

Let's Get Physical: K-12 Students Using Wearable Devices to Obtain and Learn About Data from Physical Activities

By Victor R. Lee, Joel Drake, and Kylie Williamson, Utah University State University

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Abstract

Accessibility to wearable technology has exploded in the last decade. As such, this technology has potential to be used in classrooms in uniquely interactive and personally meaningful ways. Seeing this as a possible future for schools, we have been exploring approaches for designing activities to incorporate wearable physical activity data tracking technologies to help students learn how to interpret data. This article describes four instances of designed learning activities in which wearable physical activity data tracking devices in use with K-12 students. Of special note is how the devices could be used to help students learn both content related to statistics and about physical activities in general. We also identify some of the challenges associated with the use of such devices that others who may use wearable technology in the classroom may wish to consider.

Keywords: activity trackers; sensors; statistics education; wearable computing

Three decades after the advent of the calculator watch, wearable technology is considered to be a rapidly growing sector in the space of consumer electronics. Wearable devices offer myriad capabilities in an effort to fill a niche with consumers that previously went either unfilled or unnoticed. Activity trackers from Nike, Fitbit, and Jawbone (among others) are marketed to people trying to improve their health and physical fitness. “Smartwatches”

promise greater convenience in connecting to our social networks, phones, etc. Google Glass offers “always-on” connectivity through a “heads up display” that can digitally augment reality based on one’s location. These represent just some of the possibilities in the space of wearable technologies.

While corporations and consumers continue to negotiate a permanent niche for wearable devices, let us assume that such wearable technologies are on track to become a part of our technological ecosystem in the way that laptop computers, tablets, and smartphones already have. If this is the case, we can also expect that interest in their educational potential will grow rapidly (e.g., Murray & Olcese, 2011), which leads us to ask: What might technology-supported teaching and learning activities look like when classrooms have access to wearable devices?

In this article, we examine some potential answers to this question. Although we do not intend to make an exhaustive treatment of the subject, we wish to point out that there have been some noteworthy efforts to incorporate wearable devices in educational contexts. For example, Klopfer, Yoon, and Rivas (2005) have been involved in integrating wearable technologies into participatory simulations (Colella, 2000). Using wearable “thinking tags,” students were able to explore how diseases spread through a population by looking at the rate of infection as a “disease” was transmitted from one student’s tag to another’s during an interpersonal interaction. In another project, Resnick, Berg, and Eisenberg

(2000) had children attach miniature temperature sensors to their clothing. The children then analyzed the accumulated data, uncovering a few surprises related to how dramatically temperatures changed in different settings that they had visited throughout the day.

These studies demonstrated the possibility of children using wearable devices to gather data while they go about their familiar routines, then thoughtfully inspecting and interpreting those data in such a way that the net total experience of collecting the data and reviewing it became a personally meaningful activity. We see the ability to inspect and reflect on experience and, thus, change how one relates to that experience as one of the great opportunities for wearable devices. This opportunity encourages our belief that wearables have promise in educational settings, and likely also encouraged the efforts that preceded us. However, those earlier research and design efforts took place at a time when wearable devices, even when configured to have relatively simple functionalities were ultimately limited in their long-term use and scalability by “high cost, low durability, and difficulties in programming” (Klopfer, Yoon, & Rivas, 2004, p. 249). Those aforementioned research and design teams had to make very deliberate efforts to have devices even physically available that could support instructional goals and a K-12 student population. Making the recorded data accessible to students required even more work. Not surprisingly, those studies represent the extent of early efforts to bring wearable computing to K-12 education.

Since that time, technology has advanced, interest in wearable and ubiquitous computing devices has grown, companies have invested in mass production, and wearable devices are becoming highly sought-after consumer products. Off-the-shelf devices available now at sports equipment and electronics stores are already cheaper and more durable than what our predecessors had at their disposal in the early 2000s. The need for extensive programming is mitigated as an immediate concern because many of these devices are already equipped and designed to store and transfer data.

Having off-the-shelf devices that meet our needs represents an opportunity to shift an educational technology paradigm. Rather than purposefully building new devices from scratch ourselves, we can use the abundantly available devices in new ways. This offers us a number of new instructional design opportunities. We are not alone in recognizing the educational potential of this new class of wearable technologies. Researchers have incorporated wearable GPS devices in afterschool clubs (Taylor & Hall, 2013), wearable

video cameras for classroom teachers to reflect on their practice (Sherin, Russ, Sherin, & Colestock, 2011), and accelerometer enhanced gloves into immersive and interactive museum simulations (Lyons, Silva, Moher, Pazmino, & Slattery, 2013). These efforts are noteworthy, although their primary audience has not been K-12 students and classrooms. In the sections that follow, we describe efforts we have taken to explore possible uses for wearable fitness tracking devices specifically with that population and context.

Using wearable fitness devices to analyze physical activity data

As part of a multi-year project, our research and design team has been involved in designing and implementing new teaching and learning activities that involve wearable devices that were developed for displaying and tracking data from physical activity. While our emphasis is on K-12 school settings and populations, we have also investigated how adult athletes and other active adults use such physical activity data devices “in the wild.” This branch of research was motivated by the desire to better inform our instructional design work. We believe that the ways in which the data from such technologies are made meaningful within their originating contexts may provide some purchase for us as designers attempting to repurpose them for a new setting, such as a classroom or schoolyard. This assumption has been a critical driver for what kinds of learning activities we have designed.

As mentioned above, the wearable technologies we use most frequently in our work are those that are promoted to and used by adults who want to increase their overall wellness or athletic performance. However, as researchers and designers, we use these devices as tools to create situations for students to interpret data. The core assumption here is that recall from one’s own body-based experiences provides a student with an especially productive set of conceptual resources for understanding what would otherwise be complicated displays of information (Nemirovsky, 2011). While participating in an activity, we all maintain an intuitive sense of our level of exertion and how it changes throughout the activity based on our perceptions; we can then recall those perceptions as tools for interpreting the activity represented as dots on a data display. As designers, we have sought to harness these interpretive intuitions in a number of projects. Below, we present two examples of our efforts to balance athletic activities as a context for meeting our primary instructional goal—for students to become more adept with interpreting displays of data.

Reflecting on Heart Rate Data with High School Students

The first example comes from a study we ran with high school students using Garmin Forerunner heart rate monitors. In this study, two groups of high school students participated in a series of physical activities (e.g., Frisbee, basketball) and then were asked to interpret displays of their heart rate data. We observed how the students' personal familiarity with the activities being analyzed supported productive strategies for reading visual displays of data. That is, the students used their knowledge of what happened and how active they each subjectively felt when they collected the data to push themselves toward progressively more refined ways seeing patterns and tendencies in data. Through analysis of video records of students interacting with their data, we saw that they gave less weight to outliers and maximum values and began to focus on areas of highest data density (i.e., the 'center' of the data) (Lee & DuMont, 2010).

In addition to developing new ways of seeing tendencies in data, the students in this study made discoveries with health and wellness implications—the topical context for their exploration. Specifically, the students in this study were interested in identifying athletic training activities that would make them work harder. (Two of the students were already very active in organized athletic activities and were quite competitive in sports.) In response to these interests, the students worked together to design and implement comparison studies to look at how their heart rates differed under related but different exercise conditions. One student study compared two aerobic exercise machines that involved continuous cyclical leg movement: a recumbent stationary bicycle and an elliptical trainer.

The students collected one workout session's worth of data, with each student using both machines for the same amount of time at what they considered comparable settings. They ultimately found that the elliptical trainer tended to produce higher heart rates over the same period of time than a stationary bicycle (Figure 1 on the opposite page). The data varied in how they were distributed, but the students identified clear clusters of data for each aerobic exercise machine, such that they comfortably asserted that elliptical trainers were more cardio-intensive and, thus, the machine they planned to use next time they went to the gym. These are among the things one would want to notice when learning about significant differences in inferential statistics.

Beyond successfully designing and executing their own comparison study and improving in their ability to interpret data, some of the participants also demonstrated improvement in their ability to estimate heart rates for activities that they did not test. For example, prior to working with a heart rate monitor, one student had estimated that they typically had a heart rate of 30 beats per minute while sleeping and 90 beats per minute when sprinting. At the end of the study, after using a heart rate monitor for less than two hours distributed across five days, she was able to make far more accurate estimates of 80 beats per minute while sleeping and 190 beats per minute when sprinting. Other students in this group also improved in their estimates of heart rates for activities that they did not actually complete. This suggests that beyond our goal of helping the students become more adept with data, the students also became a bit more knowledgeable about their bodies as well.

Students exploring data by quantifying their recess

As a second example of how exercise awareness could be leveraged in a learning activity to foster data awareness, we refer to a designed activity involving pairs of fifth-grade students that we refer to as "Quantified Recess" (Lee & Drake, 2013b). The motivation for this activity came from our observation that competition played a critical role in motivating data tracking and subsequent data analysis among adult athletes (Lee & Drake, 2013a). Moreover, many web services that transfer and store data from these devices foster virtual competitions among people in the same social network or in the same geographic region. For instance, the online athletic community that formed at strava.com awards a "king/queen of the mountain" or a "course record" to the athletes who upload the fastest tracker-logged times for designated routes.

In Quantified Recess, we designed a competitive activity in which the participating students wore Fitbit Ultra activity trackers to record how active they had been during midday recess. These particular wearable trackers, which have become increasingly popular as consumer devices, combine an embedded three-axis accelerometer and altimeter to determine activity levels each minute of the day. Over the course of a week, the students in this activity would review their recorded recess activity data and discuss strategies for increasing their activity levels. However, rather than simply total overall steps taken or calories burned, we set up the activity so that it focused on relative improvement from the first day to the last.

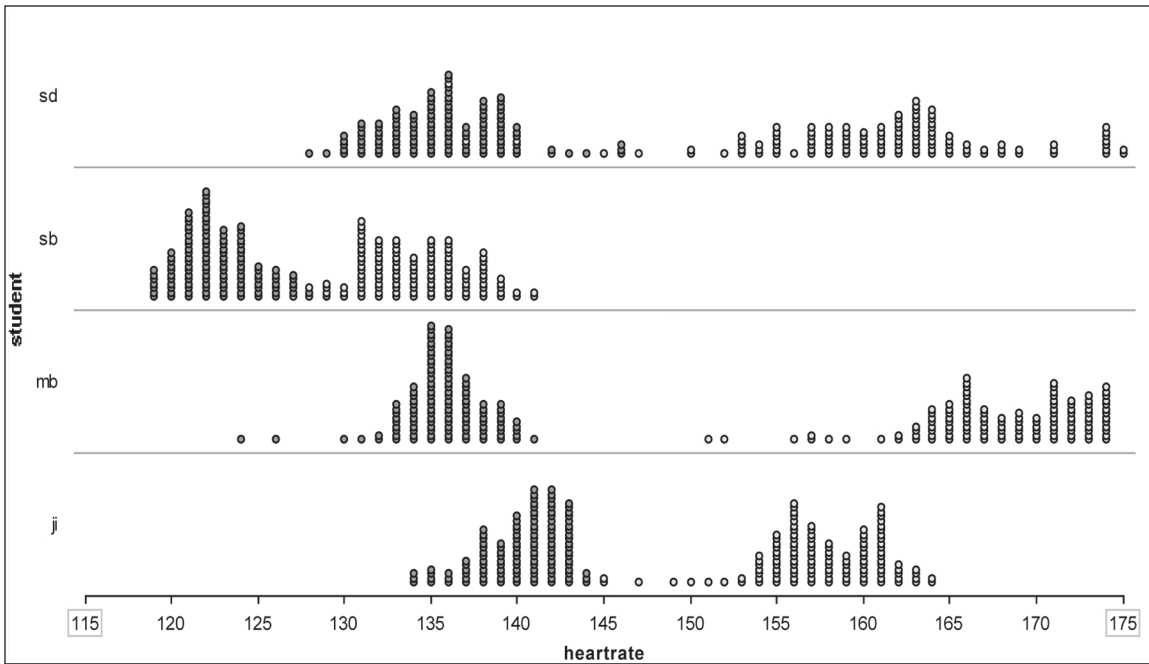


Figure 1. Data from a student study comparing elliptical training to recumbent stationary bicycling. The darker, leftmost clumps of dots are from the bicycle and the lighter, rightmost ones are from the elliptical trainer.

We also required daily scores to be derived from measures of center from each day's recess that paralleled what they were also learning in school. Specifically, in a pair, one student's net physical activity score would be the difference in the mean number of steps they had taken on the final day compared to the mean number of steps taken the first day; the other student's score would be the difference in their median number of steps from day 1 to day 5. Thus, if one student had a mean of 6 steps per minute at the beginning of the week and a mean of 94 steps per minute at the end, she

would contribute 26 points to her team's score. Her partner, who had a median of 45 steps per minute at the beginning of the week and 80 steps per minute at the end of the week would contribute 35 points. Combined, their team score would be 61; that score would be compared against the other participating teams' scores.

We intended the elaborate formula for determining scores to encourage students to explore both their recess activities and also how different measures of center were computed. One approach to increasing score would be to simply

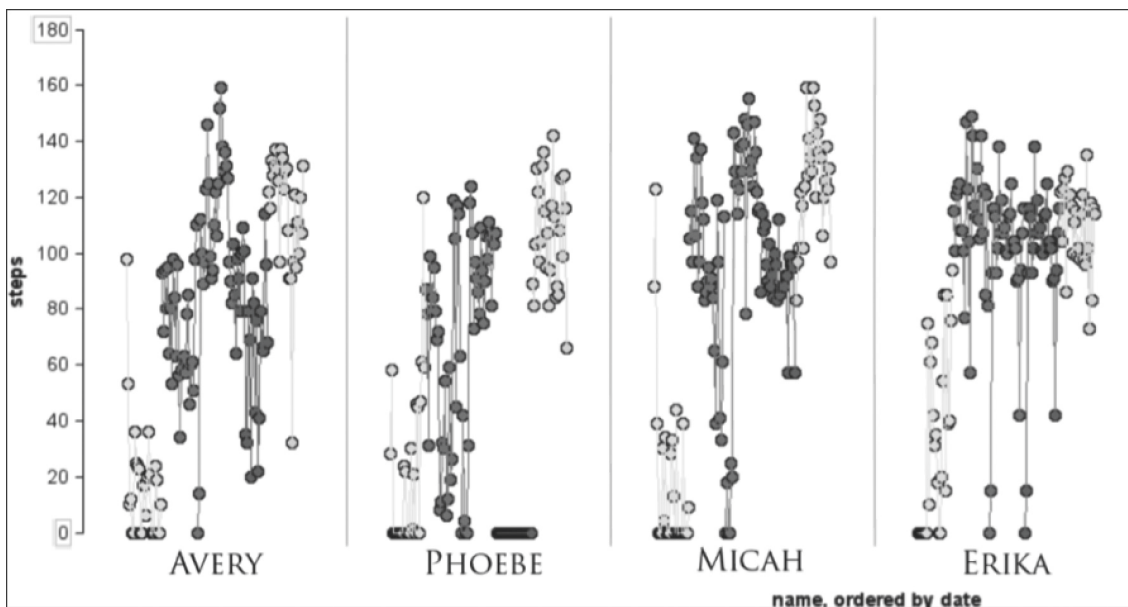


Figure 2. Quantified Recess data from four students for all five days of the competition (organized from left to right in data clumps). All names are pseudonyms.

run nonstop for the entire recess. This quickly proved dull and was not always sustainable for students who were less athletic, and they realized this quickly. During daily coaching and data analysis sessions, we encouraged students to look for ways to boost their daily numbers by trying a variety of strategies of their own design, with some proving more effective (e.g., playing soccer) than others (e.g., giving piggyback rides to friends). The combination of these plans and decisions was important in that students needed to consider each student's athleticism and stamina and how well they matched a given strategy. It simply was not feasible for some of the less physically fit students to be continuously active during the entire recess period. Of note, one pairing of an athletic boy with a less athletically inclined girl jointly discovered that it made more sense for the girl who needed to take frequent breaks from high intensity activities to be scored by her median value rather than her mean value, as the median was less sensitive to a few low scores (Lee & Drake, 2013b). This represents a level of understanding of measure of center above and beyond what many older students and adults typically are exposed to or develop (Cai, Lo, & Watanabe, 2002; Watson & Moritz, 2000).

Using wearable trackers to explore measurement

The above examples used only pairs of students in small workshop settings and explicitly highlighted physical exercise. However, as stated above, one of the central premises of this paper is that wearable technologies can be repurposed for use within classrooms. In this section, we discuss activities we have designed and implemented in partnership with classroom teachers and with full elementary school classes. These activities leveraged the counting capabilities of the Fitbit Ultra in ways that did not speak directly to health or wellness, but instead focused on activities related to topics such as measurement and accuracy.

Students Investigating Wearable Device Accuracy

One lesson we realized early in our work is that it is important to provide students with ample time to “mess around” (Ito, 2010) with these new wearable technologies. Doing so allowed them to become familiar with device capabilities and also generate some of their own questions based on their experiences using the Fitbit. For example, following the “messaging around” period that extended for two class periods, several students in one fifth-grade class questioned whether Fitbit

activity trackers were actually accurate in their ability to count steps.¹ The persistence of this question among students in the class who were skeptical that the Fitbits were even reasonably accurate created an opportunity for them to participate in a class-wide test of the accuracy of the Fitbit Ultra as a step counting instrument.

During the accuracy test, a single student wore multiple Fitbits and walked a path in the school building chosen by the class. A group of peers followed this student, acting as “accurate” step counters silently counting the Fitbit wearer's steps. A second group of peers recorded start and end step counts from each Fitbit. The class then compared the silent counts of the human step counters to the Fitbit counts. This procedure was repeated several times. Data collected from each run was compiled and given back to the students, who then used sticky notes and butcher paper to produce displays of their accuracy assessments (Figure 3). Class discussion and interpretation of these displays focused on the observation that the bulk of the Fitbit step counts were within 10 steps of the students' own counts. This observation led the students to conclude that the Fitbits were reasonably accurate and could be used as a measurement instrument for elementary students.

Comparing the Steps of Tall and Short Kids

Another question we have often encountered when students are provided with wearable activity trackers and in particular those that track steps taken, was whether height influenced the number of steps taken. Many kids know from their previous experiences walking with adults (e.g., parents) that they took more steps to cover the same distance. However, they are not sure how this would play out when considering the effect of height differences among their peers who are often in the same height range and shorter than many adults. To address this, a group of students in a fifth grade class ran an experiment to compare the steps taken by the tallest students in their class with the steps taken by the shortest students on the same outdoor walking path. They then compiled the data and created two data displays, depicted in Figure 4, which they subsequently discussed and analyzed in small groups. By looking at where there were peaks in the data and concentrations of data points, they quickly confirmed that shorter students did tend to take more steps to cover the same distance. Further, they also noticed other

¹ Early research on Fitbit accuracy, not available at the time of this design experiment, suggests that calculations of early Fitbit models differ from professional grade sensing devices by up to 11% (Waltz, 2012).

features of the data after they were displayed, such as the spread of the data, as illustrated from the recorded conversation excerpted below.

J: This one [data for short students] looks like it has more steps here, cause, well, it does. And it's clumped together. And this one [data display for tall students] is spread out.

E: So it just depends cause some tall people have short legs, and it's just the upper part of their body. That's why it varies. That's probably why it varies.

J: It's about how long their legs are.

E: Yeah.

J: Cause some people can be really tall cause they have longer legs and some people can be tall cause they are longer on top.

In this short exchange excerpt, the students from this class explicitly acknowledged that the data had different overall shapes. In the data for the shorter students, the steps data were “clumped together,” but they were more “spread out” for the taller students. While the students’ primary goal for this experiment was to find out if shorter students took more steps over the same distance than taller students, they were able to turn a peculiarity (i.e., the wide range of data for tall students) into an opportunity to consider causes

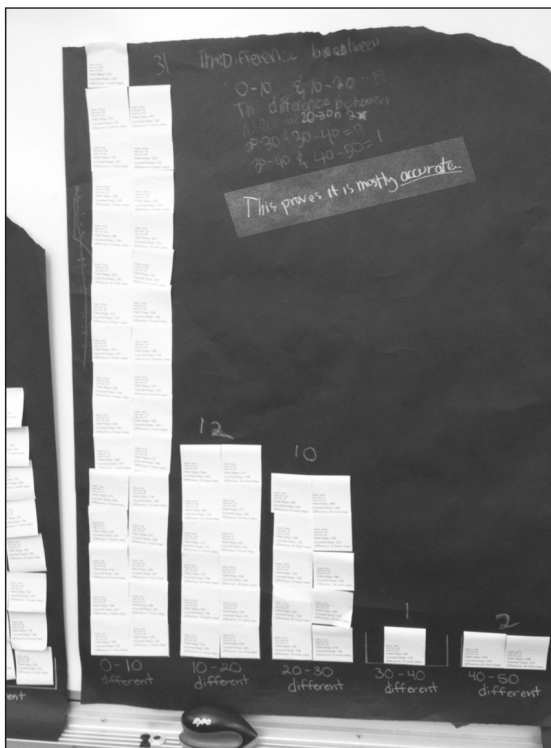


Figure 3. Student display of Fitbit step count deviation from mentally counted steps over a fixed course. Note that the students wrote on this poster “This proves it [the Fitbit Ultra activity tracker] is mostly accurate.”

of variation. This is noteworthy in that variation in data has not historically been the purview of elementary mathematics and science teaching,

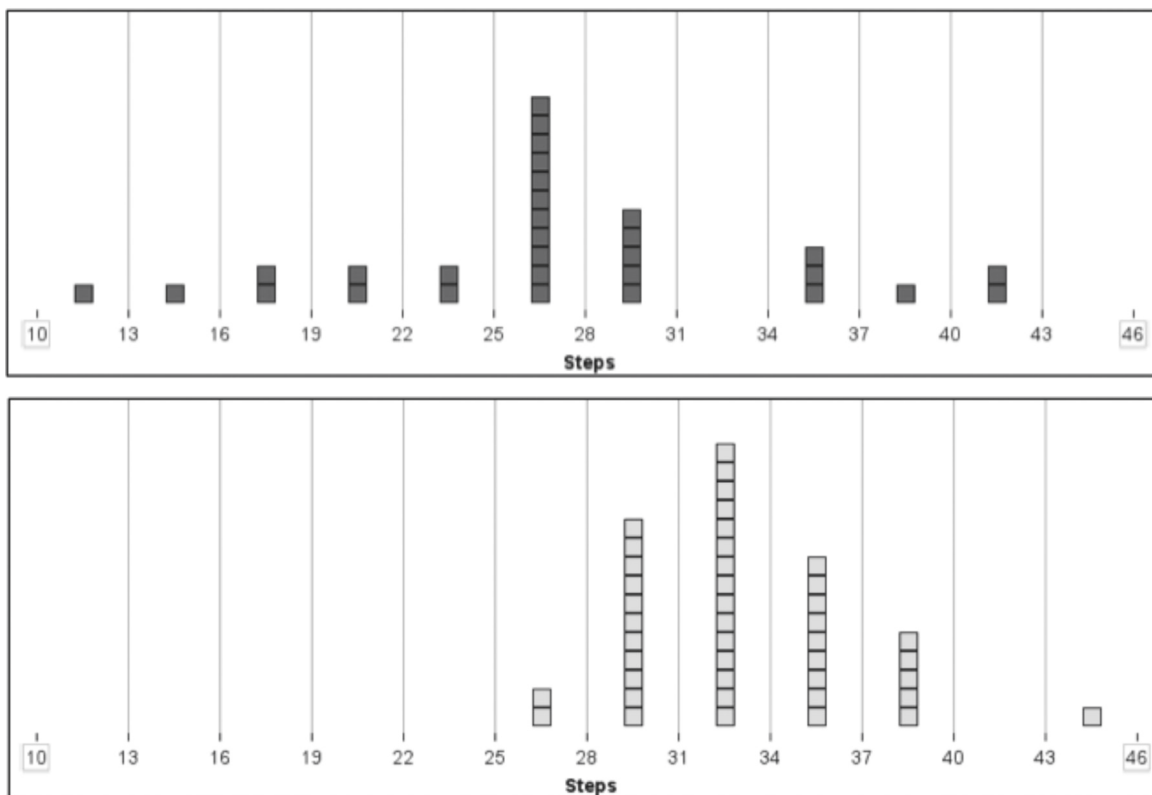


Figure 4. Step data for tall (a) and short (b) students from a fifth-grade experiment.

but has been documented as a real learning possibility in carefully designed data-intensive learning environments (Lehrer & Schauble, 2004). From one class period obtaining data by simply walking and another class period organizing and looking at their data, we saw a situation arise where students were indeed engaging with variation as a way to understand the shape of their data. Our view from experiences like the one described here is that wearable devices enable this to happen by making the process of collecting data both efficient and familiar.

What is next?

In this article, we have examined the prospect of using wearable activity tracking devices to support teaching and learning in schools. Specifically, we have described ways we have tried to support teaching and learning science and mathematics content, with a special emphasis on students making sense of visual displays of activity data. The approaches we have taken as designers of instruction has involved understanding how these devices are used in their intended contexts (by adults and by athletes) and capitalizing on students' own questions that arise as they become familiar with the devices. Both of these strategies have shown promise in our efforts to import and integrate wearable devices into classrooms.

The two main advantages of using wearable fitness tracking devices are that 1) students can passively acquire a large amount of data and 2) students will be intimately familiar with the activities in which the data were generated. As most teachers know, collecting data for an experiment or investigation can demand a great deal of classroom time and coordination. Understanding where data came from and why they look the way they do also requires a substantial time investment, especially when the students were not involved in collecting the data being examined (Hug & McNeill, 2008). Wearable devices have the potential to reduce those time investments. Using wearable fitness devices, the students can collect data while participating in familiar activities (e.g., recess, Physical Education class). When analyzing the data, the students can draw on explicit recall of the experiences that produced data and what they know from participating in a broader set of related activities. For example, in the "Comparing Tall and Short Kids" example above, the everyday experience of being shorter and having to walk extra steps alongside one's taller parents became a useful and productive resource for driving an investigation into how height affected steps.

Yet, in spite of these benefits, using wearable technologies in classrooms is not

without challenges, including logistical and privacy concerns. For example, commercial devices use proprietary services to provide access to the abundance of data records. These services are designed for use by adult fitness enthusiasts and athletes; as such, these services cannot always be expected to provide the flexibility or level of detail required for classroom investigations. For example, the Fitbit web service displays time series data in 15-minute intervals for a single user. For our projects, we needed the data to be displayable in frequency plots that combined data from multiple users. Additionally, some of the students' investigations benefitted from one-minute interval data. As a result, we had to do some behind the scenes work to obtain the information in a usable format for our classroom activities².

An additional concern is that wearable devices require a space where data can be transferred. Many currently available devices upload data to their web services wirelessly in the background. However, school firewalls intended to protect students from inappropriate content can often disallow access to these services. Ensuring that the schools and classrooms are able to send and obtain data from third party services requires additional legwork to make sure that the proper sites and services are allowed through existing firewalls.

Beyond these logistical concerns, privacy issues must be considered. Because the devices are designed for personalization, the data can be tied to specific individuals in the classroom. This is both an advantage and an important ethical consideration. In our research, we always make sure to obtain informed consent to use, access, and share these activity data. The students we worked with were enthusiastic and eager to see where their data fit into the class dataset. They also drew on their knowledge of themselves and the other students in the class when interpreting the data displays. However, data made public within the classroom and that they have consented to making available may still include details that students do not wish to share. For example, because we work with fifth-grade and high school students (i.e., adolescents) who may be self-conscious about their bodies, we have treated data related to body weight³ as private and avoid making that information publicly available. It is important to be aware of data that might be sensitive for the

2 For access to a webform we have developed to get such minute by minute data from Fitbit tracking devices, go to <http://ecds.ed.usu.edu/fitbit>.

3 Body weight has been necessary to obtain to calibrate some of the devices that students use

specific groups with which we work. It is also important to establish norms in the classroom such that there is a mutual and continually reinforced understanding that the purpose of seeing everyone's data is to help answer particular questions and not to single out students in a way that could make them needlessly uncomfortable.

Concerns such as these are not unique to wearable technologies. As with any new technology brought into schools and other learning spaces, risks and benefits come in tandem. Balancing the risks and benefits of wearable technologies, the reception we have seen so far in our own efforts has been encouraging. As the capabilities and uses of wearable technologies continue to develop, such as with wearable cameras and with wearable GPS tracking devices, we anticipate efforts will be similarly made for those to also expand into educational settings. The possibility also exists to bridge across subject areas and settings, such as from PE to physics or from afterschool soccer practice to math class, is certainly there. Some intrepid teams have begun to bridge daily activity to virtual game environments (Ching & Hunicke, 2013). We are eager to see what other designers and technologists discover as wearable devices eventually establish their own educational niche in the classroom and beyond.

Acknowledgments

Work reported in this article was supported by funding from the National Science Foundation (Grant No. DRL-1054280). The opinions expressed herein are those of the authors and do not necessarily reflect those of the National Science Foundation.

Victor R. Lee is a faculty member in the Department of Instructional Technology and Learning Sciences at Utah State University in Logan, UT. Address correspondence regarding this article to him at via email at victor.lee@usu.edu.

Joel Drake and Kylie Williamson are both affiliated with Utah State University. You may email them regarding this article at jrdrake@gmail.com or kyliewill@rocketmail.com.

References

Cai, J., Lo, J., & Watanabe, T. (2002). Intended treatments of arithmetic average in U.S. and Asian school mathematics textbooks. *School Science and Mathematics, 102*(8), 391-403.

Ching, C. C., & Hunicke, R. (2013). *GETUP: Health Gaming for "the Rest of Your Life"*. Paper presented at the Games, Learning & Society 9.0, Madison, WI.

Colella, V. (2000). Participatory simulations: Building collaborative understanding through immersive dynamic modeling. *Journal of the Learning Sciences, 9*(4), 471-500.

Hug, B., & McNeill, K. L. (2008). Use of First-hand and Second-hand Data in Science: Does data type influence classroom conversations? *International Journal of Science Education, 30*(13), 1725-1751.

Ito, M. (2010). *Hanging out, messing around, and geeking out: Kids living and learning with new media*. Cambridge, MA: MIT press.

Klopfer, E., Yoon, S., & Perry, J. (2005). Using palm technology in participatory simulations of complex systems: A new take on ubiquitous and accessible mobile computing. *Journal of Science Education and Technology, 14*(3), 285-297.

Lee, V. R., & DuMont, M. (2010). An exploration into how physical activity data-recording devices could be used in computer-supported data investigations. *International Journal of Computers for Mathematical Learning, 15*(3), 167-189. doi: 10.1007/s10758-010-9172-8

Lee, V. R., & Drake, J. (2013a). Digital physical activity data collection and use by endurance runners and distance cyclists. *Technology, Knowledge and Learning, 18*(1-2), 39-63. doi: 10.1007/s10758-013-9203-3

Lee, V. R., & Drake, J. (2013b). Quantified recess: Design of an activity for elementary students involving analyses of their own movement data. In J. P. Hourcade, E. A. Miller & A. Egeland (Eds.), *Proceedings of the 12th International Conference on Interaction Design and Children 2013* (pp. 273-276). New York, NY: ACM.

Lehrer, R., & Schauble, L. (2004). Modeling Natural Variation Through Distribution. *American Education Research Journal, 41*(3), 635-679.

Lyons, L., Silva, B. L., Moher, T., Pazmino, P. J., & Slattery, B. (2013). Feel the burn: exploring design parameters for effortful interaction for educational games. In J. P. Hourcade, E. A. Miller & A. Egeland (Eds.), *Proceedings of the 12th International Conference on Interaction Design and Children* (pp. 400-403). New York, New York: ACM.

Murray, O., & Olcese, N. (2011). Teaching and Learning with iPads, Ready or Not? *TechTrends, 55*(6), 42-48. doi: 10.1007/s11528-011-0540-6

Nemirovsky, R. (2011). Episodic feelings and transfer of learning. *Journal of the Learning Sciences, 20*(2), 308-337.

Resnick, M., Berg, R., & Eisenberg, M. (2000). Beyond black boxes: Bringing transparency and aesthetics back to scientific investigation. *Journal of the Learning Sciences, 9*(1), 7-30.

Sherin, M. G., Russ, R. S., Sherin, B. L., & Colestock, A. (2008). Professional vision in action: An exploratory study. *Issues in Teacher Education, 17*(2), 27-46.

Taylor, K., & Hall, R. (2013). Counter-Mapping the Neighborhood on Bicycles: Mobilizing Youth to Reimagine the City. *Technology, Knowledge and Learning, 18*(1-2), 56-93. doi: 10.1007/s10758-013-9201-5

Waltz, E. (2012). How I quantified myself. *IEEE Spectrum, 49*(9), 42-47. doi: 10.1109/MSPEC.2012.6281132

Watson, J. M., & Moritz, J. B. (2000). The longitudinal development of understanding of average. *Mathematical Thinking and Learning, 2*(1&2), 11-50.