Title

Transcending the classroom using digital wearables

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Abstract

'Learning by doing' is the central underpinning principle of experiential learning, an effective and proven approach for developing holistic student competencies. Laboratory environments are a crucial hands-on element in science and engineering education, but they are not always representative of practical situations that students will face in the future. Here, we describe a first-of-its-kind course specifically designed to address the challenge of offering meaningful active learning by teaching students about systems analysis, data science, Internet of Things (IoT), and digital health using data collected by the students on themselves using a digital wearable device. The breadth and depth of student experiences in this pilot course have the potential to define a new paradigm for the classroom in which instructors can employ innovative new technologies to increase student engagement by transcending the classroom learning environment and traditional practices. We highlight the opportunities, challenges, and pedagogical insights involved in employing wearable technology in a classroom, offering a blueprint to enable others to design similar hands-on courses to make science and engineering concepts more accessible through the integration of new technologies.

Introduction

Experiential Learning (EL) immerses learners in activities and real-world experiences, enabling them to analyze outcomes critically, extract key concepts, and apply newfound knowledge to different scenarios (Gosen and Washbush 2004; Katula and Threnhauser 1999; McCarthy 2010; Qualters 2010; Smart and Csapo 2007; Usher and Solomon 1999). The cornerstone of EL theory lies in its definition of learning as a dynamic process wherein knowledge emerges through the transformation of experiences. Knowledge evolves through the fusion of comprehension and the transformation of experiences (Kolb 2015; Morris 2020). The intentional immersion in experiences and reflective introspection culminate in the cultivation of novel knowledge and competencies (Lewis and Williams 1994).

The far-reaching advantages of EL extend their positive impact to learners, educators, and various stakeholders, including academic institutions, as evidenced by extensive research. From the learner's perspective, EL harnesses holistic abilities, spanning cognitive capabilities and attitudes, alongside acquiring task-specific technical and professional skills (Boose 2004; Freeman et al. 2014; Kolb and Kolb 2009). From the educator's perspective, EL facilitates instructors in adapting innovative pedagogical approaches and guiding students toward deeper insights into course concepts and their practical applications (Fenton and Gallant 2016). This pedagogical approach sustains and amplifies student engagement, motivation, and participation—crucial components of active learning—while providing a wealth of data and research insights for future advancements in pedagogy and instructional strategies. Curriculum-Integrated Experiential Learning (CIEL) is a more structured and measurable approach to improve the quality of opportunities and experiences aimed at advancing students' learning. Unlike conventional EL—which can be sporadic and may not align with the course objectives—CIEL deliberately embeds activities into the curriculum in which students purposefully apply and enhance their disciplinary knowledge and skills through real-world projects and experiences. One illustrative example can be found in computer science courses, where coding is often taught in isolation. Through CIEL, students could collaborate with local startups on actual software development projects, applying their coding skills in a real-world context. CIEL opportunities can be adapted across various environments and formats, including case studies, field schools, and laboratory sessions.

Although EL and CIEL offer invaluable learning opportunities that traditional classroom settings cannot easily replicate, creating these opportunities beyond the classroom setting is a complex endeavor. Not all experiences contribute to meaningful learning—poorly designed experiences and activities can even be counterproductive (Chan and Chen 2022; Drummond et al. 1998; Hedin 2010; Holman et al. 1997). Resource constraints add another layer of complexity, as EL often necessitates additional investments in personnel and specialized equipment, particularly in fields like engineering. Furthermore, incorporating EL into existing curricula can impose an administrative burden (Katula and Threnhauser 1999; Lewis and Williams 1994; Moore 2010). One primary limitation of CIEL is the frequency of hands-on activities, which is often constrained by limited access to expensive equipment and lab spaces. For instance, a course on signal processing across various engineering disciplines could greatly benefit from regular laboratory experiences and hands-on activities (Passino and Yurkovich 1998; Yurkovich and Passino 1999). Unfortunately, this requires access to specialized equipment and labs, making it logistically challenging. Another limitation is the narrow or specific focus of these experiences. For example, in a machine learning course, students may get opportunities to analyze data and design data-based solutions to real-world problems; they seldom get exposed to the crucial steps of data collection, preparation, and pre-processing. Industry experts affirm this is a crucial skill set, yet it is often absent from the curriculum. Student engagement presents yet another challenge; many learners are accustomed to traditional modalities, such as lectures, and may resist the increased workload and time commitments that EL entails. Democratizing access to EL to ensure inclusivity and quality is an equally pressing issue (Chan 2022). Thus, significant challenges remain in the effective implementation of EL and CIEL: *how do we provide consistent, impactful learning experiences that enrich knowledge, sharpen skills, and foster critical insights?*

The use of digital wearables has been rapidly expanding in healthcare, providing researchers and clinicians with continuous data to supplement the episodic clinical data obtained via the standard of care (Perez-Pozuelo et al. 2021). Wearable imaging devices can provide insight into previously unmeasurable modalities like exercise cardiac function (Hu et al. 2023). Devices such as smartphones, watches, and rings collect valuable data that can diagnose disease (Mason et al. 2022) and assess physiological signals relevant to student learning (Carroll et al. 2020). Virtual and augmented reality has been used as a training tool (Geroimenko 2020; Kim et al. 2023), but other wearable devices have not yet been widely integrated into the classroom as educational tools. It is clear that digital health is a growing field in which the next generation of scientists, clinicians, and engineers need training (Yurkovich et al.). Yet digital health technologies can be utilized for more than just the study of human health—they can be applied in all kinds of educational environments to transcend the current limits of classroom learning.

We attempt to address these challenges by illustrating how modern technology—in the form of digital wearable devices—can enable learning to transcend the traditional classroom environment. *Digital wearables* such as smart rings and watches offer immense potential for enhancing active and EL by overcoming previously discussed limitations. Unlike traditional methods, where the frequency of EL is sporadic and often focuses on isolated aspects, smart rings enabled continuous data collection both inside and outside the classroom. This approach helped transcend conventional classroom learning boundaries by offering students an extended and holistic experience. Throughout the semester, students engaged in real-time data collection, processing, and analysis, thus gaining a comprehensive understanding of all facets of the course. Utilizing these smart wearables in our course has led to a richer array of out-of-class activities and reflective opportunities to improve the understanding of the subject matter and enhance problem-solving skills.

Here, we outline our efforts to develop a curriculum-integrated EL opportunity for graduate-level engineering students. First, we assess the impact of integrating smart wearables into an engineering course on student engagement and skill development. Second, we examine the feasibility, advantages, and limitations of using wearables for data collection and analysis in an educational setting. Third, we provide a review of our experiences for educators looking to incorporate wearable technology into their teaching methodologies. Finally, we discuss the pedagogical goals and implications of our research program and how we hope it can impact engineering education moving forward.

Pilot course structure and design

Our initial pilot offering of the course “Systems Analysis in Digital Health” took place at the University of Texas at Dallas in the Spring 2023 semester. The class size was limited to 12 students, split evenly between the Systems Engineering (SYSE) and Bioengineering (BMEN) departments. Of the 11 students who matriculated, all were pursuing graduate degrees: 6 MS students and 5 PhD students. All 6 MS students were in the SYSE Department (there is no PhD degree program in the SYSE Department) and had received undergraduate degrees from UT Dallas in Bioengineering, while the majority of the doctoral students had backgrounds in something other than bioengineering (electrical or computer engineering).

The course was designed as a project-based course whose goal was to teach systems analysis and data science techniques using digital health data collected via a wearable device (Fig. 1). The project was designed to have students:

- collect data on themselves throughout the semester using a provided Oura Ring Gen3 (https://ouraring.com), a commercially available wearable device (Oura Health, Oulu, Finland) at no cost to the student;
- build a secure system to store, access, and analyze the data;
- and use signal processing and machine learning approaches to identify and analyze trends in collected signals.

No prior knowledge of biology or human health was required for enrollment in the course. The only prerequisite listed was a course in signals and systems, which is typically in undergraduate curricula in most engineering disciplines. Lectures covered a variety of topics, including systems analysis, data science, and digital health. As this is a highly interdisciplinary topic—and the students’ backgrounds were quite diverse—the planned syllabus was updated several times based on surveys and student feedback to cover specific topics such as principal component analysis (PCA), an introduction to supervised and unsupervised machine learning, and signal processing through wavelet analysis.

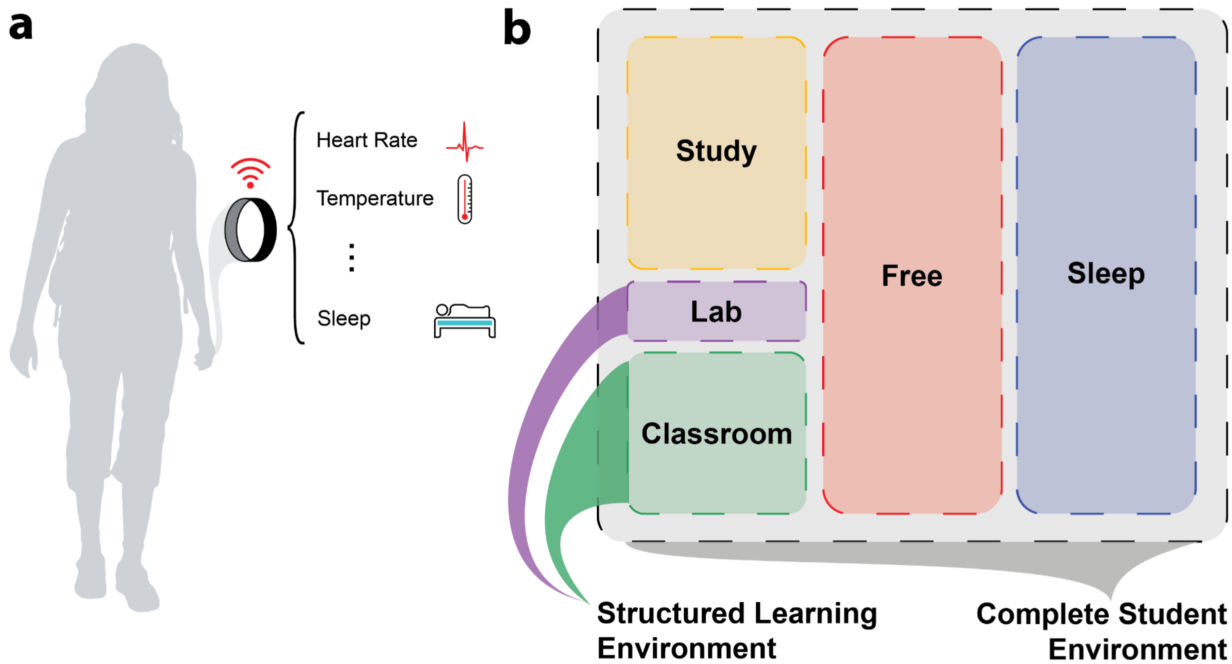

Fig. 1 Integrating a wearable device into the curriculum allows the instruction to transcend the classroom. (**a**), A wearable device worn by students captures digital health data such as heart rate, body temperature, and sleep patterns. (**b**) Students wearing the device collect data outside the typical structured learning environment, capturing their complete daily routines instead of being limited to artificial constraints for data collection.

The course learning objectives were defined as:

(1) Participate in the collection, processing, and analysis of real-world digital health data through the class project.
(2) Understand the importance of various aspects of data science (e.g., storage, normalization) in the life sciences.
(3) Be exposed to different areas of study that rely on data science to push the boundaries of human knowledge of biology and improve human health.
(4) Design and implement a full-stack systems engineering application capable of accessing real-time data from an Internet of Things (IoT) device.

To drive toward each of these learning objectives, students were also expected to read an assigned scientific article in the area of digital health systems each week. Students were given a short reading comprehension quiz designed to also teach them how to read scientific articles, followed by a short presentation of that week's article by one student each week. Each lecture was thus split into four parts:

(1) Reading comprehension quiz on that week's assigned scientific article,
(2) Presentation by a student on that week's assigned scientific article,
(3) Formal lecture by the instructor, and
(4) Hands-on project work session.

Table 1. Summary of student project study design and data collection.

Project Goal (Research Question)	Additional Data (beyond provided wearable device)
To explore the effect of caffeine intake and exercise on sleep	● Survey to assess caffeine consumption and exercise habits ● Add tags in wearable app to record caffeine consumption ● Add workouts in wearable app (if not automatically detected)
To assess the effect of college classes on students' physiological parameters	● Survey to assess class schedule ● Add tags in wearable app to record when exams/quizzes start and end ● Addgs in wearable app to record type of classroom experience (e.g., lecture, quiz)
To determine whether the color of ambient noise impacts sleep	● Add tags in wearable app to record ambient sleep conditions (temperature, humidity, noise) ● Add tags in wearable app to record the time of last exercise, food intake, and fluid intake ● Daily survey to record perceived wellness of sleep
To optimize workout efficiency using data from a wearable device	● Survey to assess typical workout activities ● Use the wearable app to record high-resolution heart rate during workouts ● Add tags in wearable app after a workout to record the type of work
To use a combination of digital wearable devices to detect stress	● Daily survey to record perceived stress level ● Data from another wearable device (student already owned and used)

The project work sessions were split between structured and unstructured sessions. Structured sessions saw students work through a designed notebook that actively demonstrated a topic discussed in the lecture. Some of these sessions used toy data (e.g., demonstrating how a machine learning classifier works), while others were based on the students' wearable data (e.g., showing students how to access a specific day's data). Unstructured project work sessions were an opportunity for students to work on their projects with the instructor present to answer any questions. These sessions turned out to be highly interactive, both with students asking questions of the instructor but also student groups working together to understand and solve mutual problems.

Student experiences in the pilot offering

Students were divided into five project teams and tasked with deriving a research question their project would answer (**Table 1**). Student assessments were built around these projects, with both written and oral proposals and written and oral presentations of final results. The oral proposals were designed to teach future researchers how a research idea is proposed and critiqued and were evaluated by a panel of four faculty members (from the Systems Engineering and Bioengineering departments).

Beyond EL, the initial intent of the pilot course was to focus on data science: the actual analysis of the data the students collected on themselves. The logistics of distributing the devices and gaining access to the full research-level data was more involved than anticipated, however, and so the analysis of the student data was delayed by several weeks. This change had the unintended positive consequence that the first third of the course was dedicated to study design and data collection—fundamental engineering concepts that are rarely effectively taught in a classroom or laboratory environment. This opportunity to design their studies that included themselves stimulated a lot of enthusiasm and excitement and many ideas for various 'biohacking' experiments the students wanted to perform.

This student enthusiasm centered around designing their own projects with their own data—data that meant something to them and to which they could relate. Over the course of the semester, students reported that they were changing their own habits (mostly around exercising and sleep) based on the data collected by the wearable devices. Students were quite ambitious with their study designs, asking that the study participants (consisting of all 11 students and the authors of this article, the first of which was the instructor for the course) collect additional, manually recorded data in addition to what was passively captured by the wearable devices (**Table 1**). Students were instructed to wear the rings while sleeping and for an additional 4-6 hours of waking time. Compliance was high, with students wearing the rings for an average of 88.6% of the available time for the semester (note that maximum is not 100% due to the devices requiring charging every 4-6 days).

At the conclusion of this pilot course, we evaluated the student experience. We determined through interaction with the students that there were three major learning outcomes for the students based on their experiences in the course:

> *Outcome 1: Training in Study Design.* One area that is particularly challenging to address in a classroom environment is study design. Standard principles related to designing hypotheses and research questions can be effectively taught, but some of the more valuable training is related to designing feasible studies, ensuring a reasonable burden on study participants (for human studies), and planning contingencies to cover unanticipated outcomes. Involving students in the design process and requiring them to carry out a 12+ week study allows them to participate in the complete process and experience common pitfalls of the design process.
>
> *Outcome 2: Training in Data Collection.* The collection of data—one of the most crucial aspects of any experimental discipline—is difficult to effectively teach because of the unpredictability of real-world research. When humans are the research subjects, this unpredictability is multiplied exponentially (Gibbs et al. 2007). In a controlled, laboratory environment, the fundamentals of good data collection practice (e.g., quality assurance, quality control) can be taught; but how do we handle edge cases that arise in research? How do we modify our processes and designs to account for missing data? Collecting real-world data exposed students to some of these challenges and potential solutions. Even more valuable, however, was that students were able to see how their own behaviors—for example, not adhering to (potentially overly strict) study protocols—impact the data and, ultimately, the scientific rigor of a study.
>
> *Outcome 3: Training in Real-World Data Science.* Traditional data science courses focus on the actual data science—the methods and algorithms that are applied to data to gain insights.

> However, it is well understood in professional and research settings that 80% or more of working with real-world data involves processing the data, with only a small fraction involving analytics (e.g., performing feature engineering, applying machine learning techniques) (Raschke and Charron 2021). By collecting data in a real-world setting (i.e., not in an artificial classroom or laboratory environment), students were exposed to these aspects of data science.

It was evident from the student projects that they were required to critically think as a result of being thrust into the research process. Multiple faculty members representing both the Departments of Systems Engineering and Bioengineering attended student proposals for study design and provided detailed feedback to students and assessed their progress. For example, one student group explored the question of "Can I trust the data from this wearable device?" by running their own validation against a gold-standard device (chest-worn heart rate monitor) and reporting the results; such critical thinking would not have occurred if the students had simply been provided with a pre-prepared dataset.

Logistical and administrative processes for using wearables

Implementing a course that included the use of wearables included additional planning to ensure that the devices were obtained, that the students had data access in time to complete the learning objectives, and that we were compliant with regulations regarding the collection of data from students and the privacy of the data (Fig. 2). In this section, we detail some of these steps to provide a blueprint for others to replicate in the future.

As our course was a graduate-level engineering course, our emphasis was on research. To allow for the use of the wearable data to be included in research studies, we involved the University of Texas at Dallas' Office of Research and Innovation as we designed and implemented the course for approval from the Institutional Review Board (IRB). An IRB-approved study protocol allows de-identified data collected by the students to be shared in scientific studies for research purposes.

There were two major hurdles faced in our initial pilot offering: (1) obtaining the devices from the vendor and (2) obtaining the high-resolution research data from the vendor. Unlike wrist-worn devices (smartwatches), rings come in various sizes and thus could not be pre-ordered before the start of the semester. Students were asked to use one of the provided sizing kits to wear a sizer overnight and report back their desired sizes. Once all students were sized, rings were ordered and received within 10 days.

Due to how the order was placed in the system, students did not get to choose their color (black or silver) and thus all received black rings; several students expressed displeasure at not being able to select the color of the device, but the aesthetics of the device were not determined to impact the compliance of whether students wore the device.

The wearable devices chosen for the course (Oura Ring Gen3) retails at US$300, with an additional monthly subscription for data access. Further, research-level data access was negotiated with the vendor for an additional monthly charge (assessed based on the number of users). This research platform allowed the data to be de-identified and accessed by the instructor, limiting concerns of data privacy. The Department of Systems Engineering sponsored the course, with no cost to the students for participation in the course. At the conclusion of the course, students returned the devices and the

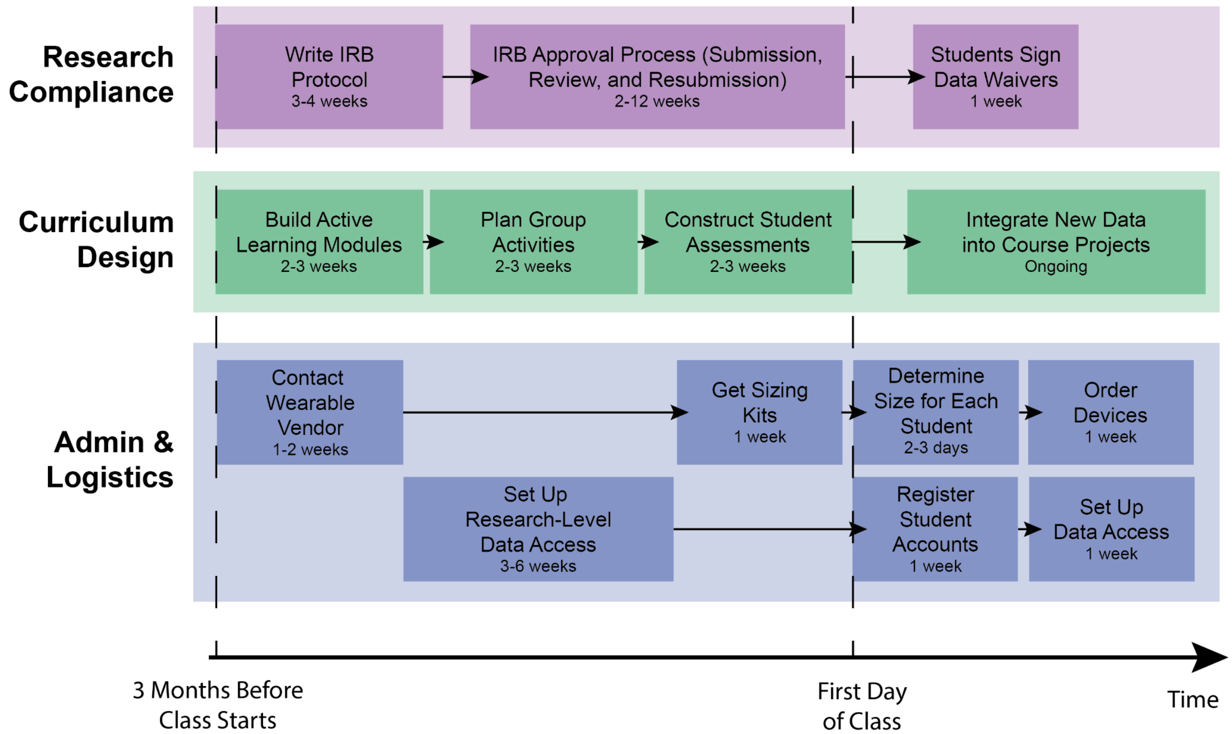

Fig. 2 Checklist and timeline for planning and implementation for a wearable-based CIEL course.

charger for the device. With each iteration of the course, we will continue to build a small library of devices, thus reducing the cost for each subsequent offering.

One of the challenges we encountered with our EL approach is the "personalized experience" conundrum: how do we ensure that students have comparable experiences in this course? We strove to overcome this challenge in two ways. First, students gave presentations to the group on their project. A proposal of their research question and project design was evaluated by a faculty panel and the other students at the beginning of the project, and a summary review of their findings at the end of the semester. Second, students participated as test subjects in all projects, not just their own. There were multiple open discussions for the entire class to decide what data various groups were asking to collect so that all students were aware of what each group was trying to do. These discussions were useful, as some students were able to piggyback on the study designs of others to address shortcomings of their own studies.

How can biometrics provide insights to improve active learning?

Advancing students' learning through technology is an increasingly pertinent topic in educational research. The use of biometric data offers an exciting frontier to understand and optimize student engagement and learning processes. We can monitor this data in real time and over extended durations by using wearables (smart rings) that collect multidimensional biometric data—such as heart rate, temperature, sleep patterns, respiration rate, and oxygen saturation. The challenge lies in identifying how these biometric indicators correlate with crucial factors influencing students' learning, such as engagement, stress levels, focus, motivation, and social connectedness. Addressing this challenge would offer actionable insights to both students and instructors. Thus, we suggest three main directions to explore:

1. the relationship between biometrics and the factors affecting student learning,
2. how students can harness this data to enhance their own learning, and
3. how instructors can use the biometric data to fine-tune instructional strategies for better learning outcomes.

In the following subsections, we discuss the transformative potential of biometric data gathered through wearables. We explore how these advanced measurements can not only quantify key factors influencing students' learning but also offer actionable insights for refining educational methodologies, thereby elevating the quality of learning experiences.

Student Engagement. Student engagement plays a pivotal role in the effectiveness of learning processes and consists of behavioral, emotional, and cognitive elements (Fredricks et al. 2004; Lawson and Lawson 2013). Numerous studies have demonstrated a tangible correlation between high levels of student engagement and improved academic performance. Accurately measuring this engagement is crucial for a range of applications, from tailoring pedagogical strategies to informing educational policy. However, capturing this multifaceted construct is complex due to its subjective and dynamic nature. Engagement is not a static construct but fluctuates over time due to various academic and non-academic factors, including classroom environment, teaching methodology, and even time of day. Short-term measurements may not capture these variations effectively. Traditional methods—such as self-reporting and observational techniques—often fall short in capturing the real-time and longitudinal aspects of engagement.

Wearable technology presents a promising avenue for enhancing the reliability and scope of engagement assessment. Unlike self-report methods, wearable devices equipped with biometric sensors provide objective, quantifiable data. These devices monitor physiological markers such as heart rate, temperature, skin conductance in real-time, allowing educators to make immediate adjustments to instructional methods. For example, sustained elevated heart rates could signify heightened cognitive or emotional engagement. By leveraging the correlation between physiological responses and human behavior, wearables can offer a more comprehensive, long-term and unbiased evaluation of student engagement. There has been increased interest in linking biometric measures and student engagement by exploring the relationship between physiological markers and cognitive or emotional states (Bustos-López et al. 2022; Darnell and Krieg 2019; Darnell and Krieg 2014; Senthil and Wong 2017; Ventura and Porfiri 2020). Although these studies suggest promising correlations, there remains many opportunities to further explore technology-mediated applications aimed at sustaining and evaluating students' participation and engagement over time.

Stress Measurements. Stress exerts a complex impact on learning by affecting memory retrieval and cognitive flexibility among students and teachers (Vogel and Schwabe 2016). Elevated stress levels can lead to academic underperformance and hinder educational outcomes. Additionally, a bi-directional relationship exists between stress and sleep, which is a critical predictor of academic success (Alvaro et al. 2013). Elevated stress impacts sleep quality and quantity (Kalmbach et al. 2018; Querstret and Cropley 2012), and there is a growing literature showing that sleep is an important predictor for success in college (Creswell et al. 2023; Herawati and Gayatri 2019; Lund et al. 2010).

Smart wearables offer a novel avenue for continuously monitoring stress through various physiological markers, such as respiratory rate and Heart Rate Variability (HRV) (Can et al. 2019; Hasanbasic et al. 2019; Iqbal et al. 2022; Sano 2016). Stress-inducing procedures lead to changes in respiratory rate and heart rate. Studies have shown a robust association between respiratory rates and stress levels among college students (Bloomfield et al. 2023). Similarly, neurobiological evidence suggests that HRV is impacted by stress and supports its use for the objective assessment of stress with lower HRV values typically indicating elevated stress levels and higher values suggesting a rested and recovered state (Kim et al. 2018). Wearables like the Oura Ring (employed in this study) have the capability to monitor HRV and sleep patterns, offering valuable insights into tracking stress levels as well as disease detection (Mason et al. 2022). Moreover, studies have validated the accuracy of heart rate and time-frequency domain HRV parameters collected by these devices (Cao et al. 2022), thus making their use and data collected from them more credible.

Therefore, smart wearables hold promise for mitigating the adverse effects of stress on student learning by enabling real-time monitoring and facilitating targeted interventions. These wearables also empower students to become more cognizant of their emotional states and stress levels, encouraging proactive stress management. Furthermore, aggregated stress data can inform institutional decision-making, leading to the development of targeted stress-reduction programs. This may include revising exam schedules, offering stress-management workshops, or enhancing mental health services on campus.

Similarly, wearable technology offers an unprecedented avenue for investigating various other factors, including *social connectedness*, that influence learning outcomes (Carroll et al. 2020). One of the key advantages of employing wearables lies in their ability to capture real-time, naturalistic measurements of students' biological and physiological responses during various activities. This granular data enables nuanced inferences about how learners react to specific pedagogical approaches. As research instruments, digital wearable devices hold immense promise for advancing our understanding of the ways in which classroom environments and teaching methods affect students' physiological and cognitive states. Moreover, they serve as a powerful conduit between the field of education and the extensive research in psychology and neuroscience concerning cognitive processes like attention, memory, and learning.

The future of digital wearables as learning tools both inside and outside the classroom

Here, we have reported on what is, to our knowledge, a novel application of digital wearable technologies in a classroom setting. We have designed a CIEL course that utilizes digital wearables to transcend the classroom environment and teach graduate-level engineering students about study design, data collection, and data analysis. This case study serves as a proof of concept, establishing the feasibility of incorporating digital wearables as educational tools in a CIEL course. One avenue we are pursuing for future iterations of our course is to include data from active research studies to provide the students with additional real-world data for their course projects. These additional data would not only improve the research-related learning objectives by increasing the sample size, but it would allow us to more directly test the hypothesis that student engagement is increased by collecting and analyzing their own data. We anticipate that new digital wearable technologies will continue to be integrated into the classroom to fuel innovative teaching approaches and allow the learning to transcend the classroom.

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