The Seductive Allure of Artificial Intelligence-Powered Neurotechnology

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Abstract

Neuroscience explanations—even when completely irrelevant—have been shown to exert a "seductive allure" on individuals, leading them to judge bad explanations or arguments more favorably. There seems to be a similarly seductive allure for artificial intelligence (AI) technologies, leading people to "overtrust" these systems, even when they have just witnessed the system perform poorly. The AI-powered neurotechnologies that have begun to proliferate in recent years, particularly those based on electroencephalography (EEG), represent a potentially doubly-alluring combination. While there is enormous potential benefit in applying AI techniques in neuroscience to "decode" brain activity and associated mental states, these efforts are still in the early stages, and there is a danger in using these unproven technologies prematurely, especially in important, real-world contexts. Yet, such premature use has begun to emerge in several high-stakes settings, including the law, health & wellness, employment, and transportation. In light of the potential seductive allure of these technologies, we need to be vigilant in monitoring their scientific validity and challenging both unsubstantiated claims and misuse, while still actively supporting their continued development and proper use.

Introduction

The effort to "decode" human brain activity and associated mental states is one of the most important of our time, promising to improve our understanding of human thinking and behavior, treat psychiatric and neurologic disorders, and enable advances in brain-computer interfaces (BCIs), among many other benefits. Yet, it is also one of our most challenging endeavors. To help make sense of the vast amounts of brain data being collected, machine learning (ML) and other artificial intelligence (AI) techniques are increasingly being applied in neuroscience research (Sejnowski, Churchland, and Movshon 2014; Vu et al. 2018). While this has proven fruitful—and could in turn drive further advances in ML and AI research (Hassabis et al. 2017)—brain decoding is still in the very early stages, with a way yet to go.

Despite this nascent state, however, neurotechnologies—and increasingly those based on electroencephalography (EEG)—are being used outside of the research lab in important, real-world contexts for which they are often inappropriate. In India, for example, a form of EEG decoding called Brain Electrical Oscillation Signature Profiling (BEOS) has been used—purportedly—to peer into an individual's mind to determine if they had committed a crime (Puranik et al. 2009). This is simply not possible given current capabilities, and yet the results of such tests have been submitted as corroborative evidence in numerous criminal cases. While there have been few if any convictions so far, and a landmark Indian Supreme Court case overturned one conviction that had included BEOS evidence because such techniques violate the "right against self-incrimination," the Court held open the possibility that BEOS evidence could still be used in cases in which a defendant voluntarily submitted to testing (Smt. Selvi & Ors vs. State of Karnataka, Criminal Appeal No. 1267 of 2004, Judgment on 5 May 2010). The possibility of such continued use and the potential to contribute to criminal convictions represents an unwarranted level of trust in an unproven technology for critical, life-altering decisions.

Unfortunately, there is a long history of using scientifically unsubstantiated techniques in ways that affect people's lives and liberties. For example, many forensic techniques—such as bite mark, firearms, and even fingerprint analyses—have minimal or even no scientific basis, but are still regularly used in court, where they have led to numerous wrongful convictions that were later overturned by rigorously validated DNA evidence (Academies 2009). Given that the best EEG decoding accuracy often barely exceeds chance levels, it is currently much more akin to discredited bite mark analysis than DNA analysis.

In addition to the legal setting, EEG devices are seeing premature use in health & wellness, employment, transportation, and other high-stakes areas of society, where they are frequently touted as being “AI powered” (e.g., BrainCo 2018). The primary danger shared across these contexts is that AI-powered EEG decoding could augment or replace traditional assessments of a person’s mental state—what they are thinking, feeling, or remembering, whether they are lying, or how they are performing—despite the fact that such decoding has not proven nearly accurate or reliable enough to be trusted in this way.

Unwarranted trust in these technologies and the potential for harm might be exacerbated by the fact that neuroscience and AI have each been shown to exert a “seductive allure” that could make AI-powered EEG devices a potentially doubly-alluring combination. For example, neuroscience imagery and explanations—even when completely irrelevant to the context—have been shown to exert this seductive allure on individuals by leading them to judge arguments or bad explanations more favorably (Weisberg et al. 2008; McCabe and Castel 2008). With AI, this seductive allure manifests as “overtrust” (Wagner, Borenstein, and Howard 2018), and is the tendency for people to defer to “intelligent” technology, even when they have just seen that technology perform poorly (Robinette et al. 2016).

It is worth noting that more recent work has painted a nuanced picture, in which brain imagery might not be especially seductive (Farah & Hook 2013), the allure of neuroscience explanations might owe primarily to their reference to reductive, fundamental components and processes rather than neuroscience per se (Hopkins, Weisberg, and Taylor 2016), and the level of trust in intelligent systems likely differs in specific contexts (Yanco et al. 2016). Still, there is enough evidence to be wary of—and reason to further study—the potential for AI-powered EEG to elicit an unwarranted amount of trust in unproven technologies that increasingly claim “mind-reading” abilities (Wexler and Thibault 2018).

Given the potential seductive allure of combined AI and EEG technology, and our lamentable history using unsubstantiated forensic techniques, safeguarding against the premature and inappropriate use of EEG decoding in high-stakes areas of society seems to present us with a difficult challenge. We need to be vigilant in monitoring the scientific validity of this technology and drawing attention to its inappropriate use, while still actively supporting its continued scientific development and proper use.

EEG Primer and Decoding Capabilities

To decide whether a particular use of EEG is valid and appropriate, it is absolutely vital to understand the scientific basis of the technology and its current capabilities in that context. In this section we underscore the promising uses of EEG in science and medicine, and why it is ill-suited for many of the important real-world contexts in which it is beginning to emerge.

EEG involves noninvasively recording (from the scalp) the electrical activity of a subset of neurons in the brain’s cortex, or outer, bark-like layer (Nunez and Srinivasan 2006). Because it is noninvasive and thus one of the few methods that can be safely used with humans, EEG has proven very useful in a number of medical and scientific applications over the last several decades, such as monitoring seizure activity (Vespa 2005) or the effects of anesthesia (Purdon et al. 2015), assessing sleep, and helping us begin to understand the brain basis of higher cognitive functions like attention, perception, memory, and language (Purves et al. 2013).

Many of these more traditional uses of EEG, particularly in medicine (e.g., monitoring seizures, sleep, or anesthesia), are not generally considered to be “decoding,” but rather informative brain monitoring and diagnostics that are performed in concert with other clinically relevant physiological and behavioral assessments under direct supervision of a physician or other healthcare professional. Instead of these more traditional uses of EEG, here we will focus primarily on attempts to decode mental states such as emotions, attention or focus, lying/truthfulness, and even individual thoughts and memories, as such attempts are the least substantiated by scientific evidence and yet most poised for inappropriate use in high-stakes contexts.

AI Techniques Applied to EEG: Promise and Limitations

Efforts to decode mental states from EEG activity have been bolstered in recent years with the application of AI techniques. These have included both unsupervised, data-driven approaches like independent or principal component analysis (Hyvarinen et al. 2010; Kottaimalai et al. 2013) and supervised, classification approaches like support vector machines (Amin et al. 2015) and state-of-the-art deep learning methods like convolutional neural networks (Schirrmeister et al. 2017). These approaches have produced some promising results. For example, accuracy in decoding emotional states like happiness and sadness can sometimes be quite high, above 90% (reviewed in Kim et al. 2013). A recent study was even able to produce impressively similar visual reconstructions of face images that had been shown to experimental participants by decoding the EEG patterns elicited when they watched the image flash on the screen (Nemrodov et al. 2018).

Despite these promising results, however, there is still a way to go before EEG devices, even those using advanced AI analyses, prove themselves accurate and reliable enough for high-stakes uses in the real world. First, it is important to emphasize that the results reported in the scientific literature represent the absolute best possible decoding capability, taking place in laboratory contexts that have many advantages over real-world contexts. In the lab, there is complete control over the experimental manipulations, data quality and quantity, and—extremely important for EEG—the exact timing of the experimental stimuli, to name just a few of the advantages. So, as impressive as Nemrodov and colleagues' (2018) ability to reconstruct what someone had seen by decoding their EEG activity may be, their ability to do so depended entirely on their experimental control over and access to the face images shown to participants. Even with state-of-the-art AI methods, such a reconstruction from experiences of faces in the real world would currently be impossible.

The successful lab results themselves may not be as accurate as they first appear or as robust as the real world would demand. For example, seemingly high accuracy in classifying emotional state is often for datasets with a very small number of classes, usually only two to six (reviewed in Kim et al. 2013); clearly, we spend our days in vastly more than two to six different mental states, making these high accuracies a gross overestimation. In many other areas, particularly in trying to classify "cognitive" states such as level of focus or what a person is paying attention to, accuracies are often statistically significant but barely above chance (e.g., Samaha, Sprague, and Postle 2016; Fahrenfort et al. 2017). Worse still, statistical comparisons to theoretical chance (e.g., 50% in a two-class problem) are often inappropriate for the small datasets typical of experiments in cognitive neuroscience (Combrisson and Jerbi 2015), leading to further overestimation.

Finally, because this limited decoding capability is probably most attributable to fundamental limitations of the EEG signal itself rather than to shortcomings in the AI analytics, it may be unlikely to improve significantly. For example, EEG (and really all neural) activity does not have a direct, unique relationship with specific mental states, and so measuring that activity often does not reveal very much by itself. And while the fact that EEG is noninvasive can be a great strength, it also means that EEG measures only a small fraction of the brain's total activity, and thus gives only a partial, incomplete window into our mental lives. On top of that, electrical signals from the brain are reduced *1000-fold* as they make their way to the scalp, where much larger electrical noise—such as from nearby electrical equipment and even from the eyes and head & neck muscles—can corrupt them. Together, these characteristics act as inherent limitations on the capabilities of even AI-powered EEG decoding.

It should be clear that, currently, EEG decoding has not established itself as accurate or reliable enough for many of the important, real-world contexts in which it is beginning to emerge. Yet, this technology seems to have gained an unwarranted level of trust—perhaps owing to a seductive allure—that is driving its increased adoption and use, and the growing potential for real harm.

Real-World Uses of AI-Powered EEG

In this section we present some of the most salient real-world contexts in which AI-powered EEG is being used and near-future uses that are beginning to appear on the horizon. The primary danger shared across these different contexts is that traditional assessments of a person's mental state are being, or have the potential to be, supplanted by AI-powered EEG decoding that is often extremely limited in its accuracy and reliability. We also discuss some of the ethical and social issues that arise from this often inappropriate use and present some policy recommendations.

Law

As discussed above, the putative EEG-based decoding of mental content—such as BEOS in India and related forms of "memory recognition" in the US (Harrington v. State, 659 N.W.2d 509, Iowa 2003)—has entered the legal setting, where it is threatening to supplant traditional forms of evidence and human judgment in a way that could imperil people's lives and liberties. For example, what if the kind of impressive memory "reconstruction" from the Nemrodov et al. (2018) study cited above—which, again, would not be possible in the real world—began to influence or even replace traditional means of determining the credibility of a witness's memory? What if the increasingly—but deceptively—high accuracy in decoding emotional state led to its being applied to determine the underlying emotional character of testimony, or even its truthfulness? Developments like these would be highly concerning.

Fortunately, it does seem that much of this potential harm is—so far at least—unrealized. The Indian Supreme Court, for example, overturned a criminal conviction that had included BEOS evidence (Smt. Selvi & Ors vs. State of Karnataka, Criminal Appeal No. 1267 of 2004, Judgment on 5 May 2010), and the Iowa Supreme Court set a favorable precedent by not even considering the EEG-decoding evidence in Harrington v. State (Harrington v. State, 659 N.W.2d 509, Iowa 2003). And recent, much-needed empirical work on the topic of EEG memory-recognition evidence found that, although people's evaluations of (fictional) criminal defendants were in fact impacted by the presentation of EEG evidence, it was not "seductively" so, and instead the primary determinant was the overall strength of the case (Shen et al 2017).

While this recent work is important and worth considering, it is part of a larger literature that remains controversial and very much unsettled. Much more work needs to be done, especially on the potential seductive allure of AI-powered EEG specifically, which to our knowledge has not been studied. Further, in light of our regrettable history using unsubstantiated forensic techniques that demonstrably led to wrongful convictions (Academies 2009), we all—especially neuroscientists and AI researchers, in addition to ethicists, lawyers, and judges—need to remain vigilant and prepared to challenge the use of AI-powered EEG decoding in the courtroom.

Health & Wellness

For improving traditional, clinical uses of EEG (i.e., brain monitoring and diagnostics)—and thus people's lives—the application of increasingly advanced analysis techniques, including from AI research, does hold great promise. For example, convolutional neural networks have been used to help improve seizure prediction (Truong et al. 2018), and support vector regression has helped improve the tracking of brain maturation in preterm infants (Stevenson et al. 2017). Importantly, these types of clinical brain monitoring are performed in a rich medical context, collected in concert with other physiological measures and behavioral assessments, and used to augment the expert decision-making of physicians and other trained professionals.

In contrast, there is a growing market for direct-to-consumer, AI-powered EEG devices that, while explicitly marketed for "general wellness," often make implicit claims or allusions to medical benefit that are largely unsubstantiated by scientific evidence (Wexler and Thibault 2018). These claims are often predicated on the ability to decode, in real time, a user's mental or emotional state. For example, a company called NeuroPlus markets an EEG-based system that claims to measure levels of attention and provide neurofeedback "attention training" using games for children, employing "advanced AI analytics" on the back end (NeuroPlus 2019). Their website features salient allusions to helping children with ADHD, followed by more hidden, explicit disclaimers to the contrary.

While some of these consumer EEG devices might do little more than waste people's time and money, ones with clearer allusions to medical benefit could lead people to base important medical decisions, such as whether to seek professional help or continue an existing treatment, on unsubstantiated claims. But, since the device companies are careful to avoid explicit medical claims, they avoid regulation by the Food and Drug Administration (FDA 2016), which has largely chosen not to enforce regulation on low-risk devices marketed for general wellness purposes. Regulation instead falls to the Federal Trade Commission (FTC), which is charged with holding businesses accountable for deceptive claims; however, such claims from consumer EEG companies remain as yet unchallenged by the FTC. It is thus important to continually draw attention to any unsubstantiated claims, warn consumers of their dubious nature, and challenge consumer EEG companies to either back up their claims with legitimate evidence or remove them.

Employment

In the hopes of gaining a competitive advantage, major companies around the world are beginning to employ a rapidly growing panoply of AI-powered biometric technologies, including facial expression, speech, and, on the horizon, EEG analysis. For example, companies like Unilever are using facial expression analysis to assess applicants' emotions during the hiring process (Zetlin 2018), and a company called Humanyze sells employee ID badges that monitor employees' conversations for things like tone and who participated—the content, they say, is left out (Heath 2016; Nicholas 2018). What many of these companies are ultimately after is a way to assess employees' mental states—their emotions, level of focus, stress, etc. Given that EEG is actually a measure of brain activity, it represents something of a "holy grail" of such AI-powered biometric analyses, and already several companies are marketing the use of AI-powered EEG decoding in professional settings (e.g., Versus 2018; Emotiv 2018).

While it is unclear at this point which companies are actually using EEG devices at any kind of scale in the US, a recent report from China suggests that already several companies, some backed by the government, are engaging in large-scale "brain monitoring" of workers by using EEG sensors embedded in the hats and helmets of their uniforms and sending the data to "computers that use artificial intelligence algorithms to detect emotional spikes such as depression, anxiety or rage" (Chen 2018). Such "emotional spikes" can get a worker reassigned to another post or sent home for the day.

Despite the dearth of evidence that such AI-powered EEG determinations of employees' mental state are accurate or provide any novel insight, they already seem to have begun supplanting established, often interpersonal, evaluation and assessment methods in the workplace. Not only does this threaten workers with arbitrary consequences that can negatively impact their livelihoods, it raises important issues of personal, mental privacy and sets a dangerous precedent for a possible future when legitimately accurate brain decoding actually does exist. To set a better precedent, employers should look beyond the hype and avoid using AI-powered EEG in the workplace; workers and workers' rights advocates should draw attention to any such proposed use; and lawyers and regulators should be prepared to issue challenges if such use does become more widespread.

Transportation

Manufacturers of automated vehicles have for several years been exploring the use of EEG-based systems to decode human drivers' mental states to enhance communication between driver and vehicle (e.g., O'Kane 2018; Kastrenakes 2015). There is a great need for such enhanced communication—especially in semi-automated vehicles that require a human driver to stay engaged and be prepared to take control when necessary (NHTSA 2017)—as there is abundant evidence that humans are not able to sustain attention for extended periods, especially in routine, monotonous tasks like driving (Langner and Eickhoff 2013). Further underscoring the urgency of this need, there have already been several fatal crashes involving semi-automated vehicles that were attributable to human-engagement failures (NTSB 2018a, 2018b) and in fact "overtrusting" the capabilities of the vehicle.

We need to ensure, however, that possible enhancements to driver-to-vehicle communication actually improve the situation and make it safer, rather than pursue solutions that seem alluring but are actually ineffective and potentially harmful. In this regard, EEG-based decoding of mental states exists in a gray area. For example, given that the stages of sleep are largely defined by EEG (Purves et al. 2013), it is certainly plausible that an EEG-based system could be used to detect driver drowsiness. But, given EEG's limitations, to merit such use a system would first need to prove demonstrably accurate for a wide variety of drivers in real-world contexts. Ideally, it would also perform better than more traditional alternatives, such as camera-based ones with increasingly robust eye-closure and gaze detection (Fridman 2018), or even basic self-monitoring mechanisms ("I'm tired, I should pull over and rest") that could be eroded by overtrusting the EEG's decoding capabilities.

Jaguar's approach highlights the potential for real harm: they have teamed up with Freer Logic, the maker of a brain-decoding headrest that they claim can detect drowsiness "as much as 4 minutes before one's eyes begin drooping or drifting, giving [this] technology a leg up on camera-based drowsiness detectors" (Freer Logic 2019). In addition, it can supposedly decode a driver's cognitive load, distraction, relaxation, emotion, and stress. Incredibly, they claim to be able to do all this without actually contacting the driver's head, instead operating successfully from up to 6-10 inches away. These claims are not only completely unsubstantiated by evidence, they are truly unbelievable and dangerous.

To prevent further, potentially fatal harm, vehicle manufacturers should seriously consider avoiding semi-automated vehicles that require sustained engagement from drivers. Given how unlikely this seems, companies should at least be very skeptical of the value, and wary of the harms, that even AI-powered EEG systems could add. The National Highway Traffic Safety Administration (NHTSA), which is currently taking a very hands-off approach to regulating automated vehicles (NHTSA 2017), should demand more from makers of semi-automated vehicles to ensure that their driver-to-vehicle communication functions are effective and safe, a demand that consumers should echo. Finally, as is always a useful first step, attention needs to be drawn to these potentially inappropriate uses of AI and EEG technology, especially by experts in AI, neuroscience, and human factors.

Conclusion

While promising, EEG decoding—even when backed by our most advanced AI analysis methods—is still an immature science. Despite this immaturity, however, such decoding has begun to leave the research lab and enter important, real-world contexts for which it has not proven itself nearly accurate or reliable enough, including the law, health & wellness, employment, and transportation. Compounding the potential for harm, research has shown that *AI-powered* EEG technology, as it is increasingly branded, might exert a potent, seductive allure to be overly trusted and dangerously misused. Our primary goal here has been to draw increased attention to this evolving situation, propose some possible policy solutions, and encourage broader engagement and vigilance from a diversity of stakeholders, from experts with important domain-specific knowledge to ethicists, lawyers, policymakers, and members of the public.

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