Analog vs. Digital: Amplifying Feedback for Learning

Nicholas Armendariz
University of Central Florida
Orlando, FL
Nick.armendariz@knights.ucf.edu

JJ Walcutt
Clay Strategic Designs
Orlando, FL
drjjwalcutt@claystrategicdesigns.com

ABSTRACT

Information accessibility continues to expand as technology becomes ubiquitous across platforms within arm's reach. A particular area in which this accessibility has been seen is the availability and prevalence of bioinformatics. Personal electronic devices and wearables are shifting the way people view, understand, and utilize technology to receive feedback about themselves. The development of smart technology and nanotechnology has improved the ability for tools to be ergonomically designed and, perhaps more importantly, be cost-effective to consumers. Drivers exist for data-driven and personalized learning, but a road map is often not given. The aim of this paper is to provide a broader understanding of how these tools may be utilized in enhancing the cognitive processes and shaping the modernization of personalized learning. Included in the discussion will be a review of current and emerging technologies, tools, and software to gain insight into their capabilities and leverage points for learning. The paper will discuss trends in the cognitive sciences to demonstrate how findings like 4E Cognition may help improve the understanding of benefits gained from these tools' feedback. Feedback is embedded in the military training and education process and enhanced by existing M&S tools. The appropriate synthesis and application of these scientific findings and innovative tools can make the information received more impactful by providing a path forward on its utilization. Finally, this paper intends to demonstrate a framework for learners and facilitators of learning to integrate these tools and science to develop more efficient, effective learning.

ABOUT THE AUTHORS

Nicholas Armendariz is an ABD Doctoral student at the University of Central Florida's School of Modeling, Simulation, and Training. He is pursuing his PhD in Modeling and Simulation, with a focus in the cognitive sciences, an area in which he has already completed a Graduate Certificate. He is a former USMC Naval Flight Officer in the EA-6B platform and is currently serving in the US Navy as an Aerospace Experimental Psychologist, serving as the department head at the Naval Aerospace Medical Institute's Operational Psychology department.

JJ Walcutt is a learning scientist and strategic designer of modeling and simulation training systems. Her current work focuses on optimizing human cognition and performance across a wide spectrum of learning programs, including neuro-informed military training, data-driven higher education planning, and talent development optimization.

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INTRODUCTION

With each passing year, the development of technology has continued to progress by leaps and bounds at a seemingly record-breaking pace. One highlight of this progression is increased ease of access to technology devices that provide physiological feedback to users. What began as very basic data in the early stages of wearable technology has integrated data into applications, websites, and personalized intelligence. Essentially, this development has resulted in the transition of laboratory-only wearables to omnipresent, inexpensive, commercially available products that are widely used across the public sector. The next phase of this progression is to make meaning from their information. Initially, there will be questions about the accuracy of such information and about how it is presented to the user. Is it delivered in a digestible message that they can understand and ultimately act on? Just as a concerto composed and played without error to the untrained ear is just a song, the raw, unfiltered, unprocessed information are just numbers on a page. Thus, this paper has in view to discuss the types of information made available with these technologies, understand what they aim to provide to the users, and more importantly, bring focus to how facilitators of training and education, as well as learners themselves, can make deliberate and useful meaning from the information that is being provided.

History of Biosensing

A biosensor is a device that takes a biological response and turns it into a digital signal (data) (Mehrotra, 2016). The onset of biosensors can trace its roots back to the early 1960s with Leland Clark, the scientist who designed the first oxygen detector (Mohanty & Dougianos, 2006). Since then, significant advancements have occurred with more parts of the body being analyzed, and while technology with biosensing capabilities, often referred to as wearables, are not new, the fidelity of their data has varied over time. The most common wearable, the watch, demonstrates the progression of the data available to the user. At first, these were common, but the intelligent version of wearables has only become prevalent in recent years. To be utilized more often and easily, the objects needed to be, as they state, wearable, as well as convenient, compact, and readily incorporable with other devices. Early on, the terminology of "smart" meant that it did more than tell time in the case of watches. With the availability to connect via Bluetooth or other connection and ability to connect to the internet of things (IOT), these technologies increased their functionality, the parts of the body on which they could be worn, and the variability in the metrics returned (Xue, 2019). Growth of these devices has predominantly focused on two categories: wearability and connectivity (or ability to be a smart device).

Over the past decade, the accuracy and volume of data has substantially increased, and when combined with the heightened accessibility to multiple wearables, a data rich environment for the savvy user has been created. Accordingly, developers are becoming increasingly focused on finding a means to the raw data from the body and providing it to the user by creating a connection through an application or interface take for the user to understand the information provided (Hassib et al., 2016). For the purposes of this paper, the authors propose biosensing as any tool that provides physiological, emotional, medical, or mental data.

Data in Learning Settings

To date, education has largely followed an industrial model that treats learners as widgets moving through a factory, receiving a series of add-ons as they progress through the metaphorical factory line. At the end, each widget is certified as able to perform the same tasks as all the other widgets. For the military, this has been a necessity, for large volumes of personnel were needed to fill all the positions for national defense. As can be seen in the three-year typical rotation cycle, the ability to fill any position with nearly any qualified human was crucial. But as the war of cognition evolves and becomes prominent, it will be the minds and decisions of our service members that need to be optimized and specialized.

This evolution has urged the research community to determine how to enhance cognitive capabilities, increase decision making agility, and create self-regulated learners. It is no longer enough to provide one-size fits-all curricula; there is too much to learn, and the sophistication of the material is increasing beyond levels that every person can comprehend. Rather, it is important to adjust teaching materials and pathways to the leaner's unique needs in order to clarify and optimize their specialized skills and raise all other capabilities at a rate faster than that in a generalized setting. To accomplish these goals, decisions for training must be data-driven, and the data needs to be of the highest quality, be provided in real-time, be analyzed just as quickly across multiple experiences, and be compared to multiple learners. More precisely, data-driven, personalized learning interventions based on neurological data are expected to improve learning outcomes by 44% (Chae, 2020).

Using data allows for a deeper understanding of the learner and what they need, which in turn leads to an increase in the precision of intervention application. The guesswork required by humans to interpret behavior as representative of emotions, cognitive readiness, and ability is removed. Personalization of the material, pathway, and timing of application allows all interventions to be purposeful and targeted. It reduces redundancy of material that is already mastered, substantially reducing negative training by adjusting instruction or experiences in real time. Wearables have been the necessary, albeit elusive, key to these types of training structures. The early prototypes included too much noise in the data to be useful, and the apparatus was too cumbersome for operational use. Now that these products are largely commercially available, inexpensive, and non-invasive, their ability to provide the needed data has accelerated. With this data, so many decisions can be made and modernized learning structures can be created, but more is still needed: we need a data highway to manage all this information; we need analysis capabilities that allow us to make sense of the information; and we need to know what to buy and how to best apply it to drive training. Thus, the primary research areas are beginning to look less at the development of neuro-assessment apparatus and more at what they can afford the learner, instructor/facilitator, and military training enterprise. Central areas of focus currently include the ability to control actions with the mind alone and the ability to provide trainees, or even in operations, technology elements that will offload data and analytical cognitive activities in favor of managing the human's cognitive load during learning or stress or on the battlefield (Walcutt et al., 2022).

FEEDBACK

Biofeedback

There are various basic types of biofeedback that supply information about the body's functioning. Some examples include electromyography (EMG), photoplethysmography (PPG), thermal or temperature, electrocardiograph (ECG), electrodermography (EDG), and electroencephalography (EEG). While there may be others, these are the most common methods of biofeedback used in the systems discussed in this paper. The most understood of these are EEG (which uses sensors on an individual's head to capture brain waves) and ECG (which measures heart rate and heart rate variance through sensors). Wearables have also taken advantage of items such as EDG (measures the activity of sweat glands) and photoplethysmography (uses light sensors to measure blood volume changes) by incorporating them into their devices to give the user additional data.

Bioinformatics

Bioinformatics aligns itself with biology and computer science. More on the computational side – conducting analyses at the molecular level – it centers on the acquisition, storage, analysis, and dissemination of biological data in DNA and amino acid sequences (*Bioinformatics*, 2016). This type of biosensing and analyses will not be discussed in large part in this paper but is worth defining to disambiguate from the others.

Biohacking

Biohacking is when humans use technology to enhance their performance, health, well-being, or even their interactions with technology. While early examples, like smart fasting or meditation, could be viewed as interventions aimed at improving body health and performance, recent research has shown that individuals are now turning to technological augmentation to improve themselves. Typically, these are embedded technologies in the form of electronic tattoos (biostamps), memory chips, magnetic implants, or even guidance systems (Gangadharbatla, 2020). The similarities between wearables and biohacking align with the real-time capture of personal data. But the differences grow from there, as biohacking often has more risk associated with its adoption and requires the user to be more knowledgeable about the technology in order to create the connections for use (Gangadharbatla, 2020).

Neurochemical Measurement

While it is not new to focus on the neurobiological processes that are involved in learning, applying knowledge of how these basic elements in the body affect efficiency and effectiveness in real-world training contexts is just emerging. Dating back to the late 1990s, research that combines education and training practices with real-time neurophysiological measurements has been funded by the US military (Walcutt et al., 2020). In its infancy of application, the focus was almost entirely on how to accurately measure what was happening in the brain during learning experiences in simulated environments. These early prototypes were messy (they required gel to be applied to the scalp for the electrodes to read accurately), cumbersome (upwards of 180 electrodes were needed to capture data), and noisy (sensors gathered accidental data from the environment and subject movement that reduced accuracy). Based on these issues, work in this area of research largely ceased from prominence until recently (Walcutt et al., 2020), as newly developed apparatus addresses these issues and provides robust data that can deepen our understanding of the unique learning experiences of each trainee and possibly help personalize their experience for optimization.

To that end, ten neurochemicals are of particular interest to the learning community. These include excitatory chemicals (endorphins, glutamate, noradrenaline, adrenaline, and dopamine), regulatory (serotonin, oxytocin, and GABA), cognitive (acetylcholine), and stress (cortisol; see fig. 1). Combined, they have notable impacts on the emotional state of learners, their awareness of material and other elements, and arousal, which allows them to attend and digest the information being provided. More specifically, serotonin regulates mood and sleep cycles (Jenkins et al., 2016), norepinephrine supports attention (Beane & Marrocco, 2004), oxytocin allows students to feel relaxed during learning (Borden, 2020), and dopamine promotes confidence (Badri et al., 2018), while endorphins are the fuel for thinking and understanding material (Koestler, 1981). Finally, glutamate and cortisol are regulatory chemicals that manage boredom and anxiety (Seli et al., 2019). Once these are understood and measurable, it is easy to imagine an optimized formula that defines "learning readiness" and a set of target chemical levels to achieve across each quadrant. Accordingly, direct feedback to the learner, instructor, or simulation can drive decisions or interventions to help create an optimal internal chemistry environment, like a common goal to design a classroom, or an optimal external learning environment.

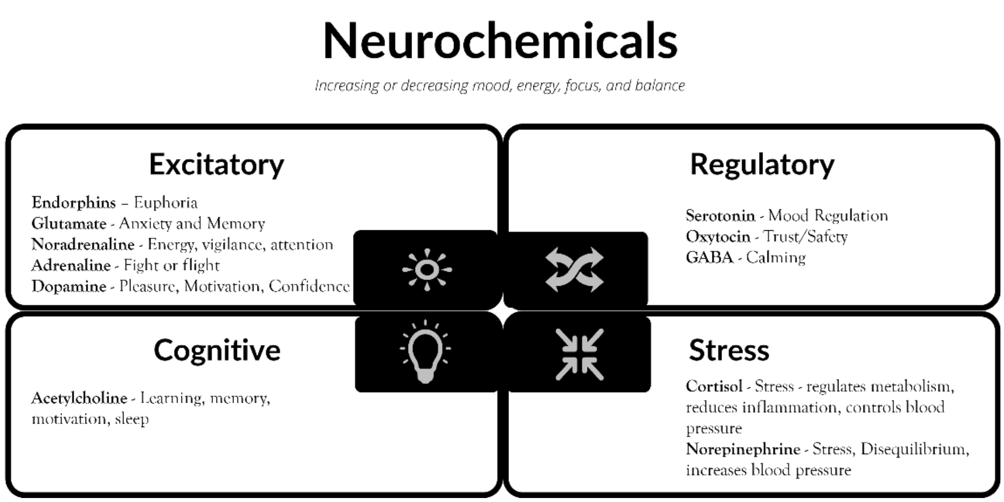

Fig. 1. Neurochemicals involved in learning.

4E COGNITION

To connect the data provided by biosensors of varying types to the learning process, it is necessary to consider the research in cognition and theories that can best guide actionable interventions. Specifically, advances in the cognitive sciences have led to a framework, known as 4E cognition (4EC), that represents four areas of cognition as one: embedded, embodied, enactive, and extended. Ecological cognition should be viewed as an add-on to this model as well. 4E cognition is a means to holistically understand how the brain and body interact with the environment for learning and work to enhance the learning experience (Walcutt et al., 2022). Collectively, these areas of cognition function as an ecosystem impacting one another in the cognitive process (Newen et al., 2018).

Embodied cognition involves knowledge of the body's involvement with and understanding of the environment around it, specifically with how the distribution of information is concerned (Wilson & Foglia, 2011). This distribution of information is across the brain, body, and environment and is supported by the interaction of the three to receive, infer, and digest information. Embedded cognition refers to information that is either received from and affected by the changes in the environment or made more tangible by environmental cues, which affect human understanding (Dawson, 2014). Enactive is driven by the combination of activity and cognition, merging the internal processing with the interaction of the environment surrounding a person (Gallagher & Lindgren, 2015). One can liken this to a baseball outfielder who has to track the ball off the bat and move their body in time and space, all while making the calculations to arrive at the ball before catching it in the glove. Lastly, extended cognition extends the mind out into the environment (Aizawa, 2014). This is the most understood portion of 4EC, as the cognitive processes are offloaded onto environmental supports like a piece of paper or whiteboard, connecting one's ideas in palpable ways (Clark & Chalmers, 1998).

Holistic Change to Person

Keeping 4EC in mind, one can begin to make the connections with wearables, cognition, and then to learning. The more enriched the data available to learners, the more it can, first, help them understand themselves better and, second, understand perhaps when they are best prepared to learn and further utilize the information to convert it into holistic improvements for themselves.

Take, for instance, the example of jewelry wearables like the Oura ring, which combines the use of PPG, EDG, temperature, and an accelerometer to track various user activities and provide a metric for understanding quality of sleep, activity, and overall readiness. It does this by producing a quantitative sleep score comprising several factors: various levels of sleep, including REM sleep and deep sleep patterns; activity from comparisons of physical activity patterns; readiness, which incorporates resting heart rate, heart rate variability, temperature, prior sleep, and activity (Carper et al., 2020). These are presented via the interconnectedness of an application viewed on a personal electronic device. The question, in addition to opportunity, is whether the user can understand the information given to them.

Items such as the Fitbit and Apple Watch have been around for quite some time, giving users tracking of their physical activity and, with recent updates, even their sleep patterns. But what does it mean to consider an overall readiness score? The DoD measures readiness from a unit's ability to fight and meet the demands of their assigned mission (DoD, 2017), but its domain is at the higher level. Wearables like the Oura ring then have the potential to have discussions at the individual level and, if consolidated, a combined level. The individual may now consider the holistic effects of physiological factors like sleep, physical activity, and rest periods to determine their potential for performance. This awareness can habituate users to their normal patterns in life and alert them to changes, as well when those changes may be harmful or indicative of something else. The US National Basketball Association (NBA) even saw these used in the early onset of COVID-19 in 2020 as a potential early predictor of contraction of the virus by alerting users to changes in sleep patterns or body temperature change (Pickman, 2020). Evidently, the opportunity exists for users to understand far more about themselves as a system than ever before.

What it Means for Learning

Human performance is not restricted to physical performance, and if the information is properly gathered, analyzed, and implemented toward change, it can see an increasing influence on learning. Given the NBA's and other sports teams' uses of devices that inform users of the impacts their life patterns have on future performance, consider how this would affect learning.

It is not uncommon for a student to claim that they just had a bad test day, or that they "weren't up for the task" on that given day. If they had a device to notify them of their patterns, perhaps they would have known that they would not be ready to perform that day. If learners, like athletes, were able to determine when to perform based on readiness scores, could the indices of their learning improve? Would they be able to identify patterns in or trends for various types of performance that can help educate them on subtle changes to improve their performance?

Another example of technology that may improve the understanding of these cognitive patterns is the EEG. Traditionally speaking, these have been bulky items that were not conducive to tracking users during movement or outside of a laboratory setting. However, recent improvements have allowed for sensor improvement and even creation of a lighter headset. The EEG is growing in research for its direct measurement capabilities and, with these advancements, uses of as few as 8 nodes (Walcutt et al., 2020). These measurements can be meaningful to demonstrate brain activity and items such as alertness, frustration, attention, and cognitive load (Vogel-Walcutt, 2019). Systems that provide these measurements, like the QNeuro headset, can apply these patterns to optimizing users' learning efficiency and knowledge retention by staying in the heightened state of alertness or optimal position for the cognitive load.

NEUROSCIENCE

Understanding the science behind the data is key. We have described the basics of the neurochemicals and their impact on the body during learning, but it is the organization of these and management of their levels that will have a significant impact on learning readiness, engagement, and ultimately the ability to apply what is learned in context. Thus, the goal is to create a safe-feeling learning environment that will allow the mind to be focused entirely on the material at hand rather than loaded with concerns about other facts, such as the rank of other trainees, complexity of the material, or fear of failure. Ensuring that oxytocin, serotonin, and GABA are high is important, while managing cortisol release is mandatory (Walcutt et al., 2022).). Being alert and engaged requires endorphins, adrenaline, and dopamine, but the levels of these chemicals need to be optimized rather than aiming for as high as they can be produced (Kruger & Dunning, 1999). Too much of the excitatory chemicals and one is easily distracted, while too little of them results in poor performance. Acetylcholine can help with the processing of information, helping align it with previously learned material that now resides in long-term memory (Beane & Marrocco, 2004).

The information needed then is a general wave of data that clarifies where, relative to self, these chemical levels lie in comparison to where the optimal levels should be for the best learning readiness. To accomplish this, wearable devices would need to output in standard form readings of each of these chemicals' levels, combine them meaningfully using advanced analysis techniques, and then provide that information to the learner, instructor/facilitator, and/or synthetic platform to help drive various interventions that will affect these chemicals and keep the learner in a constant state of heightened flow (Walcutt et al., 2020). Even basic interventions – such as taking a walk when arousal declines, listening to music when cortisol rises, or ensuring a proper breakfast that supports serotonin levels – can have a positive effect (Chae, 2020). More targeted interventions are expected to have a substantive increase in utility and impact.

SYNTHESIS AND APPLICATION OF FEEDBACK

Design of Learning

Designing learning interventions based on neuro-data can be relatively simple to highly complex. At the lowest level of intervention, a dashboard providing a diagnostic review of the learner prior to learning can inform the individual or instructor about their readiness to learn and possible manually applied interventions, such as walking, focusing on specific types of knowledge, like declarative or integrated, or choosing a specific subject to learn. At the highest level, a highway of data, also known as a total learning architecture (Smith, Gallagher, Schatz, Vogel-Walcutt, 2018), can be created to ingest the neuro-data into a data lake of other information and use artificial intelligence analyses to determine the optimal interventions, focus areas, speed of instruction, and pathway for learning, which can be combined into an algorithm that drives optimized outputs for the learner and uses their created experiences to generate more data that continually improves the personalized model. Both levels, and many in between, are currently in development for deployment in the operational training areas. The precision of intervention is expected to correlate with the impact, but how much is necessary to achieve the optimized balance of data and personalized instruction has not yet been determined. For military specifically, the important lesson in this design phase is that the collection of data is necessary. However, this reality is likely the most difficult to overcome, as it will require a shift in thinking about personal ownership over internal experiences that, to date, have not been readable by outside entities.

Actionable Information

One of the most important aspects of these technologies is to make the information actionable. This is where devices have failed in the past – by creating uninterpretable data dumps with which users are unable to do anything. Much like the NBA players with the Oura ring, learners would need to understand the "so what" of the data that is presented to them. In the context of the DoD, it would require individuals and supervisors alike to be able to read the data and interpret how they affect the current mission or daily task to be completed.

The data cannot be overly simplified, either. A criticism of producing seemingly arbitrary scores, like readiness from the Oura ring, is their ambiguity, and without an understanding of what the data mean, the user is left to treat them as just that: arbitrary scores. However, it can help when the user knows that the readiness score incorporates body temperature, heart patterns, and sleep, and tools can further assist the learner by providing guidance on what those mean. Oura has done this in recent updates, indicating that scores below 60, for instance, mean to "take action to rest and recharge" (Carper et al., 2020).

Information Accessibility

The unfortunate side of application is trying to determine who has rights and privileges to the information that is gathered. Though these wearables provide information helpful to the user, how then can their organization, whether in a classroom or on a battlefield, be able to utilize the information without gathering the rest of it? The other question being if the instrument were able to provide additional information, would it be utilized?

Take, for example, the roll out of Garmin watches that were provided to the US Navy's F/A-18 and E/A-18 Growler aircrew. They were provided these watches to alert crews to the cockpit physiological episodes in the aircraft. The watch (Garmin 3 series) has the capability to track heart rate, physical metrics, sleep patterns, and even altitude, but the focus was on the physiological episodes. Could patterns have been tracked, or information gathered on aircrew's restfulness, by requiring them to log their data to the Operations Duty Officer (ODO) before going flying? Likely, but then who would have control of the data? While it is a requirement for aircrews to have a minimum of eight hours uninterrupted rest prior to a flight event (Chief of Naval Operations, 2021), it is not enforced, despite the information being readily available.

Like this thought, would the current DoD training and education framework be amenable to shifting learning battle rhythms and timelines for students who may not be ready in alignment with training and readiness milestones for their particular career path?

Make Meaning of Information

Moving forward, this will challenge learners, facilitators, and policy makers to define utility, discuss privacy, and intentionally plan for implementation of the information that can be provided by these wearables.

At the individual level, they must take inventory of where their individual gaps may lie and, if offered the opportunity to utilize one or more of these tools, take into consideration where it may have improvements. If they are not provided by an organization, then the return on investment should be considered for purchase on one's own.

Additionally, the unit or organization must determine the worth of the information. As human performance optimization in the past has focused on physical readiness considering physical exercise and activity, diet, and mental readiness, it must consider in the future the ability to track the data, understand what their compilation means, and how to use the information. The organization must then also be ready and willing to adapt training plans or, when able, adjust mission to take advantage of the optimal state of readiness as collective of the unit's individuals.

Finally, policymakers need to question whether the right to data privacy outweighs the opportunity for optimization or even the ability to increase safety within a unit. Consider the example of the Garmin series watches given to an aircrew. Was a unit able to determine if there was chronic fatigue among its aircrew, and did it then have the ability to prevent the next mishap due to poor decision making, which likely was a side effect of fatigue? Is the ROI then worth the cost of a wearable and understanding its data?

SUMMARY

Technology comes at a rapid pace, often at an increasing price, and with promises of affordances to the user. The key, however, is blending the emergent findings of cognitive science, research of modeling and simulation, and experience of training and education to make the most of it. Deliberately planning for the integration of the research into practice is the first step to this increase in return on investment. The next step is understanding what these technologies can present in feedback, potentially leading to the bigger leap toward improving human performance. Leadership should reflect on their organization's receptiveness to these changes and adaptability to implement them. When they do, this feedback becomes immediately actionable and can result in growth in learning.

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