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

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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

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