Digital Technologies and Instructional Design for Personalized Learning

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A volume in the Advances in Educational Technologies and Instructional Design (AETID) Book Series

Published in the United States of America by
IGI Global
Information Science Reference (an imprint of IGI Global)
701 E. Chocolate Avenue
Hershey PA, USA 17033
Tel: 717-533-8845
Fax: 717-533-8661
E-mail: cust@igi-global.com
Web site: http://www.igi-global.com

Library of Congress Cataloging-in-Publication Data

Names: Zheng, Robert, editor.
Title: Digital technologies and instructional design for personalized learning / Robert Zheng, editor.
Description: Hershey, PA : Information Science Reference, [2018]
Identifiers: LCCN 2017024205| ISBN 9781522539407 (hardcover) | ISBN 9781522539414 (ebook)
Subjects: LCSH: Individualized instruction--Computer-assisted instruction. | Instructional systems--Design.
Classification: LCC LB1031 .D54 2018 | DDC 371.39/4--dc23 LC record available at https://lccn.loc.gov/2017024205

This book is published in the IGI Global book series Advances in Educational Technologies and Instructional Design (AETID) (ISSN: 2326-8905; eISSN: 2326-8913)

British Cataloguing in Publication Data
A Cataloguing in Publication record for this book is available from the British Library.

Chapter 7
Personal Analytics Explorations to Support Youth Learning

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ABSTRACT

While personalized learning environments often include systems that automatically adapt to inferred learner needs, other forms of personalized learning exist. One form involves the use of personal analytics in which the learner obtains and analyzes data about himself/herself. More known in informatics communities, there is potential for use of personal analytics for design of instruction. This chapter provides two cases of personal analytics learning explorations to demonstrate their range and potential. One case is of a high school student examining how sleep influences her mood. The other case is of a sixth-grade class of students examining how deviations from typical walking behavior change distributional shape in plotted step data. Both cases show how social support and direct experience with data correction are intimately involved in how youth can learn through personal analytics activities.

INTRODUCTION

One widely recognized model of personalized learning involves using computational tools to exogenously recognize and respond to the immediate conceptual needs of a learner and automatically adjusting the learning environment accordingly; for instance, an intelligent tutoring system can infer the knowledge state of a user and then present appropriate tasks and instructional content to move them closer to a more expert-like understanding (e.g., Graesser, Chipman, Haynes, & Olney, 2005). Yet there are still several other ways in which personalization could take form in a technology-supported learning environment. As examples, consider how using personalized story scenarios that map onto students' out-of-school interests can boost student learning in mathematics (Walkington, 2015; Walkington, Petrosino, & Sherman, 2013) or how personalization can also be achieved and supported by providing youth with generative and expressive computational media where they can design and engineer artifacts that are specific to their own interests and prior expertise (Peppler & Kafai, 2007). In this chapter, my goal is to further

DOI: 10.4018/978-1-5225-3940-7.ch007

expand the space of personalized learning by highlighting what opportunities exist when students are able to explore “personal analytics”.

Personal analytics (Ruckenstein, 2014; Wolfram, 2012) refers to a set of data-related practices that have been associated with the area of personal informatics (Li, Dey, Forlizzi, 2010) and the Quantified Self (Nafus & Sherman, 2014). All typically involve collecting and analyzing aggregates of data obtained through “self-tracking” (Lee, 2017). The use of the term has generally varied depending on the scholarly community (i.e., personal informatics is more common parlance in the information sciences). Arguably, there are nuances that distinguish the terms, but for current purposes, it is acceptable to think of personal analytics as being comparable to the kinds of analytics that one might do with website data but instead do so with data about one’s own self. At its core, personal analytics is self-inquiry using data. While data collection and inquiry about one’s own self has been practiced for several years in a range of communities (e.g., Kopp, 1988; Lee & Drake, 2013; Wallace, 1977, Wheeler & Reis, 1991), the widespread availability of consumer-level mobile and wearable devices and automated data collection systems (such as clickstream recording) has reduced some of the initial barriers associated with analyzing data about one’s self (Lee, 2013) and popularized this approach. This has thus enabled some initial pioneering work to integrate personal analytics routines and practices into the design of learning environments. Some noteworthy examples include asking youth to use personal analytics data and gaming environments to motivate healthier lifestyle behaviors (Ching & Schaefer, 2015) or to support interactive exhibit design at settings such as zoos and museums (Lyons, 2015).

While some promising opportunities have been noted (Rivera-Pelayo, Zavharias, Müller, & Braun, 2012), much still remains to be understood about how educational designers can best support learning that invites students to do the work of personal analytics. Part of this has to do with the disparity between the most visible and noteworthy examples of expert-like learning through personal analytics and what needs and challenges are encountered by novices. For example, noted polymath Stephen Wolfram (2013) has presented some detailed cases and visualizations of his own personal analytics of email use, phone calls, and meeting participation over the course of years. Power users who identify with the Quantified Self movement (also known as QSelf-ers or QSers) regularly convene in major urban areas to share personal analytics projects that they have pursued and how that helped them to gain new insight and learn about themselves (Choe, Lee, Lee, Pratt, & Kientz, 2014; Lee, 2014). Such examples are informative and aspirational for the future, but they also presume proficiency with powerful visualization tools, fluency with data and data representations, some formal understanding about correlational and potentially experimental design, and instrumentation. Each of these could be, in a designed educational setting, a set of learning goals on their own.

Moreover, personal analytics has been by and large dominated by an orientation toward using personal data about one’s self to support planned behavior change, self-improvement, and performance optimization (Li et al., 2014). Empirical examination of adults who self-track and analyze their own personal data actually suggests that the reasons for participation in self-tracking communities and activities are actually more nuanced, with only a fraction of the broader population of self-trackers having aspirations of behavior change in mind. Many are simply curious to see what possible stories come from their numbers or if their intuitions match an existing quantified scale (Epstein, Ping, Fogarty, & Munson, 2015). Furthermore, the standards of scientific rigor are not always met nor understood by those who undertake self-tracking and self-experimentation projects (Choe et al., 2014). With those observations in mind, it is reasonable to expect that students and youth who are charged with performing personal analytics work to support their own learning may introduce other challenges or complications. Learning to read graphs, for instance, is an ongoing challenge for many students (Leinhardt, Zaslavsky, & Stein, 1990).

Still, the idea of using data from and about students with those very same students holds appeal and has been tantalizing enough for some to explore through educational research and design. The gap from ideation to execution has only recently begun to be filled. This chapter is an effort to continue with that gap-filling by presenting two cases of student learning activities with personal analytics obtained over the course of a multi-year research program to explore the potential of personal analytics for youth learning. The first case is of high-school student who participated in a multi-week afterschool program where each participant was charged with embarking on her own personal analytics project. The goal here was to modestly emulate what had been pursued in more advanced hobbyist practice (Choe et al., 2014) and understand what supports were needed for youth to pursue similar endeavors. The second case comes from a designed unit in a sixth-grade classroom where students worked continuously with data from their own activities. In this second case, the data obtained were a count of steps required to walk across the school playground and did not require sophisticated wearable devices. However, the case was noteworthy in that the visualization of activity showed some abnormal walking behaviors and spurred productive classroom discussion about distributions and how data were generated. Together, these two cases illustrate some of the potentials for personal analytics to support learning, with different lessons gleaned from each. The first hints at some of the supports that are needed and concerns that get raised in the context of individual inquiry, but also provides the reader with a sense of what kinds of content can be learned through personal analytics endeavors. The second demonstrates how the core commitment of personal analytics – the examination of data about the self – can be sensibly integrated into a classroom activity and how awareness of data creation can be conducive to classroom discussions about visual representations of aggregated data.

BACKGROUND

Many who have documented self-tracking and personal analytics practices identify 2007 as the year in which a community and sociotechnical movement (the "Quantified Self") emerged in the Silicon Valley, with Wired magazine editors Kevin Kelly and Gary Wolf being attributed as primary initiators (Choe et al., 2014; Lee, 2014). Since that time, informal groups of self-trackers have appeared in over 100 cities around the world, and an annual conference that brings together hobbyists, entrepreneurs, tool-makers, medical professionals, and academic researchers boasts consistently strong attendance (i.e., a few hundred attendees regularly). However, it is worth noting that like many activities popularized through the Silicon Valley, self-tracking had actually existed in various forms for decades prior in academic communities such as behavior analysis and organizational studies (Burns, 1954; Wallace, 1977; Wheeler & Reis, 1991).

Independent of the designated sociotechnical movement or prior behaviorist-oriented work, my research group and I had been exploring student learning opportunities with wearable device-obtained data about their own selves since 2008. From 2008 to 2017, we have been developing and pursuing integrated and overlapping lines of educational research and development oriented toward personal analytics approaches to supporting teaching and learning. That has involved a number of design experiments (Cobb, Confrey, diSessa, Lehrer, & Schauble, 2003) with youth working in small groups and collectively as full classrooms (Lee & DuMont, 2010; Lee & Thomas, 2011). The two cases presented below come from the broad data set obtained over those years in which different learning configurations and supports were provided and examined throughout the years of our work. The primary data source had been hundreds of hours of video footage. Video-based research in education is an increasingly common approach for conducting research that has developed an emerging set of best practices, strategies, and procedures for their analysis that we have attempted to follow in our own work (Derry, et al., 2010). In both of the following cases, group video footage was used, although the larger corpus of data and the results discussed in other reports include analyses of artifacts and written test data (e.g., Lee, Drake, & Thayne, 2016). The cases are presented to illustrate directions and potentials for learning by way of personal analytics.

Stated very simply, virtually all endeavors with youth in our work has involved providing youth individually with at least one wearable tracking device for their own use and providing them some means to examine the data collected from that wearable. Devices used ranged from Fitbit activity trackers to Garmin heart rate monitors to GPS enabled watches (that predated the smartwatch era). Over the years, our research team developed some tools that enabled extraction of the data so that the data could be imported into data visualization software designed for educational purposes – a hack that is usually restricted to proprietary apps. The most commonly used data visualization software in our studies was *TinkerPlots*, a novice-friendly data visualization tool developed to enable elementary students and above to use drag and drop interactions to produce dynamic data visualizations (Konold & Miller, 2005). The original self-tracked data records (e.g., number of steps taken) were stored along with video footage of student completion of some pre-planned learning task. An example task might involve asking students to determine which of multiple conditions shown in the data visualization software reflected more exertion and to explain why (Lee & DuMont, 2010). Such a prompt was intentionally ambiguous for participating students. For them to make a determination, the students typically needed to consider issues related to statistics and measurement content, such as measures of center, variability, and distribution and trade-offs associated with various approaches.

The two cases presented in the current chapter were selected simply for illustrative purposes. They were not subject to systematic code and count procedures nor detailed interaction analysis (Jordan & Henderson, 1995). Rather, they served formative purposes over our years of designing and evaluating learning activities. Neither case had been presented nor published before the current writing, but had been noted in content logs and notes as being especially noteworthy to revisit because they involved moments of student confusion and some ultimate resolution of that confusion. As a heuristic, such moments were suggestive of moments where learning had been unfolding. The two cases are also presented with an eye toward diversity to show the different kinds of data that could be obtained by youth and to demonstrate that personal analytics learning activities are usable with youth at different grade levels, with different levels of technology, and in different participation structures (i.e., working individually vs as a whole class). The first case comes from an effort to emulate the existing hobbyist learning structure that exists in the broader Quantified Self sociotechnical movement. Specifically, it involved a group of Latina high school girls who met afterschool for five weeks to learn more about personal analytics activities and self-tracking technologies and culminated in each pursuing an effort to each do their own personal analytics project (Lee & Briggs, 2014). The second case comes from a rural sixth-grade class that enacted a designed multi-week unit on elementary statistics using students' own data. The unit emphasized counting steps through automated and manual means to consider issues of measurement and distribution. Both cases are presented predominantly as narrative accounts based on review and summary of the originating video footage and accompanying observer notes.

CASE 1: MELISSA AND SLEEP TRACKING

Of five Latina high school girls who were recruited to participate in an exploratory weekly afterschool program to understand some of the obstacles and concerns rural youth from non-majority populations would encounter with self-tracking technologies and routines, Melissa (a pseudonym, as are all proper names of participants in this chapter) was able to initially claim the Jawbone Up (First edition) wrist-based tracking device from our research group as the one she would try first. This particular item was one that Melissa reported to us that she was most interested in trying out largely based on its sleek, snake-like appearance, in comparison to the bulky Bodymedia Fit armbands, the large Garmin GPS watches, the chest-worn heart rate monitoring straps, and the Fitbit step-counting devices that looked to her that they were intended to be worn on the waistline or hanging off of one's pocket. When Melissa selected the Jawbone Up device, she was provided with the original product packaging and operating instructions to take home and explore. She and the other participating youth were to treat the device as if they belonged to them for the duration of the program.

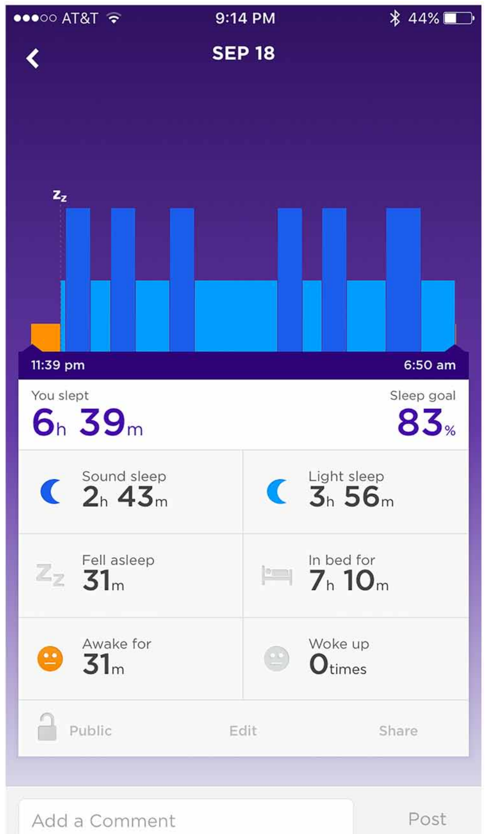
After seeing a sample personal analytics project on the first day of the afterschool session, Melissa and her fellow participants were asked to explore their respective devices at home and over the course of the week. Melissa specifically was tasked with determining if the functionalities of the Jawbone Up were satisfactory to her such that she would commit to using it for five weeks and if so, to report back to the group some of the tracked values that she considered potentially interesting for her to pursue her own personal analytics project.

On the second week of the program, Melissa reported being most enthusiastic about the Up's ability to track sleep. While it could track steps and activity like some of the other device options, she found the sleep recording functionality to be novel. The interactions required to operate sleep tracking seemed fairly simple. Melissa only needed to press the lone button on the Up device when going to bed and pressing it again upon waking. The built-in accelerometers would infer sleep patterns from how much movement took place during that period of time. To examine the data, Melissa need only remove the cap on one end of the device to expose a 3.5mm audio jack that would be inserted into the headphone jack of her personal smartphone, and the data would transfer automatically for display in the proprietary Up mobile app (note: this was prior to the ubiquity of Bluetooth data synching for wearable devices). Melissa could then see her own step and sleep data (see Figure 1), and was also prompted each day to mark her mood from one of five selectable options, in increasing order of enthusiasm: "Dragging", "Meh", "Good", "Energized", and "Pumped up".

As she shared the device's sleep functionality to other participants in the group, Melissa reported that what surprised her most was that according to the Up device, she woke up several times in the night. That she woke up at night was was not treated as being in question; rather it was accepted as a reliable and accurate statement from the device. Melissa commented that waking up in the middle of the night was not something that she recalled doing, but others in the room chimed in with what they knew about sleep. This included sleep going through different stages and that most people change positions a few times a night without consciously realizing it between sleep cycles. That information helped Melissa to realize that a distinction made by the Jawbone device between "light sleep" and "deep sleep" potentially mapped onto the amount of time she spent in different stages of sleep. This was new knowledge for her.

Melissa also commented to everyone present about how much attention the device got her at school when her classmates saw it on her wrist. She was, as many early users of new wearable devices were, enthusiastic about trying it out and the novelty of the device. Melissa reported being an avid examiner

Figure 1. A screen capture of the Jawbone Up mobile device app that reports light and deep (sound) sleep and number of times woken up



of her data, regularly checking her step data after she got home from school and checking her sleep data after she woke up. She would also log her mood according to the five-point scale since it prompted her when she opened the app on her smartphone after synching her sleep data. At the end of the session that week, when asked whether she wanted to try out some of the other devices or explore some other functionality, she opted to stick with the Jawbone device and trying to see if her middle-of-the-night awakenings were related to her mood as it was recorded.

On the third week of the program, she showed the group of girls and researchers some of the records she had obtained and expressed uncertainty about what the data all meant. She did note a specific day in the week that stood out to her because she remembered she was not in a good mood that day and had recorded it in the corresponding app. According to the Up device, she took 27 minutes to fall asleep and woke up at 5:30 AM on that lower mood day. In total, according to Jawbone, she got about six hours of sleep and by her own account, did not feel good. Melissa stated that she just did not think that was enough sleep and speculated that the overall amount of sleep was what contributed to her sluggish mood the next day. It is worth noting that this was the first articulation of a hypotheses related to total amount of sleep might affect her mood. Immediately following, she began to consider a number of sleep variables that could impact her mood. These included number of wake ups, time spent awake before falling asleep, and total amount of sleep. A member of the research team suggested she store this information in a spreadsheet, which Melissa reported not having prior experience using. This led to a short one-on-one tutorial of how to put data into a spreadsheet, and Melissa spent the remainder of her time of the video recorded research session inputting the records from her Up app manually into a spreadsheet.

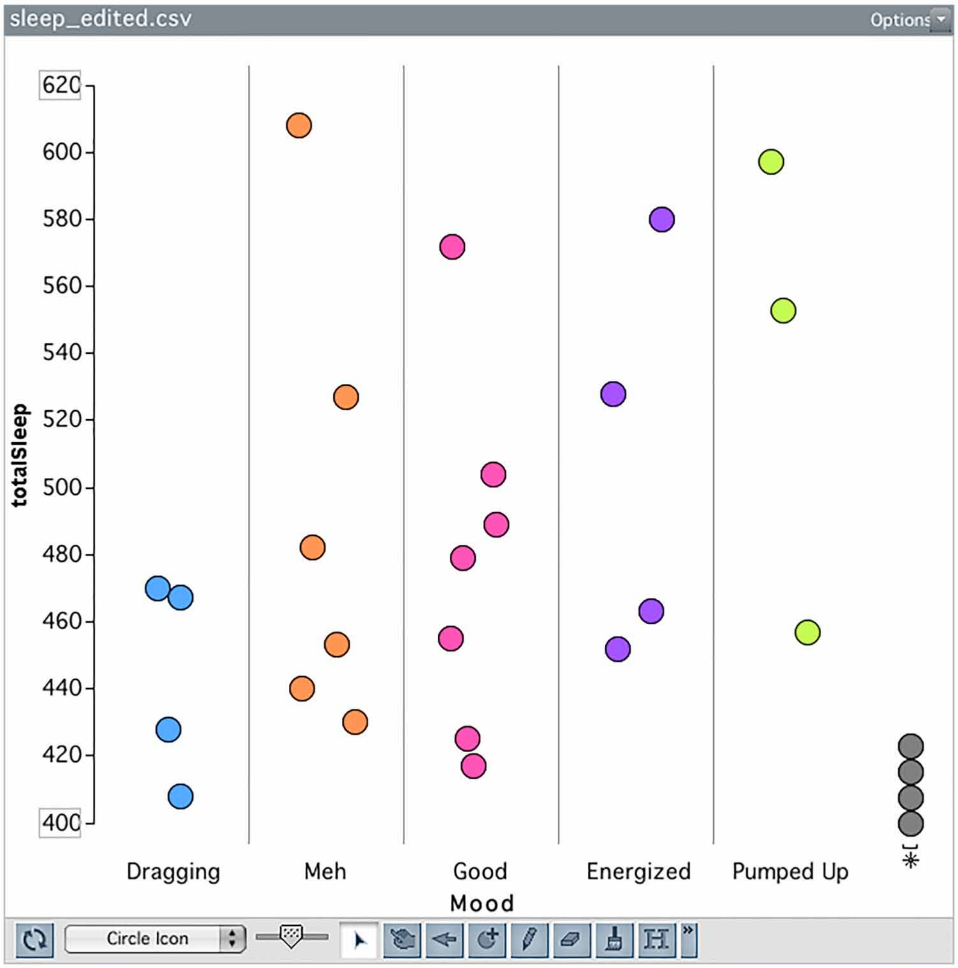
When it was the fourth week of the program, Melissa began the session as the first teen to speak and was enthusiastic about reporting how she wore the device to her school dance the previous weekend and was quite surprised by what information she had gotten from that night. First, she made the admission that she actually did not *want* to wear the device to the dance that night because while it looked attractive for everyday wear, she had a different set of concerns and colors she wanted to emphasize for her dance appearance. Her date, however, had brought her a corsage that made the device less visible and because she was participating in the project for multiple weeks, she felt some obligation to keep wearing the device and tracking her activities. What ultimately struck her and what she wanted to show the other girls was how she had essentially four hours of continuous step data from all the dancing – a feat she had not accomplished in any of her previous tracking, which confirmed to her that she had been very active that night. She was clearly excited about this observation and keenly recovered that record and showed others. Melissa also noted that the sleep cycle that followed was much longer than usual, which she attributed to the many hours at the school dance.

While other girls participating in the project shared their own observations, experiences, and difficulties with the devices that they had tried, Melissa proceeded to pay partial attention to them and also entering the new values she obtained from the Up device into the spreadsheet she had started the week prior. After she had inputted the numbers and mood ratings, and other girls had been organizing their data, Melissa scanned the columns of her spreadsheet and expressed concern that she could not see an obvious correlation between her mood and the number of times that she had woken up. Someone suggested that instead she look at the deep sleep, but she immediately found a row showing a night where the deep sleep value was not especially high but the mood that corresponded with it was high. Another suggestion was made that she look at the time that she went to bed, but she immediately found another anomaly. For Melissa, the data she had obtained became problematic for any claims she wanted to make because she could find individual exceptions. Concerned, Melissa left the session planning to continue to track data with her Up device, but with the sense that what she recalled about specific days and nights was a more important accounting of why she was in a good or bad mood and the data were not supportive of consistent stories.

The fifth and final week of the program involved the participating girls transferring any remaining data that they had and then importing those data into *TinkerPlots*, the data visualization software program to which they had been introduced the week prior. They were then given time with assistance on demand to prepare various data displays. Melissa puzzled over several displays, stating that there was nothing that could be discerned except for odd exceptions to any claims she wanted to make that were plainly visible. Eventually, a member of the research team suggested one last configuration, shown in Figure 2, that the researcher was unsure would be of use. At the same time, each of the other girls found, with some assistance from research team members, one or two data plots that they felt offered the most for them to talk about and took turns projecting their data display in front of the group and sharing what they believe they had discovered, similar to what takes place in a hobbyist Quantified Self group.

When Melissa presented the plot shown in Figure 2, she was skeptical. The night with the most sleep was in the "Meh" category, so she did not feel that the amount of sleep was tied to her mood. The also noted that many of her "Good" mood days were accompanied by 500 or fewer minutes of sleep. It took another girl's comment that even though those exceptions existed, there did appear to be some upward

Figure 2. The final plot Melissa and the others examined comparing mood against number of minutes of sleep on the preceding night, rendered in TinkerPlots



trend with the “Dragging” bin having much lower values for minutes of sleep and the “Pumped Up” bin having the second highest number minutes of sleep. Furthermore, its lowest value was still higher than the lowest of all the other bins. Upon having that highlighted, Melissa acknowledged that there may indeed be some trend. She did add the caveat that the trend was not definitive and that more data would be needed for her to be sure. Following her presentation and response to comments from others, Melissa’s and the other girls’ involvement ended, all devices were returned, and the program concluded.

Commentary on Melissa’s Case

Much of what Melissa did seems close to what we might expect for an adolescent user of a personal analytics tool. First, and not to be dismissed as a trivial, Melissa judged her device selection on its appearance. The appearance of the device that she was going to be wearing all day and night mattered a great deal and motivated her selection of the Up over other given options. In the second week of the afterschool program, she appeared enthusiastic about the inquiries she got from her peers about the device on her wrist when they noticed it. Yet as time went on, Melissa also described a time when she did not want to wear the device because of how it looked relative to her planned appearance. As developers of wearables are beginning to appreciate, the form factor is indeed consequential. Indeed, others have noted concerns youth have with form factor of wearables when they are given the opportunity to use them (Schaefer, Ching, Breen, & German, 2016).

Additionally, the data obtained from the device were taken at face value. Melissa accepted that she must have woken up in the middle of the night because the device told her she did. Such immediate acceptance is not always the case. In some situations, youth can be inherently skeptical about what a device tells them. That skepticism can be an important learning opportunity about measurement, approximation, and instrumentation (Lee, Drake, & Williamson, 2015). Regardless, the idea that she must have awoken in the middle of the night provided Melissa a new way to think about sleep and was supported by comments from others. She had not previously thought about deep or light sleep as a meaningful distinction, the difference between bedtime and the time when she fell asleep, and how waking momentarily figured into sleep behavior. These distinctions later provided her and the others in the program with a set of quantities to consider as potentially important for affecting her mood.

By the time that she began to reflect on possible trends in her sleep and mood data (the latter three weeks), she repeatedly commented about days that were exceptions to possible claims that she and others generated about how her sleep influenced mood. It was only right around the end of the program and through someone else's observation that she began to accept an overall trend (more sleep seemed to correlate with better mood) existed despite some variability in how data points were distributed. This was not obvious to her, but the contributions of others who were with her at the time helped direct her attention to possible trends. Ultimately, it seemed that Melissa learned some new ideas about sleep, about her own sleep behavior, about how to log and manage data, and possible correlations between different variables. These may not have taken place had she embarked on this personal analytics project on her own, but various moments of support were provided that helped her to make headway by the end. We take from this the observation that personal analytics projects are feasible but benefit from peer and knowledgeable adult support, that the categories of tracked quantities can introduce youth to established ideas about a common phenomenon (i.e., that sleep has different cycles and periods of semi-wakefulness), and that they can negotiate both skepticism and recognition of correlations when looking at their own data.

CASE 2: STUDENTS WALKING STRANGELY ACROSS THE PLAYGROUND

The second case comes from a rural sixth grade classroom in a different county than the first case that was implementing a new personal analytics-themed unit to cover required elementary statistics content as part of their regular mathematics instruction. This school was receiving the most refined iteration of the unit, designed for four weeks of classroom instruction and covering topics such as variability, distributions, measures of center, and informal inference based on data. The student population was typical of American rural communities, being predominantly white and many youths coming from families where the adults worked in agriculture or manufacturing. The class discussed here was one of two sixth grade classrooms in the school and was sorted intentionally to include the students who had lower performance on a beginning of year mathematics assessment than their peers.

Each student in the class was provided with a Fitbit wrist-based activity tracking device to wear daily at school, and the data obtained from their own daily activities played a central role in the designed classroom instruction. Daily activities for each mathematics lesson included reviewing one or a few students' previous day's activity data and working on reading minute-by-minute data displays rendered in *TinkerPlots* showing how many steps were taken throughout the day. These daily data-review activities spawned a number of questions and investigations that were pursued throughout the unit (Drake, Cain, & Lee, 2017).

There were several noteworthy class discussions and activities that showed high levels of student participation and joint sense-making of activity data involving students in this class and at this school. Of interest to the current chapter was one set of activities that the classroom teacher, in a post-unit interview with the research team, explicitly identified as being a critical moment for her students in how they thought about their activity data. This activity took what we have called elsewhere a "quantified selves" approach in which classroom data of the same activity done at the same time were pooled together for student examination rather than a longitudinal data set from the same individual, which would be more typical of a "quantified self" project (Lee, Drake, & Thayne, 2016). The activity that produced the pooled data was a planned walk back and forth across their playground in which each student in the class walked across 12 times while manually tracking the number of steps required to make each trip. The point of the activity was to produce normally distributed data from counts of footsteps, which had become a familiar measure of activity for the class based on daily interaction with tracker data, and to begin to see patterns of distribution as being common across many different kinds of measures (such as with measures of length obtained by rulers and estimations and measures of steps obtained by a device and by mentally counting).

What was unanticipated in the implementation of this activity was students deliberately modifying their walking so as to produce deviant results. For instance, after a few passes across the playground, some students began to take miniature shuffle steps to see how large of a number they could produce. Other students began taking exaggerated leaping steps or hopping with their feet together and counting those (Figure 3).

These numbers ultimately introduced more variability in the data than had been expected in the design of the lesson. The resulting data were aggregated and viewed in *TinkerPlots* the following day, with a 'long tail' of high step values being a distinguishing characteristic especially when compared to data that were obtained when other classes of students had done this activity in earlier iterations of the unit (Figure 4).

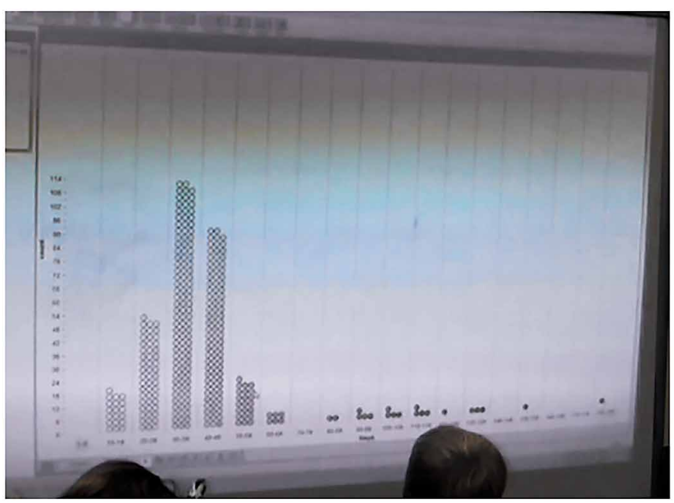
Some students, were delighted with this distribution. When this plot was projected in front of the class, one student exclaimed "I have the top one! I had 185 last time", which the teacher acknowledged with laughter as she recalled several students taking intentionally abnormal steps across the playground. While the anomalous data could have been problematic, this class of students turned this into a productive discussion of what transpired and why the data looked the way that it did. To illustrate, consider the following transaction between the teacher and a student, Melinda, who went to the front of the class to draw the overall shape of the data.

Ms. Hayley: So what can you tell me from the shape of that information? What can you conclude or talk about?

Melinda: From 30-39, more people got that steps because most people just walked back and forth, and they got between 30 and 39 [steps]. That's how much they got. But some people did different things.

Figure 3. Students in Ms. Hayley's class walking across the playground while counting steps. Note the two girls on the right doing intentionally abnormal forms of walking to change the number of steps that they are recording.

Figure 4. Histogram showing all student step records from the playground walk. Note the long tail distribution that extends to the right.



I know me and Stella, we ran and we skipped and other people did that and stuff, and we got more steps back over here *(motions over the long tail of the distribution)*. So this part *(motions over the peak of the data)* is more the majority of the steps.

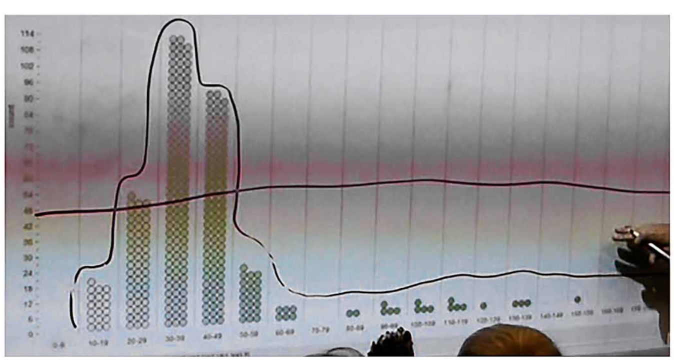
Ms. Hayey: So it's more typical information?
Melinda: Yes.
Ms. Hayley: So you saw what was happening out there. What do you think was affecting that shape?
Melinda: I think right here *(motions over the leftmost quartile of the distribution)* people were taking like really giant steps *(imitates a giant step in front of the class)* to get less, and right here *(motions over the peak)* people were walking normal back and forth, and I think like Hudson who was over here *(motions over to the rightmost point in the distribution)* was like taking really tiny steps *(imitates tiny steps).*

Of note here is the ease with which Melinda could read the histogram display. She quickly identified the bin that contained the mode of the distribution (30-39 steps) and explained that as being the result of regular walking behavior. She was aware that the further out that deviations from the mode were reflective of deviations from regular forms of walking. Her explicit naming of fellow students reflects some acknowledgment of the familiarity of the data with respect to the members of the class and knowing what each did. To make sense of this representation of the class's data, she was creatively constructing interpretations that embedded specific events and activities that had taken place (Lee & Sherin, 2006).

However, while Melinda was reading the histogram sensibly, the teacher discovered that there was at least one way in which her understanding of data distributions needed to be further refined. Following her description of why the data looked how it did, Mrs. Hayley asked Melinda to draw the shape of the distribution had everyone in the class walked normally instead of some running and some taking tiny steps. Melinda drew a horizontal line across the middle of the plot (Figure 5).

Following this, Ms. Hayley asked if having roughly equal numbers of points in each bin (thus making the straight line across the plot) was what Melinda had expected would be produced. Melinda confirmed this was what she intended, and Mrs. Hayley opened up the discussion to the rest of the class. Students began to raise objections to Melinda's prediction and suggesting that rather than having a distributional shape appear like a straight horizontal line, the peak of the existing distribution should instead get taller. Melinda objected and maintained that she thought while there may be some unevenness – what she described as "spikes" across all bins – the distribution should still generally resemble a horizontal line. Hudson then went to the front of the class to explain why he thought the horizontal line distribution was unlikely and instead the peak would get taller.

Figure 5. The horizontal line drawn by Melinda showing her prediction for how the distributional shape would look had all students walked normally



Hudson: This is one person *(points to the data point in the rightmost bin)*. One dot means it has one person, and in order for these groups, and in order for there to be spikes [in the rightmost bin], the person had to do it multiple times or there had to be a group of students getting the same number of steps. But if you take all that *(motioning over the long tail of data points)*, and we are all trying to do the same amount of steps, you see this is the average *(points to the tallest bin of points)* and they'd all end up around there. If they weren't doing crazy things and just doing normal stepping, everyone would be there [near the tallest bin].

Following this statement from Hudson, more students raised their hands to add their thoughts, with the class general concurring with Hudson's interpretation. The straight line distribution did not make sense. Mrs. Hayley called on Isaac to speak, and he offered the following to further counter Melinda's straight line distribution prediction.

Isaac: The only possible way that it [the distributional shape] could be like a straight even line is if you like assigned how many steps each person would take.

Hudson: And have groups that are supposed to take more, actually gaining, because the higher numbers over here *(motions over rightmost bin)*, they are higher numbers and you have to have a certain number, like three each group *(motions over the right most bin)* and three each group *(motions over an adjacent bin)* so like three kids taking a certain amount of steps, three kids taking a certain amount of steps, and so on to get that [horizontal distribution].

Mrs. Hayley: So what I'm gathering that you're saying is that that won't happen naturally. It would take so much work you'd have to kind of orchestrate that. You'd have to assign people to take that many steps. Why do you think that?

Isaac: Because um, a lot of the time, it's like, since we're all around the same age, around the same size, and so we take about the same amount of, same size of steps, so it would be more like a big tall spike.

Both Hudson and Isaac could present explanations for what was incorrect about Melinda's interpretation. Hudson first made the point that the most likely outcome would be an increase in the number of points near the average. Isaac then also added that without some deliberate planning, a uniform distribution would be unlikely. Hudson agreed with this and articulated in some detail what would need to be in each bin of the histogram to make Melinda's prediction work. Finally, in response to a later question from Ms. Hayley, Isaac also provided justification for why there should be an increase in the number of points near the average by making an appeal to the relative sameness of all the students in the classroom. As far as Isaac was concerned, there was no reason to expect that students who were about the same age and size and stride length would produce things results that far from what most other students had produced. The class took these comments as valid points and proceeded onward with their unit.

Commentary on the Playground Walking Case

This in-class discussion about steps taken to get across the playground at school was not originally planned. We had expected that students would walk normally and produce normally distributed data through this activity. At the time of step data collection, Ms. Hayley did not find the odd walking behaviors to be a major concern, and it opened up a substantive conversation the next day among students about why their distribution had a prominent peak and also a long tail. The students, having been the authors of the data, knew and could talk about the data distribution meaningfully because the distribution was about them and what they had experienced.

Personal analytics involves working with what one already knows from their own experience and being both the producer and interpreter of data. Personal analytics applied to a learning environment implies using one's own personal awareness as a bootstrap to develop and refine new understandings. In the classroom, where there is a larger social setting in which multiple people are examining the data, gaining insight can come about by noticing what others can see and hearing how they explain the data. This represents an important consideration for how personal analytics activities could be sensibly implemented in schools and other learning environments. Designers and educators should recognize that even though the data might be about the students and that provides some means for students to think about what is being represented, the insights and perspectives offered by other students who are already around can also be useful resources for supporting learning and reflection.

Additionally, it is important to acknowledge that Mrs. Hayley contributed to the effectiveness of this discussion in an important way by giving the students ample opportunities to share their thinking out loud with one another and to make explicit their predictions for how the data distribution could change. She asked them to draw their predictions of shape and interjected herself in the students' conversation to make sure they explained their thinking. Moreover, the software data tool used here also enabled quick rendering of the compiled student data so that there was a common object for class discussion. It created a common pooled data object available for the class to debate. Yet, while acknowledging the importance of both the teacher and software supports being present for this particular conversation, it is easy to imagine a scenario where both of those were present, but this kind of talk about the data fails to happen. Through appeals to what they themselves did when the data were produced and what they observed others in the class were doing, they could make assertions for why the data looked the way that it did and how it could have been different. Thus, we suggest from this case that the combination of personal connection to the data, along with the software tool and the teacher's facilitation of the discussion all jointly enabled the realization of a substantive learning opportunity.

CONCLUSION

The overarching aim of this chapter was to suggest that personal analytics approaches represent an important area of personalized learning in today's digital ecosystem. In contrast to other forms of personalized learning experience represented in this volume, the emphasis when using personal analytics for learning is to have the learner create data from their own activities and then be in the position of examining their own data. What is to be taught and learned by students is not automatically determined nor recommended to them; it is encountered in the process of making sense of what the data say about the students and their experiences. For the past several years, my group has been exploring the potential of these incidental encounters in learning environments for youth.

Two cases from our work with personal analytics learning activities were presented. The first was of a high school student who participated in an afterschool program where she used a wearable device to explore possible relationships between her sleep and her mood. Through the course of multiple weeks, she gained exposure to different aspects of sleep that she did not previously know and gained experience with some new tools that she had not previously used. There were some challenges encountered, in that she placed a great deal of emphasis on specific records of data that she had collected and needed some help to notice trends in the data. However, according to our records, she seemed to get there. In looking toward the future, learning activities for individual novices and youth doing personal analytics work should incorporate supports to help students notice patterns and understand more about the phenomenon that they are quantifying through their projects. Even if done as an individual learning experience, leveraging peer social support, in the form of feedback and outsider perspectives on what is in the data could be valuable as well. Also, with youth there are considerations of appearance and form factor associated with data collection technologies that should be noted and may affect willingness or desire to collect enough data to be worth analyzing.

The second case involved a full class of sixth-grade students and adapted the personal analytics approach to accommodate a collective classroom community. In this modified approach, an entire class of students produced and examined pooled data all together. While it was unanticipated, deviations in how the data were collected that led to productive conversations among students. These conversations built upon familiarity that the students already had with what others in class had done and what they themselves had done in the process of creating their data. That familiarity enabled students to explain why the resulting distributional shape appeared the way that it did and correct one another's predictions for how that distributional shape would be modified under different data creation conditions. Of note for this case in contrast to the first was that it involved some simpler technologies, at least at the data creation phase. While each student had a wearable device that would track their steps and the students examined data from those throughout the larger unit, the specific activity discussed here involved analytics on manually collected data. Still, they were able to use those records in productive ways, suggesting that while personal analytics is gaining in prominence because of increased availability of individual tracking devices, those are not absolutely essential for this sort of instructional approach to work.

Thus, the prospects for personal analytics learning explorations to become an option for those who want to support personalized learning are promising. There are questions that remain for us as a field to examine, such as what conditions promote an initial desire from students to look at their own data, how to support learning with different software tools, and what kinds of social configurations around a personal analytics learning activity enables broader participation and deep inspection of data. However, in both the cases presented here, and elsewhere in the gradually accumulating literature (Lee, 2015), there is evidence of learning and growth by building upon experiences that youth can have when they examine data they have obtained about themselves. The opportunities for personal analytics to establish a meaningful presence in the landscape of personalized learning environments are abundant and worthy of more investigation by more researchers and educators.

ACKNOWLEDGMENT

This work was supported in part by funding from the National Science Foundation under Grant No. DRL-1054280. The opinions expressed herein are those of the authors and do not necessarily reflect those of the National Science Foundation. Thanks to Amy Wilson-Lopez, Joel Drake, Jeffrey Thayne, and Ryan Cain for their assistance related to these two cases. Also thanks go to the participating youth and teachers.

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KEY TERMS AND DEFINITIONS

Activity Trackers: Wearable device that monitor motion or other environmental changes to infer numbers of steps, calories, or other metrics related to physical activity.

Digital Ecosystem: The array of ubiquitous and mobile technologies that are abundantly available to many people who have current network connectivity and resources to access and exchange information.

Jawbone Up: A wrist-worn wearable device that in its early models had no visual feedback display and could transfer data through a 3.5mm pin.

Personal Analytics: The extension of data analytics practices to quantified self-data.

Personal Informatics: The field of research related to the collection, storage, and analysis of information systems related to personal actions or behavior.

Quantified Self: A sociotechnical movement referring to the practices of persistent recording and tracking of information in a quantified format for subsequent examination, reflection, and analysis.

TinkerPlots: A data-visualization tool designed for elementary and middle school students that allows for direct manipulation of data records through drag-and-drop interface controls.