neurotechnologies can promote the widespread collection of neural data and use of neural training systems. The concerns surrounding these issues are summarized in Table II.

A. Collection and Broad Use of Neural Data

As described previously, neuroimaging devices have great potential for detecting neurological diseases. Early detection can help lead to early interventions, which can mitigate the disease's impact. However, this potential is limited if individuals only have access to neurotechnologies in a clinic. This can be overcome with widespread and consistent use of consumer-operated headsets, which can be used in an everyday setting and can be accessible to individuals at a low-cost. These headsets can be used like at-home kits that allow consumers to send blood or DNA samples to the lab, which serve as a means for alerting early signs of a serious disorder. These headsets are becoming more available as manufacturers develop diagnostic capabilities (with proper FDA compliance), enhance ergonomics, and reduce costs in current neurotechnology.

Identifying biomarkers for neurological diseases has been difficult due to confounds associated with concurrent drug effects, comorbidities with other disorders, and a poor understanding of typical neurological development [80]. These issues are exacerbated by the limited sample sizes and short-term studies done in a research setting. This shortcoming can also be addressed with broader collection of neural data through consumer-operated neuroimaging headsets. A wide-scale database of the broad population's neural data could yield powerful findings related to neurological diseases. There is already a strong push within the scientific community for sharing data recorded in research settings. The public sharing of data opens the door for researchers to probe previously uninvestigated scientific questions and attempt to reinforce the findings of existing studies. These endeavors can lead to advancements in diagnostic technologies and a greater scientific understanding. The FDA has taken similar approaches in the past with the Sentinel system, through the 2007 Food and Drug Administration Amendments Act, which characterized the efficacy and risks of FDA-approved drugs [109]. The FDA also proposed in their upcoming "Pre-Cert" program, that certified software companies would be encouraged to collect "real-world data" throughout a software's life cycle, which could potentially include raw neural data and medical information [102].

While shared neural data can yield benefits in managing diseases, there are concerns that they could also be used to draw unintended inferences about individuals. This concern exists with corporate actors in the employment sector. Recruiters might try to use a candidate's raw neural data to draw inferences about their personality or cognitive aptitudes, based on poorly validated hypotheses that such data offer a more authentic reading of the candidates' true qualities that can be hidden or difficult to assess in interviews. Employers might then select for sought-after personality qualities, or worse, select against hidden qualities such as the presumed presence of a neurological disorder. Similar issues could occur in other areas that evaluate individuals including health insurance, housing, and monetary loans. The potential for neural data to be used against individuals has been raised before, spurring calls for stronger data protections [3]. These could include obtaining informed consent from individuals to use or share their data, anonymizing datasets, and having companies disclose how neural data are managed [3]. These concerns mirror those raised by genetic data, where legislation such as the Genetic Information Nondiscrimination Act (GINA) has been enacted to limit discrimination based on genetic data [110].

B. Unresolved Risks and Self-Enhancement

Finally, we comment on potential risks associated with consumer devices that are related to neural training applications. It is thought that these devices are generally harmless, with

most studies reporting mild side effects: stimulation devices are usually associated with minor skin burns [111] while neurofeedback techniques at worst have been reported to induce headache or fatigue [112]. While these side effects are reported on a short time scale, their intended mechanism of action through neural plasticity is generally understood to work on a much longer time scale. Plasticity is often thought to work to the user's benefit (usually in the context of stroke rehabilitation), but it might also induce neurological diseases as well. Conditions related to chronic pain [113] or depression [114] have been linked with what is known as maladaptive plasticity [115]. The risk of inducing maladaptive plasticity with neurotechnologies is small in clinical scenarios where a medical professional is likely to monitor the patient's progress and change the intervention at the first signs of any side effects. For consumer devices, however, end users might not be aware of this potential risk and unknowingly cause harm to themselves. While this risk is likely to be small for well-defined applications (such as improving meditation), this risk could be exacerbated with open-ended do-it-yourself kits. Consumers can freely change the parameters of a device (such as stimulation strength) or use the device well beyond what was intended or studied. For these reasons, some researchers have proposed that consumer-grade neural training devices should be regulated like medical devices [116].

Even if the risk of maladaptive plasticity with these consumer devices is confirmed, many consumers may feel strongly about keeping unrestricted access to them as they provide a means of self-enhancement. These concerns are similar to those related to at-home gene editing kits, which potentially allow individuals to enhance themselves genetically but carry unquantified risks of genetic damage [117]. Specific regulatory details may be different—for example, gene editing kits are likely to fall under biologics and drug regulations while neural devices fall under device regulations. However, the pros and cons of imposing paternalistic restrictions for the consumer's safety are similar, as are questions about whether existing regulators have adequate legal authority to effectively regulate all forms of consumer-driven self-experimentation and the repurposing of products by consumers for use on themselves [118].

VI. Conclusion

The blurred boundary between medical and consumer neurotechnology can lead to potential uses outside of the original intended use of the technology. Furthermore, advances in consumer devices may lead to widespread adoption of neurotechnologies in medical, consumer, and commercial spaces. While the scope of ethical, legal, and regulatory issues cannot be fully foreseen at this time, this article provides a starting point to help developers and regulators frame further discussion around these emerging technologies.

References

[1] V. L. Feigin *et al.*, "Global, regional, and national burden of neurological disorders, 1990–2016: A systematic analysis for the global burden of disease study 2016," *Lancet Neurology*, vol. 18, no. 5, pp. 459–480, May 2019.

[2] Neurotech Reports, "The market for neurotechnology: 2020-2024 a market research report from neurotech reports executive summary," 2020. Accessed: Sep. 26, 2020. [Online]. Available: https://www.neurotechreports.com/pages/execsum.html

[3] M. Ienca, P. Haselager, and E. J. Emanuel, "Brain leaks and consumer neurotechnology," *Nature Biotechnology*, vol. 36, no. 9, pp. 805–810, Oct. 1, 2018.

[4] G. O'Connell *et al.*, "The brain, the science and the media," *EMBO Rep.*, vol. 12, no. 7, pp. 630–636, Jul. 2011.

[5] C. O'Connor, G. Rees, and H. Joffe, "Neuroscience in the Public Sphere," *Neuron*, vol. 74, no. 2, pp. 220–226, Apr. 2012.

[6] M. J. Farah and P. R. Wolpe, "Monitoring and manipulating brain function: New neuroscience technologies and their ethical implications," *Hastings Center Rep.*, vol. 34, no. 3, pp. 34–35, May 2004.

[7] K. S. Rommelfanger *et al.*, "Neuroethics questions to guide ethical research in the international brain initiatives," *Neuron*, vol. 100, no. 1, pp. 19–36, Oct. 2018.

[8] B. Lee and A. Newberg, "Neuroimaging in traumatic brain imaging," *NeuroRX*, vol. 2, no. 2, pp. 372–383, Apr. 2005.

[9] I. Popp, W. A. Weber, S. E. Combs, W. T. C. Yuh, and A. L. Grosu, "Neuroimaging for radiation therapy of brain tumors," *Topics Magn. Reson. Imaging*, vol. 28, no. 2, pp. 63–71, Apr. 2019.

[10] R. G. González and L. H. Schwamm, "Imaging acute ischemic stroke," in *Handbook of Clinical Neurology*, vol. 135. Cambridge, U.K.: Cambridge Univ. Press, 2016, pp. 293–315.

[11] A. Lenartowicz and R. A. Poldrack, "Brain imaging," in *Encyclopedia of Behavioral Neuroscience*. Amsterdam, The Netherlands: Elsevier, 2010, pp. 187–193.

[12] R. M. Rothschild, "Neuroengineering tools/applications for bidirectional interfaces, brain–computer interfaces, and neuroprosthetic implants—A review of recent progress," *Frontiers Neuroeng.*, vol. 3, pp. 1–15, 2010.

[13] B. Lee, C. Y. Liu, and M. L. J. Apuzzo, "A primer on brain–machine interfaces, concepts, and technology: A key element in the future of functional neurorestoration," *World Neurosurgery*, vol. 79, no. 3–4, pp. 457–471, Mar. 2013.

[14] American Association of Neurological Surgeons, "Epilepsy." Accessed: Jul. 10, 2020. [Online]. Available: https://www.aans.org/en/Patients/Neurosurgical-Conditions-and-Treatments/Epilepsy

[15] F. Cendes, W. H. Theodore, B. H. Brinkmann, V. Sulc, and G. D. Cascino, "Neuroimaging of epilepsy," in *Handbook of clinical neurology*, vol. 136. Amsterdam, The Netherlands: Elsevier, 2016, pp. 985–1014.

[16] E. H. Middlebrooks, L. Ver Hoef, and J. P. Szaflarski, "Neuroimaging in Epilepsy," *Current Neurology Neurosci. Rep.*, vol. 17, no. 4, Apr. 2017, Art. no. 32.

[17] M. K. Sidhu, J. S. Duncan, and J. W. Sander, "Neuroimaging in epilepsy," *Current Opinion Neurology*, vol. 31, no. 4, pp. 371–378, Aug. 2018.

[18] R. J. Janssen, J. Mourão-Miranda, and H. G. Schnack, "Making individual prognoses in psychiatry using neuroimaging and machine learning," *Biol. Psychiatry Cogn. Neurosci. Neuroimaging*, vol. 3, no. 9, pp. 798–808, Sep. 2018.

[19] E. Pellegrini *et al.*, "Machine learning of neuroimaging for assisted diagnosis of cognitive impairment and dementia: A systematic review," *Alzheimer's Dementia Diagnosis, Assess. Dis. Monit.*, vol. 10, no. 1, pp. 519–535, Jan. 2018.

[20] N. Yahata, K. Kasai, and M. Kawato, "Computational neuroscience approach to biomarkers and treatments for mental disorders," *Psychiatry Clin. Neurosci.*, vol. 71, no. 4, pp. 215–237, Apr. 2016.

[21] Q. J. M. Huys, T. V. Maia, and M. J. Frank, "Computational psychiatry as a bridge from neuroscience to clinical applications," *Nat. Neurosci.*, vol. 19, no. 3, pp. 404–413, Mar. 2016.

[22] J. M. Mateos-Pérez, M. Dadar, M. Lacalle-Aurioles, Y. Iturria-Medina, Y. Zeighami, and A. C. Evans, "Structural neuroimaging as clinical predictor: A review of machine learning applications," *NeuroImage Clin.*, vol. 20, pp. 506–522, 2018.

[23] U.S. Food and Drug Administration, "Clinical decision support software draft guidance for industry and food and drug administration staff," 2019. [Online]. Available: https://www.fda.gov/media/109618/download

[24] A. B. Arrieta *et al.*, "Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI," *Inf. Fusion*, vol. 58, pp. 82–115, Jun. 2020.

[25] A. Adadi and M. Berrada, "Peeking inside the black-box: A survey on explainable artificial intelligence," *IEEE Access*, vol. 6, pp. 52138–52160, 2018.

[26] A. M. Barrett, M. Oh-Park, P. Chen, and N. L. Ifejika, "Neurorehabilitation: Five new things," *Neurology Clin. Pract.*, vol. 3, no. 6, pp. 484–492, Dec. 2013.

[27] M. O. Krucoff, S. Rahimpour, M. W. Slutzky, V. R. Edgerton, and D. A. Turner, "Enhancing nervous system recovery through neurobiologics, neural interface training, and neurorehabilitation," *Frontiers Neurosci.*, vol. 10, pp. 1–23, Dec. 2016.

[28] R. T. Roemmich and A. J. Bastian, "Closing the loop: From motor neuroscience to neurorehabilitation," *Annu. Rev. Neurosci.*, vol. 41, no. 1, pp. 415–429, Jul. 2018.

[29] S. M. Hatem *et al.*, "Rehabilitation of motor function after stroke: A multiple systematic review focused on techniques to stimulate upper extremity recovery," *Frontiers Human Neurosci.*, vol. 10, pp. 1–22, Sep. 2016.

[30] H. Mitchell, "Robotic therapy is on the rise. Here's why," OT Potential Occupational Therapy Resources, Feb. 2018. [Online]. Available: https://otpotential.com/blog/active-assistive-robotic-therapy

[31] N. Takeuchi and S.-I. Izumi, "Combinations of stroke neurorehabilitation to facilitate motor recovery: Perspectives on Hebbian plasticity and homeostatic metaplasticity," *Frontiers Human Neurosci.*, vol. 9, pp. 1–15, Jun. 2015.

[32] A. Venkatakrishnan, G. E. Francisco, and J. L. Contreras-Vidal, "Applications of brain–machine interface systems in stroke recovery and rehabilitation," *Current Phys. Med. Rehabil. Reports*, vol. 2, no. 2, pp. 93–105, Jun. 2014.

[33] S. R. Soekadar, N. Birbaumer, M. W. Slutzky, and L. G. Cohen, "Brain–machine interfaces in neurorehabilitation of stroke," *Neurobiol. Disease*, vol. 83, pp. 172–179, Nov. 2015.

[34] J. Ushiba and S. R. Soekadar, "Brain–machine interfaces for rehabilitation of poststroke hemiplegia," *Neurobiol Disease*, vol. 228, pp. 163–183, 2016.

[35] R. Carvalho, N. Dias, and J. J. Cerqueira, "Brain-machine interface of upper limb recovery in stroke patients rehabilitation: A systematic review," *Physiother. Res. Int.*, vol. 24, no. 2,, Apr. 2019, Paper e1764.

[36] E. López-Larraz, A. Sarasola-Sanz, N. Irastorza-Landa, N. Birbaumer, and A. Ramos-Murguialday, "Brain-machine interfaces for rehabilitation in stroke: A review," *Neuro Rehabilitation*, vol. 43, no. 1, pp. 77–97, Jul. 2018.

[37] M. A. Bockbrader, G. Francisco, R. Lee, J. Olson, R. Solinsky, and M. L. Boninger, "Brain computer interfaces in rehabilitation medicine," *PM&R*, vol. 10, no. 9S2, pp. S233–S243, Sep. 2018.

[38] M. Alam, W. Rodrigues, B. N. Pham, and N. V. Thakor, "Brain-machine interface facilitated neurorehabilitation via spinal stimulation after spinal cord injury: Recent progress and future perspectives," *Brain Res*., vol. 1646, pp. 25–33, Sep. 2016.

[39] R. Sitaram *et al.*, "Closed-loop brain training: The science of neurofeedback," *Nat. Rev. Neurosci.*, vol. 18, no. 2, pp. 86–100, Feb. 2017.

[40] M. Reiner, J. Gruzelier, P. D. Bamidis, and T. Auer, "The science of neurofeedback: Learnability and effects," *Neuroscience*, vol. 378, pp. 1–10, May 2018.

[41] L. R. Hochberg *et al.*, "Neuronal ensemble control of prosthetic devices by a human with tetraplegia," *Nature*, vol. 442, no. 7099, pp. 164–171, Jul. 2006.

[42] L. R. Hochberg *et al.*, "Reach and grasp by people with tetraplegia using a neurally controlled robotic arm," *Nature*, vol. 485, no. 7398, pp. 372–375, May 2012.

[43] J. L. Collinger *et al.*, "High-performance neuroprosthetic control by an individual with tetraplegia," *Lancet*, vol. 381, no. 9866, pp. 557–564, Feb. 2013.

[44] B. Wodlinger, J. E. Downey, E. C. Tyler-Kabara, A. B. Schwartz, M. L. Boninger, and J. L. Collinger, "Ten-dimensional anthropomorphic arm control in a human brain- machine interface: difficulties, solutions, and limitations," *J. Neural Eng.*, vol. 12, no. 1, 2014, Art. no. 16011.

[45] T. Aflalo *et al.*, "Decoding motor imagery from the posterior parietal cortex of a tetraplegic human," *Science*, vol. 348, no. 6237, pp. 906–910, May 2015.

[46] J. R. Wolpaw *et al.*, "Independent home use of a brain-computer interface by people with amyotrophic lateral sclerosis," *Neurology*, vol. 91, no. 3, pp. e258–e267, Jul. 2018.

[47] A. Rezeika, M. Benda, P. Stawicki, F. Gembler, A. Saboor, and I. Volosyak, "Brain–computer interface spellers: A review," *Brain Sci.*, vol. 8, no. 4, pp. 1–38, Mar. 2018.

[48] E. M. Mugler, M. C. Tate, K. Livescu, J. W. Templer, M. A. Goldrick, and M. W. Slutzky, "Differential representation of articulatory gestures and phonemes in precentral and inferior frontal gyri," *J. Neurosci.*, vol. 38, no. 46, pp. 9803–9813, Nov. 2018.

[49] M. Angrick *et al.*, "Speech synthesis from ECoG using densely connected 3D convolutional neural networks," *J. Neural Eng.*, vol. 16, no. 3, Jun. 2019, Art. no. 036019.

[50] G. K. Anumanchipalli, J. Chartier, and E. F. Chang, "Speech synthesis from neural decoding of spoken sentences," *Nature*, vol. 568, pp. 493–498, 2019.

[51] H. A. Agashe, A. Y. Paek, and J. L. Contreras-Vidal, "Multisession, noninvasive closed-loop neuroprosthetic control of grasping by upper limb amputees," in *Progress in Brain Research*, 1st ed. vol. 228. Amsterdam, The Netherlands: Elsevier, 2016, pp. 107–128.

[52] U.S. Food and Drug Administration, "Statement from FDA Commissioner Scott Gottlieb, M.D., on efforts to spur development of innovative devices, including new advancements in novel brain implants, that can help patients with paralysis or amputation gain mobility," 2019. [Online]. Available: https://www.fda.gov/news-events/press-announcements/statement-fda-commissioner-scott-gottlieb-md-efforts-spur-development-innovative-devices-including

[53] U.S. Food and Drug Administration, "Implanted brain-computer interface (BCI) devices for patients with paralysis or amputation—Non-clinical testing and clinical considerations: Draft guidance for industry and Food and Drug Administration staff," 2019. [Online]. Available: https://www.fda.gov/downloads/MedicalDevices/DeviceRegulationandGuidance/GuidanceDocuments/UCM631786.pdf

[54] U.S. Food and Drug Administration, "Brain-computer interface devices for patients with paralysis and amputation; public workshop; request for comments," Regulations.gov. 2014. [Online]. Available: https://www.regulations.gov/document?D=FDA-2014-N-1130-0001

[55] J. J. Shih, D. J. Krusienski, and J. R. Wolpaw, "Brain-computer interfaces in medicine," *Mayo Clin. Proc.*, vol. 87, no. 3, pp. 268–279, Mar. 2012.

[56] G. Sharington, "The true cost of prosthetic limbs: What it means for families," Jordan Thomas Foundation, Jun. 2017. [Online]. Available: https://jordanthomasfoundation.org/true-cost-prosthetic-limbs/

[57] Medicare Payment Advisor Commision, "An overview of the medical device industry," *Rep. Congr. Medicare Health Care Del. Syst.*, pp. 207–242, 2017, [Online]. Available: http://www.medpac.gov/docs/default-source/reports/jun17_ch7.pdf?sfvrsn=0

[58] U. S. Social Security Administration, "Social Security Act §1862." [Online]. Available: https://www.ssa.gov/OP_Home/ssact/title18/1862.htm

[59] Amputee Coalition, "Insurance Fairness for Amputees," [Online]. Available: https://www.amputee-coalition.org/wp-content/uploads/2018/04/insurance-fairness-white-paper.pdf

[60] Gram, Dave. "Amputees fight caps in coverage for prosthetics," USA Today. 2008. [Online]. Available: https://usatoday30.usatoday.com/news/health/2008-06-09-prosthetics-insurance_N.htm

[61] E. Ratti, S. Waninger, C. Berka, G. Ruffini, and A. Verma, "Comparison of medical and consumer wireless EEG systems for use in clinical trials," *Frontiers Human Neurosci.*, vol. 11, pp. 1–7, Aug. 2017.

[62] R. Maskeliunas, R. Damasevicius, I. Martisius, and M. Vasiljevas, "Consumer grade EEG devices: are they usable for control tasks?" *Peer J.*, vol. 4, Mar. 2016, Paper e1746.

[63] A. Hakim and D. J. Levy, "A gateway to consumers' minds: Achievements, caveats, and prospects of electroencephalography-based prediction in neuromarketing," *Wiley Interdiscip. Rev. Cogn. Sci.*, vol. 10, Mar. 2019, Paper e1485.

[64] M.-H. Lin, S. N. N. Cross, W. J. Jones, and T. L. Childers, "Applying EEG in consumer neuroscience," *Eur. J. Mark.*, vol. 52, no. 1/2, pp. 66–91, Feb. 2018.

[65] M. DelPozo-Banos, C. M. Travieso, C. T. Weidemann, and J. B. Alonso, "EEG biometric identification: a thorough exploration of the time-frequency domain," *J. Neural Eng.*, vol. 12, no. 5, Oct. 2015, Art. no. 056019.

[66] S. Marcel and J. R. Millan, "Person authentication using brainwaves (EEG) and maximum a posteriori model adaptation," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 29, no. 4, pp. 743–752, Apr. 2007.

[67] V. A. Maksimenko *et al.*, "Human personality reflects spatio-temporal and time-frequency EEG structure," *PLoS One*, vol. 13, no. 9, Sep. 2018, Paper e0197642.

[68] C. Prata *et al.*, "Callousness and meanness traits are associated with increased N2 amplitude in a community sample of adolescents and adults," *Neurosci. Lett.*, vol. 706, pp. 1–8, Jul. 2019.

[69] V. Paban, J. Modolo, A. Mheich, and M. Hassan, "Psychological resilience correlates with EEG source-space brain network flexibility," *Netw. Neurosci.*, vol. 3, no. 2, pp. 539–550, Jan. 2019.

[70] D. A. Waldman, P. A. Balthazard, and S. J. Peterson, "Leadership and neuroscience: Can we revolutionize the way that inspirational leaders are identified and developed?" *Acad. Manag. Perspect.*, vol. 25, no. 1, pp. 60–74, Feb. 2017.

[71] National Center for Statistics and Analysis, "Drowsy Driving 2015," (Crash-Stats Brief Statistical Summary. Rep. DOT HS 812 446), National Highway Traffic Safety Administration, Washington, DC, USA, Oct. 2017.

[72] R. C. Coetzer and G. P. Hancke, "Driver fatigue detection : A survey," in *Proc. AFRICON*, Sep. 2009, pp. 1–6.

[73] C.-S. Wei, Y.-T. Wang, C.-T. Lin, and T.-P. Jung, "Toward drowsiness detection using non-hair-bearing EEG-based brain-computer interfaces," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 26, no. 2, pp. 400–406, Feb. 2018.

[74] M. Awais, N. Badruddin, and M. Drieberg, "A hybrid approach to detect driver drowsiness utilizing physiological signals to improve system performance and wearability," *Sensors*, vol. 17, no. 9, p. 1–16, Aug. 2017.

[75] M. Ogino and Y. Mitsukura, "Portable drowsiness detection through use of a prefrontal single-channel electroencephalogram," *Sensors*, vol. 18, no. 12, Dec. 2018, Art. no. 4477.

[76] T. Lees *et al.*, "Electroencephalography as a predictor of self-report fatigue/sleepiness during monotonous driving in train drivers," *Physiol. Meas.*, vol. 39, no. 10, Oct. 2018, Art. no. 105012.

[77] T. Brandmeyer and A. Delorme, "Meditation and neurofeedback," *Frontiers Psychol.*, vol. 4, pp. 1–3, 2013.

[78] D. Crivelli, G. Fronda, I. Venturella, and M. Balconi, "Supporting mindfulness practices with brain-sensing devices. Cognitive and electrophysiological evidences," *Mindfulness*, vol. 10, pp. 301–311, Feb. 2019.

[79] Y. Wang, S. Hong, and C. Tai, "China's Efforts to Lead the Way in AI Start in Its Classrooms A fast-spreading use of artificial intelligence in schools from kindergartens to universities provides the country with an unrivaled database," *Wall Street J.*, New York, NY, USA, pp. 1–4, 2019.

[80] H. M. Bednarz and R. K. Kana, "Advances, challenges, and promises in pediatric neuroimaging of neurodevelopmental disorders," *Neurosci. Biobehav. Rev.*, vol. 90, pp. 50–69, Jul. 2018.

[81] L. Q. Uddin, D. R. Dajani, W. Voorhies, H. Bednarz, and R. K. Kana, "Progress and roadblocks in the search for brain-based biomarkers of autism and attention-deficit/hyperactivity disorder," *Transl. Psychiatry*, vol. 7, no. 8, pp. e1218–e1218, Aug. 2017.

[82] V. Abeln, J. Kleinert, H. K. Strüder, and S. Schneider, "Brainwave entrainment for better sleep and post-sleep state of young elite soccer players – A pilot study," *Eur. J. Sport Sci.*, vol. 14, no. 5, pp. 393–402, Jul. 2014.

[83] H. Wahbeh, C. Calabrese, H. Zwickey, and D. Zajdel, "Binaural beat technology in humans: A pilot study to assess neuropsychologic, physiologic, and electroencephalographic effects," *J. Alternative Complementary Medicine*, vol. 13, no. 2, pp. 199–206, Mar. 2007.

[84] U.S. National Library of Medecine, "Comparison of dreem to clinical PSG for sleep monitoring in healthy adults," ClinicalTrials.gov, 2018. [Online]. Available: https://clinicaltrials.gov/ct2/show/NCT03725943?term=03725943%5C&rank=1%7D

[85] U.S. National Library of Medecine. "Comparison of Dreem to Clinical PSG for Sleep Monitoring in Apnea Patients," ClinicalTrials.gov, 2018. [Online]. Available: https://clinicaltrials.gov/ct2/show/NCT03725943?term=03725943%5C&rank=1

[86] A. R. Brunoni and M.-A. Vanderhasselt, "Working memory improvement with non-invasive brain stimulation of the dorsolateral prefrontal cortex: A systematic review and meta-analysis," *Brain Cogn.*, vol. 86, pp. 1–9, Apr. 2014.

[87] A. T. Hill, P. B. Fitzgerald, and K. E. Hoy, "Effects of anodal transcranial direct current stimulation on working memory: A systematic review and meta-analysis of findings from healthy and neuropsychiatric populations," *Brain Stimulation*, vol. 9, no. 2, pp. 197–208, 2016.

[88] C.-H. Chang, H.-Y. Lane, and C.-H. Lin, "Brain Stimulation in alzheimer's disease," *Frontiers Psychiatry*, vol. 9, no. 201, pp. 1–13, May 2018.

[89] W.-Y. Hsu, Y. Ku, T. P. Zanto, and A. Gazzaley, "Effects of noninvasive brain stimulation on cognitive function in healthy aging and Alzheimer's disease: A systematic review and meta-analysis," *Neurobiol. Aging*, vol. 36, no. 8, pp. 2348–2359, Aug. 2015.

[90] K. E. Ravenek, D. L. Wolfe, and S. L. Hitzig, "A scoping review of video gaming in rehabilitation," *Disability Rehabil. Assistive Technol.*, vol. 11, no. 6, pp. 445–453, Mar. 2016.

[91] H. Gurkok and A. Nijholt, "Affective brain-computer interfaces for arts," in *Proc. Humaine Assoc. Conf. Affect. Comput. Intell. Interact.*, Sep. 2013, pp. 827–831.

[92] S. Cass, "Anouk Wipprecht: dynamic dresses merge high fashion and technology," *IEEE Spectr.*, vol. 53, no. 2, pp. 19–20, Feb. 2016.

[93] E. Todd, J. G. Cruz-Garza, A. Moreau, J. Templeton, and J. L. Contreras-Vidal, "Self-conscience/physical memory: An immersive, kinetic art installation driven by real-time and archival EEG signals," in *Brain Art*, A. Nijholt, Ed. Berlin, Germany: Springer, 2019, pp. 309–323.

[94] G. Liberati, S. Federici, and E. Pasqualotto, "Extracting neurophysiological signals reflecting users' emotional and affective responses to BCI use: A systematic literature review," *NeuroRehabilitation*, vol. 37, no. 3, pp. 341–358, Oct. 2015.

[95] Cornell Law School, "21 U.S.C. § 321(h)," Legal Information Institute. [Online] Available: https://www.law.cornell.edu/uscode/text/21/321

[96] govinfo.gov. "public Law 114-255-21st Century Cures Act. 2016. [Online]. Available: https://www.govinfo.gov/app/details/PLAW-114publ255

[97] Cornell Law School, "21 U.S.C. § 360j(o)(1)," Legal Information Institute. [Online]. Available: https://www.law.cornell.edu/uscode/text/21/360j

[98] U.S. Food and Drug Administration. "General wellness: Policy for low risk devices; guidance for industry and food and drug administration staff," 2019. [Online] Avialable: https://www.fda.gov/media/90652/download

[99] U.S. Food and Drug Administration, "Overview of device regulation." Accessed: May 8, 2019. [Online]. Available: https://www.fda.gov/medical-devices/device-advice-comprehensive-regulatory-assistance/overview-device-regulation

[100] L. Beaver, "DIGITAL HEALTH BRIEFING: Apple Watch, Fitbit can detect AFib, study shows — Over half of mHealth apps make $10,000 per year or less — Ex-ATA CEO forms AI group for healthcare - Business Insider," *Business Insider*, 2018. Accessed: May 7, 2019. [Online]. Available: https://www.businessinsider.com/digital-health-briefing-apple-watch-fitbit-can-detect-afib-study-shows-over-half-of-mhealth-apps-make-10000-per-year-or-less-ex-ata-ceo-forms-ai-group-for-healthcare-2018-3

[101] U.S. Food and Drug Administration. "Sec. 801.4 Meaning of intended uses," CFR - Code of Federal Regulations Title 21. 2019. [Online] Available: https://www.accessdata.fda.gov/scripts/cdrh/cfdocs/cfcfr/CFRSearch.cfm?FR=801.4

[102] U.S. Food and Drug Administration, "Digital health innovation action plan," 2017. [Online]. Available: https://www.fda.gov/media/106331/download

[103] U.S. Food and Drug Administration, "Digital health software precertification (Pre-Cert) program," 2020. Accessed: May 7, 2019. [Online]. Available: https://www.fda.gov/medical-devices/digital-health/digital-health-software-precertification-pre-cert-program

[104] A. Manero *et al.*, "Implementation of 3D printing technology in the field of prosthetics: past, present, and future," *Int. J. Environ. Res. Public Health*, vol. 16, no. 9, p. 1641, May 2019.

[105] D. G. Blazer, S. Domnitz, and C. T. Liverman, *Hearing Health Care for Adults*. Washington, DC, USA: National Academies Press, 2016. [Online]. Available: https://pubmed.ncbi.nlm.nih.gov/27280276/

[106] B. Blankertz *et al.*, "Neurophysiological predictor of SMR-based BCI performance," *Neuroimage*, vol. 51, no. 4, pp. 1303–1309, Jul. 2010.

[107] P. Hutt, R. Merrill, and L. Grossman, "Food and drug law," 2014.

[108] United States v. Travia, US Dist Court, 180 F. Supp. 2d 115. 2001. [Online]. Available: https://casetext.com/case/us-v-travia

[109] U.S. Food and Drug Administration, "The sentinel initiative," 2010. [Online]. Available: https://www.fda.gov/media/79652/download

[110] B. J. Evans, "The genetic information nondiscrimination act at age 10: GINA's controversial assertion that data transparency protects privacy and civil rights," *William Mary Law Rev.*, vol. 60, no. 6, pp. 1–93, 2019.

[111] H. Matsumoto and Y. Ugawa, "Adverse events of tDCS and tACS: A review," *Clin. Neurophysiol. Pract.*, vol. 2, pp. 19–25, 2017.

[112] M. Luctkar-Flude and D. Groll, "A Systematic review of the safety and effect of neurofeedback on fatigue and cognition," *Integr. Cancer Therapies*, vol. 14, no. 4, pp. 318–340, Jul. 2015.

[113] R. Kuner and H. Flor, "Structural plasticity and reorganisation in chronic pain," *Nat. Rev. Neurosci.*, vol. 18, pp. 20–30, Jan. 2017.

[114] W. Liu *et al.*, "The role of neural plasticity in depression: From hippocampus to prefrontal cortex," *Neural Plast.*, vol. 2017, 2017.

[115] E. Nava and B. Röder, "Adaptation and maladaptation," *Progress Brain Res.*, vol. 191, pp. 177–194, 2011.

[116] H. Maslen, T. Douglas, R. C. Kadosh, N. Levy, and J. Savulescu, "The regulation of cognitive enhancement devices: Extending the medical model," *J. Law Biosci.*, vol. 1, no. 3, pp. 68–93, 2014.

[117] P. J. Zettler, C. J. Guerrini, and J. S. Sherkow, "Regulating genetic biohacking," *Science*, vol. 365, no. 6448, pp. 34–36, Jul. 2019.

[118] B. J. Evans, "Minding the gaps in regulation of do-it-yourself biotechnology," *DePaul J. Health Care Law*, vol. 21, no. 3, 2020.