Data&Society

Personalized Learning: The Conversations We're Not Having

Working Paper 07.22.2016

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The Promise of Personalized Learning

> "…if instead of having mass education as we now have, must have, with a curriculum, once we have outlets, computer outlets in every home, each of them hooked up to enormous libraries where anyone can ask any question and be given answers…then you ask, and you can find out, and you can follow it up, and you can do it in your own home, at your own speed, in your own direction, in your own time, then everyone will enjoy learning.
> Nowadays, what people call learning is forced on you and everyone is forced to learn the same thing on same day at the same speed in class. And everyone is different. For some it goes too fast, for some too slow, for some in the wrong direction. But give them a chance in addition to school — I don't say we abolish school, but in addition to school — to follow up their own bent from the start…"

—Isaac Asimov, Interview with Bill Moyers, PBS, 1988

In an interview with Bill Moyers in 1988, science fiction writer Isaac Asimov described the potential for computers to catalyze a revolution in learning. He described how in the past, wealthy families could afford individual tutors for their children, allowing for learning experiences tailored to the needs of the child, guided by an experienced mentor. Asimov predicted that computing could allow such a personalized, one-teacher-one-student experience to be available to the masses, replacing or supplementing the one-teacher-many-students experience of most classrooms. He criticized the generic structuring of education, and offered an alternate vision of schooling that meets kids where they are, whether that means slowing down or speeding up the curriculum, or adjusting instruction to individual interests. "Everyone will enjoy learning," Asimov predicted, if only they had access to the world's collective knowledge and freedom to pursue their "own bent."

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The pursuit of personalized education at a mass scale still drives a number of current technology initiatives in education. (Please see Appendix A for discussion of investors and key actors.) New technology is promised to level the playing field, effectively creating equal access to learning opportunities by democratizing information and instruction. Advocates hope that a technology-enabled shift (e.g., from teacher-based classroom interventions to personalized tablets and data-driven individualized learning plans) can provide a new incarnation of the one-teacher-one-student model—tailoring the learning experience to individual progress, interests, and goals. Classrooms could then be spaces in which advanced students and struggling students alike not only have their needs met, but are supported in the curious and creative pursuit of their own paths. Through personalized learning, these lofty goals seem within reach.

How does personalized learning work? There's a long history of techniques, from teacher-developed individualized learning plans to student-centered instruction, but increasingly advocates are turning to large-scale data collection and analysis to enable technologically-mediated solutions. Some types of student data are restricted by state and national laws and/or industry good practice standards, but the approach being used for data-driven or adaptive personalized learning is the same as the one that recommends purchases on Amazon or movies on Netflix. For many personalized learning systems, student data such as age, gender, grade level, and test performance are analyzed against idealized models of student performance, or students of the same background or class, or nationwide pools of grade and/or competency level. A profile is created for each student that typically categorizes her or him as part of a group that performs similarly or demonstrates shared interests or demographics. Then, data-driven content recommendations are sent either directly to the student or to the teacher for further intervention.

Over the past couple years, the collection and use of student data has become increasingly controversial. The potential for data-driven learning analytics to improve student learning competes with concerns about safeguarding student privacy. As of January 2016, 188 student data privacy bills had been introduced nationwide (Anderson, 2015; Vance, 2015). Yet, while the use of student data has been a focus of discussion and critique, the promise of personalized learning remains mostly unchallenged. Key questions explored in this primer include: what, exactly the rhetoric surrounding personalized learning is promising, and why? Can an analysis show whether this technology is delivering what it promises? And what other concerns, absent from the discourse, do we need to be most attendant to when the educational sphere imports a framework of data collection from the world of start-ups and tech giants? This primer presents a typology of personalized learning systems that draws from media coverage, research, interviews, and informal discussions.

What is Personalized Learning?

Descriptions of personalized learning encompass such a broad range of possibilities—from customized interfaces to adaptive tutors, from student-centered classrooms to learning management systems—that expectations run high for their potential to revolutionize learning. Less clear from these descriptions are what personalized learning systems actually offer and whether they improve the learning experiences and outcomes for students. In this section, the boundaries of personalized learning–what it is and what it isn't—are explored.
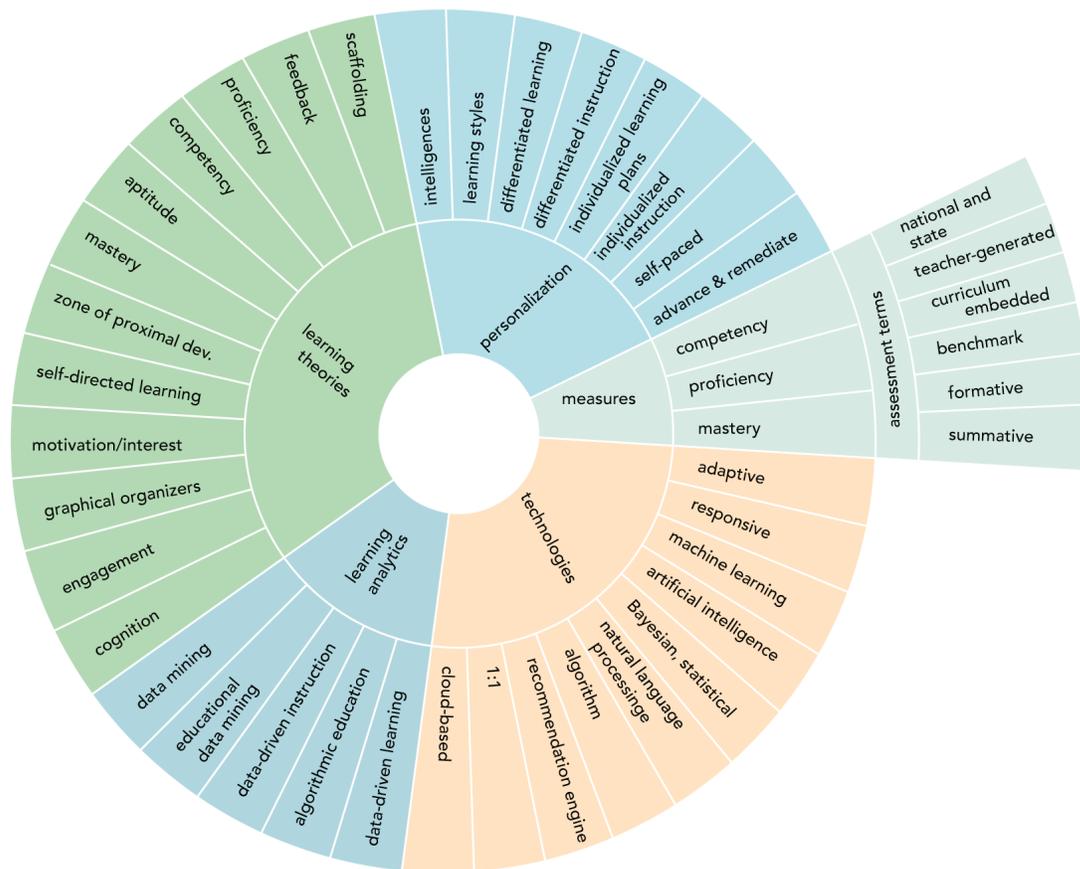
Figure 1: Personalized Learning Terms Used in Marketing Materials and Media

It is no wonder that personalized learning is a popular buzzword symbolizing the potential for data use in education. Its definitional reach is broad, borrowing terms, like 'student-centered instruction' or 'instruction tailored to individual student needs' that traditionally describe strong teaching practice, to include under its ever-expanding umbrella (see Figure 1). Technology-enabled personalized learning describes varying degrees of tailoring or customization of a learning experience through apps and/or

platforms. And yet, there are no established standards for describing or evaluating the extent to which a learning experience is personalized, and often the difference between responsiveness and adaptiveness is not accounted for in product descriptions. Independent evaluations of the level of personalization or its efficacy in improving learning outcomes are rare. This prompts two important questions: 1) what categories of "personalization" are deployed in these technologies, and 2) to what degree does "personalization" actually serve the goals of education?

While news articles and product websites use personalization to mean a range of functions, in an educational context, personalized learning describes adaptation to a students' unique combination of goals, interests, and competencies and the ongoing process of shifting instruction as these conditions change. Even without the use of new data-driven learning technologies, it is important to realize that every teaching environment is in some way personalized: everyday interpersonal interactions involve a degree of personalization as people respond to each other's shifting moods by reading facial expressions (Walden & Ogan, 1988). In classrooms, teachers rely on these interpersonal cues, combined with their subject matter expertise, knowledge of how people learn, and knowledge of each student, to determine individual needs, adjusting their lessons in response to questions and behaviors (Brophy, 1985; Fredricks, Blumenfeld, & Paris, 2004; Wineburg, 2008). For example, a teacher describing how to arrive at the sum of 5+2 might write the numbers on the board, but also engage students in an activity to understand the physical quantities, like asking students to count out five popsicle sticks or five marbles. Walking around the classroom to gauge how students are completing an assignment is one way teachers personalize instruction—checking in on those struggling or challenging those already finished. Personalization in classrooms is thus not strictly technology dependent, but is dependent on an understanding of students' learning needs. Normally referred to as learner-centered instruction, such personalization is a long-established tenet of good teaching (Bransford, Brown, & Cocking, 2000). In recent studies funded by the Bill and Melinda Gates Foundation, personalized learning was measured using the broad definition of traditional, not tech-enabled student-centered teaching practice (Rand Corporation, 2014, 2015). Likewise, AltSchool, a network of micro-schools in California and New York are described by founder Max Ventilla as a personalized, student-centered experience that has little to do with onscreen learning, even as technology venture capitalists fund the school (Dalgaard & Ventilla, 2015).

Competency-Based Education and Common Core

Several developments in learning are occurring simultaneously and are often placed under the 'personalized learning' umbrella. One reform movement is *competency-based education,* which shifts the measures of grade-level progress from time spent in school to demonstration of skills, with an aim to enable students to progress more quickly through lessons they understand and to pinpoint areas

where more instruction is needed (Anand & Schimke, 2015). Schools such as Hodgkins Elementary in Colorado or U School in Philadelphia offer blended grade levels, allowing students to begin work in the grade above, or review work in the grade below depending on their skill level. Competency-based education is in part a pushback against *summative assessment*, occurring at the end of a unit or term, in favor of *formative*, often iterative *assessment* occurring more regularly and isolating the demonstration of specific skills.

The Common Core Standards, introduced in 2009, present an interesting counterpoint to competency-based education. They are summative, rather than formative assessments, however, their focus is on discrete skills. For example, in kindergarten students are tested on their ability to name numbers as one skill, or count from 1 to 100 as another, rather than a summative assessment which might bundle them together. Efforts to coordinate data collection around the Common Core assessments are in early stages. As NPR points out in their Common Core Standards overview, there are no official Common Core aligned curricula or instructional materials (National Public Radio, 2014). Yet, in our review of product websites, we frequently encountered claims that a feature of the personalized learning product was that instructional modules and testing followed the standards framework of the Common Core.

The promise of personalized learning is often bundled within competency-based education and/or Common Core, making it difficult to separate the performance of one from the other, or truly distinguish personalized learning from associated assessments or teaching of competencies. At the same time, the controversies surrounding Common Core and competency-based education also tend to shape impressions of personalized learning.

Adaptive vs. Responsive

Another confusing dimension of personalized learning concerns the promise of adaptive processes, when many of the services that purport to be personalized are in fact responsive in approach. *Personalized* learning tools ideally adapt uniquely to an individual's goals, interests, and competencies, shifting instruction as they change. This level of sensitivity and adjustment to an individual learner's needs enacts the role of tutor, responding to a student through the circuitous process of learning, the struggles, dead-ends, frustration, boredom, and "a-ha" moments (Nye, Graesser, Hu, 2014). Adaptive systems aim to functionally mirror and support the learning process, which is a flexible and changing, rather than fixed, process. Responsive systems are more limited, essentially offering an interface to pre-determined content, like a hyper-linked menu or a series of digital buttons. In comparison to truly *adaptive* systems, *responsive* systems are further from the neurological processes of teaching and

learning, offering something much closer to an interactive textbook than a tutor. Much of the promise hyped by investors and enthusiasts revolve around the image of the truly adaptive private tutor, even if what is more commonly delivered is simply responsive. SmartSparrow Founder and CEO Dror Ben-Naim observes that "Many of the so-called 'adaptive learning' platforms are really more like content recommendation systems -- like Amazon or Netflix. I don't see where the learning is adaptive. The content is not changing in response to the students" (Waters, 2014).

Typology of Technologically-Enabled Personalized Learning System

5 Types of Personalized Learning Systems

Responsive Systems			Adaptive Systems		
Custom Interface	**Learning Management**	**Data Driven**	**Adaptive Learning**	●●●	**Intelligent Tutor**
Invites student to personalize learning experience by selecting colors and avatars.	Platforms that automate a range of classroom management tasks. Includes systems that allow students to choose their own path through material.	Management systems that provide materials appropriate to a students' proficiency level based on data collection.	Data-driven learning that potentially moves beyond a pre-determined decision tree and uses machine learning to adapt to a students' behaviors and competency.	Currently in development	The image of a proactive learning guide, that could inspire questions, or use facial recognition to respond to emotional states

Figure 2: 5 Types of Personalized Learning Systems

There is tremendous ambiguity surrounding the possible definitions of personalized learning. With this in mind, the above typology of technologically-enabled personalized learning systems provides a clearer spectrum of possibilities described by *personalized learning* as a product. Technology-enabled *personalized learning* can range from simple customization of a learning interface to a system that adapts content delivery depending upon user performance. These systems can be grouped into five categories that increase in responsiveness:

- *Customized learning interface*: Invites student to personalize learning experience by selecting colors and avatars, or uses interest, age or geographic indicators to tailor the interface.

  o For example, in Cloud Math, students may select between a cloud, sun, balloon or soccer ball as their avatar as they move through math-based games.

  o Modifying an interface to reflect personal tastes has been shown to increase student

interest, but falls short of the tailored learning experience promised by personalized learning.

Figure 3: Cloud Math Customized Learning Interface (choice of avatar)

- *Learning management*: Platforms that automate a range of classroom management tasks, for example Blackboard, Class Dojo, Canvas, and Schoology.

  o For teachers, this can include managing attendance, grades, and assignment records, and maintaining communication with parents.

  o In higher education, learning management platforms range from enabling students to select courses that suit schedules and instructional needs to providing all supplemental support for a given course, including readings, assignments, grades, and contact with teachers and peers.

  o Rather than tailoring particular content based on student competencies, these systems serve more of a tracking and organizing role.

- *Data-driven learning*: A majority of platforms described as 'adaptive' fall into this category of efficient management systems that provide materials appropriate to a students' proficiency level.

    o   Generally, students complete proficiency assessments to determine instructional needs. These assessments (referred to as 'adaptive' or 'personalized') are a cornerstone of technologically-enabled personalized learning, with advocates asserting that personalized testing can pinpoint recommendations for individualized instructional focus.

Figure 4: Practutor Data-driven Learning Proficiency Assessments

    o   Data-driven platforms use analytics that include grade level, performance on proficiency assessment, or number of incorrect tries to recommend an instructional plan (see Figure 5). This instructional plan, also referred to as a "playlist" serves as a checklist, and once modules are completed, proficiency and/or mastery is conferred and the student is advanced to the next module or level.

    o   Based on initial testing, the platform develops tailored reporting of student progress and behaviors to students, teachers, and parents (see Figure 6).

o   The reporting can include actionable recommendations and individualized learning plans (a series of learning modules best suited for a students' proficiency level), which may be updated as the student progresses through the modules, but may simply alert teachers to struggling students without providing actionable recommendations.

o   For teachers, this reporting can inform instructional interventions by identifying students who are struggling or particular tasks that caused difficulty for a proportion of the students.

o   Parents and students can use these recommendations as guidance for homework and supplemental practice. This category is large and includes PracTutor, Amazon's TenMarks, McGraw-Hill Thrive, and Rosetta Stone's Lexia.
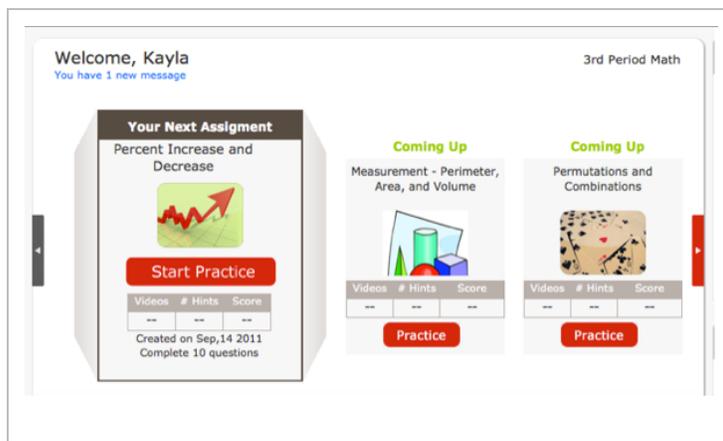

Figure 4: TenMarks Customized Learning Pathways[1]

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[1] Image source: *http://techcrunch.com/2011/09/16/tenmarks-raises-3-million-for-personalized-math-learning-saas/*
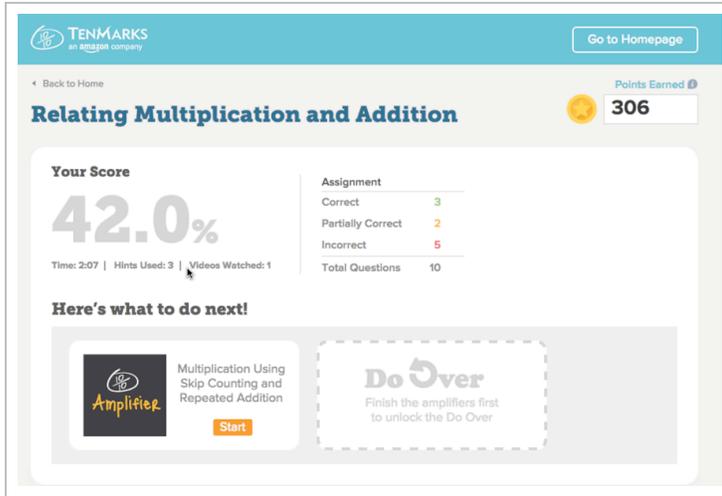
Figure 6: TenMarks Personalized Assessment Reporting

- *Adaptive learning*: Data-driven learning that potentially moves beyond a pre-determined decision tree and uses machine learning to adapt to a students' behaviors and competency.

  o   While not verified by independent research or evaluation, SmartSparrow and Knewton claim to provide adaptive platforms.
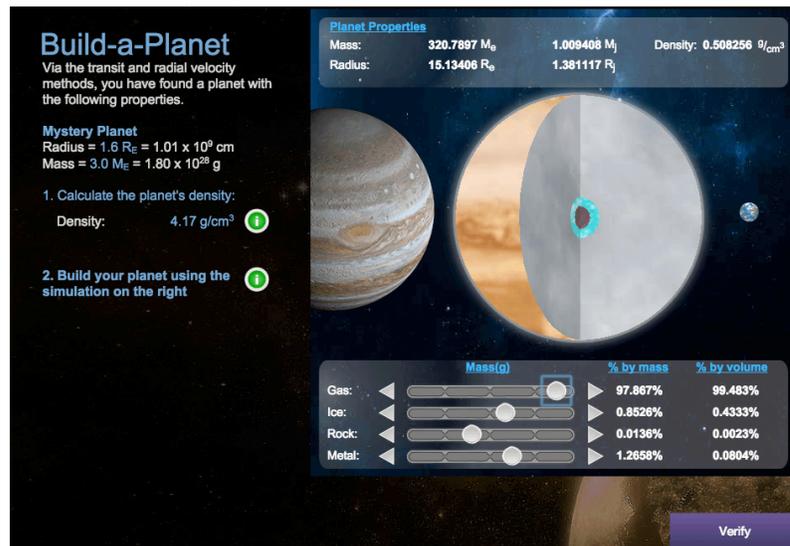
Figure 7: Build-a-planet Adaptive Learning Instructional Module on Smart Sparrow (from https://www.smartsparrow.com/case-studies/habworlds/)

- *Intelligent tutor:* Instead of providing answers and modular guidance, inspires questions, interacts conversationally and has enough options to move beyond a limited decision tree.

   o   Uses facial recognition to respond to emotions such as frustration or interest, feels more social than automated.

   o   Extends past the realm of assistant and becomes a proactive learning guide.

   o   This level is more promise than reality, but the Cognitive Tutor from Carnegie Learning[2], IBM's Watson (High, 2012), and AutoTutor (Nye, Graesser, & Hu, 2014) seem promising prototypes.

Areas of Concern

How Good is Personalized Learning Content?

While the responsiveness of personalized learning systems hold promise for timely feedback, scaffolding, and deliberate practice, the quality of many systems are low. Most product websites describe the input of teachers or learning scientists into development as minimal and after the fact (Guernsey & Levine, 2015). Products are not field tested before adoption in schools and offer limited to no research on the efficacy of personalized learning systems beyond testimonials and anecdotes. In 2010, Houghton Mifflin Harcourt commissioned independent randomized studies of its Algebra 1 program: Harcourt Fuse. The headline findings reported significant gains for a school in Riverside, California. The publicity did not mention that Riverside was one of four schools studied, the other three showed no impact, and in Riverside, teachers who frequently used technologies were selected for the study, rather than being randomly assigned (Toby, et al., 2012). In short, very little is known about the quality of these systems or their generalizability.

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[2] For information about current projects, see the Pittsburgh Advanced Cognitive Tutor Center (PACT) at Carnegie Mellon University (http://pact.cs.cmu.edu/)

Will Tech Replace Teachers?

The major personalized learning platforms describe themselves as supplementing instruction, providing recommendations to instructors but in no way planning to replace the teacher. Yet at the same time, technical discussions raise questions about scale—whether and how a single instructor can meet the differing needs of 25+ students. David Liu, Chief Operating Officer of Knewton describes: "When faced with two students, a teacher can easily differentiate instruction to best fit each of their unique needs. But it's much more difficult to scale that process to multiple classes of 30+ students. We have a limited capacity to take in information about students' distinct progress, evaluate thousands of possible lessons, rank them, and recommend a different sequence to best support each individual student" (Liu, 2014).

There is an implication in technologically-centric education reform that technology can outperform a teacher in meeting students' instructional needs. While there seems to be no evidence demonstrating that personalized learning systems can consistently maximize classroom materials, expert teachers have been shown to be capable of exactly the type of large-scale application that Liu doubts. In the late '80s, several comparative studies were done with teachers using the same textbooks to determine whether novice and expert teachers would have the same outcome. Wilson and Wineburg (1988) found that teachers' subject matter expertise influenced their curricular decisions and most notably, a teacher's lack of expertise impacted how they modeled the subject for the students. Student achievement is tied to a teacher's capacity to "carry the content to them personally through active instruction…" (Brophy, 2006). In another study of high school science instruction, teachers with deep knowledge of the subject matter and a strong understanding of how students best learned, maximized use of educational technologies, moving from simply using them as a homework supplement to pushing students toward a more generative engagement with physical science (Hennessy, et al., 2007). These findings, along with the issues of affordability and sustainability,[3] indicate that personalized learning systems are best deployed as supplements to teachers, rather than their replacements.

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[3] For example, approved vendor assessments from the Ohio Department of Education describes 2015-2016 costs for Amplify as $400 set-up per school, $14.90 per student annually (not including assessments).
Available at http://education.ohio.gov/getattachment/Topics/Teaching/Educator-Evaluation-System/Ohio-s-Teacher-Evaluation-System/Student-Growth-Measures/Approved-List-of-Assessments/Amplify_DIBELS_AD_Form_C_FINAL.pdf.aspx; interviews with educational researchers say that training time on a new system, including uploading and adjusting lessons is around 2-3 years.

What are the unintended consequences for autonomy and social interactions?

Praise for personalized learning systems often focuses on student performance and how promised improvements will benefit school systems and student grade progression. Less attention is paid to how this focus on performance and the individualization of the learning experience may impact a student's psychological well-being. Self-determination theory posits that students have basic psychological needs that must be met for optimal well-being, which include feelings of competence (confidence that they can achieve academic goals), autonomy (belief that they have choice and independence in identifying and pursuing goals), and relatedness (development and preservation of close personal relationships) (Deci & Ryan, 2000; Currie, et al., 2012).[4]

A risk of personalized learning systems is that the wealth of data now available to track and report students' progression will translate into a laser focus on numbers and performance metrics. When parents and teachers are involved in trying to urge students toward a particular outcome, quantified daily, and the focus becomes on a score or finishing a particular set of modules rather than the process of learning itself, there is a danger of initiating a feedback loop in which the student may perceive that if they don't achieve an A or a particular score, or completion, that they will fall out of favor with the teacher or parent. This scenario pits a desire for competence against concerns around relatedness. Students may pursue performance goals in an effort to achieve a score to please teachers or parents rather than learning the value of the process and in working hard (Yeager and Dweck, 2012). Recent education reform efforts and portions of the Common Core testing attempt to provide credit for the problem-solving process, even if the student answers incorrectly.

Touting individualized learning pathways as a feature of personalized learning systems also potentially ignores the social dimensions of learning. A key finding of classroom studies is that in K-12, students are learning to learn and learning to do so with others (Roschelle, 1992). There is a value in collaborative work, in learning teamwork skills, and in learning to communicate, that is not readily apparent in current personalized learning systems. None of the demos or descriptions of personalized learning reviewed for this primer mentioned verbal interaction, or address students' need for relatedness. Collaborative learning is currently something not achieved when working solely with personalized systems. Yet Gallagher (2016) describes a lively classroom in which she

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[4] For more information about student motivation research, see Self-Determination Theory, http://selfdeterminationtheory.org/theory/

directs the personalized learning systems in terms of assessment and assignments, leveraging its strengths to better identify and understand student needs, and then applying to collaborative assignments. Gallagher's example shows that personalized learning tools do not happen in isolation, but are dependent upon the social and instructional contexts – the tools alone do not create a dynamic learning experience, but can support teachers in fusing the social dimensions of learning with data-driven recommendations.

Student motivation is an essential topic in learning research (Pintrich, 2003). Studies show that an essential skill for academic success is the practice of self-regulation (determine progress, what else is needed, a plan for working toward goals) and self-determination (support intrinsic tendencies toward healthy and effective behavior) within the learning experience (Deci & Ryan, 2000; Ames & Archer, 1988). Since personalized learning systems are relatively new and largely untested, their impacts on students' regulation of their learning remains unclear. The systems may remove choice and agency by assigning tasks, and tracking how progression happens through the module; however, systems could be designed to model productive choices and pathways and inform students' regulation practices.

Where is Evidence that Differentiated Instruction Improves Learning Outcomes?

Support for personalized learning systems often stems from intuitive or anecdotal enthusiasm without a strong base in empirical evidence. Ryan Russell (2015), Assistant Superintendent at the Metropolitan School District of Warren Township compares schooling with and without personalized learning using an analogy of watching TV. Russell says that schooling now is similar to watching TV in the 80s, "I sat there at a certain time, I had classes at a certain time, no matter what I needed or wanted, I got a certain dose of instruction." In contrast, *personalized learning* provides "specific access for students to get what they want, when they want it, any time they want it." While personalized learning systems *can* provide a type of flexible access similar to modern digital television, what is unclear from such a comparison is why it is beneficial to structure classrooms like entertainment platforms.

Such assumptions of the benefits of personalized learning hinge on the belief that differentiating access and instruction improves academic achievement. Defined as "to recognize students' varying background knowledge, readiness, language, preferences in learning and interests, and to react responsively," *differentiated instruction* can occur with and without technology (Hall, et al., 2003). Brophy's (1988) comprehensive study of teacher effects on student learning found that instruction that "begins the students at their level and moves them along at their own pace" was conceptually a

very sound approach, however, in practice placed heavy responsibility for learning upon the students and materials, and shifted it away from the teachers. Brophy found:

> Such independent learning demands a combination of functional literacy, direction-following skills, independent learning skills and habits, and sustained concentration and motivation that is almost nonexistent in the primary grades and likely to be seen in only a minority of students in the intermediate and secondary grades. (p. 243)

In their evaluation for the Department of Education, Hall, Strangman, and Meyer (2003), found that while dimensions of differentiated learning (e.g., guided feedback, zone of proximal development, learner-centered instruction) might be independently supported by learning research, the total package (including students working independently, teacher support, quality of materials) lacked empirical validation. They acknowledge a number of testimonials and classroom examples available on corporate websites, but a dearth of validated empirical studies.

Where is Evidence that Data-Driven Instruction Improves Learning Outcomes?

Despite decades of standardized assessment, researchers find no clear feedback loop between assessment data and informing instructional practice (Militello, et al., 2013; Selwyn, 2015). While used for ranking and accountability purposes, the potential for these large-scale collections for improving student learning outcomes remains unclear (Militello, et al., 2013). Since many personalized learning systems are based on the large-scale gathering and analysis of data, it becomes important to determine how effective such practices are at supporting instruction and improving student learning outcomes.

In a survey of 500 K-12 teachers from 64 schools in central Virginia, Hoover and Abrams (2013) found that, as part of daily practice, teachers used several forms of assessment in their classrooms, including national benchmark assessment, testing generated by curriculum providers, testing developed by the teacher, and summative and formative assessments conducted by the state or district. While many teachers described using data to inform daily warm-ups, re-visiting of materials, and offering of extra practice, the researchers felt that teachers relied upon simple analyses (aggregated averages) and missed out on the potential more sophisticated analyses offered, though precisely what this potential might be remains an open question.

In 2011, the Department of Education found that a majority of K-12 teachers had received little to no training in data interpretation (Department of Education, 2011). Yet a more recent study suggests improvement. In 2015, a Gates study of 4600 K-12 teachers showed that a nearly even split between those who had difficulty interpreting data reports and those who found them useful (Bill & Melinda Gates Foundation, 2015).

The benefits of learning analytics are more apparent in higher education, where larger scale tests are possible within a single course (500 students per large lecture class instead of the usual 25-30 in an elementary classroom). Benefits are most frequently seen in well-defined subjects (with clear right or wrong answers) such as math and science (Nye, Graesser & Hu, 2014). The benefits of data in informing instruction in K-12 are less clear.

Examination of the types of data collected reflect potential naiveté on the part of technology developers. As mentioned earlier, teachers are often consulted as an afterthought in design of personalized learning systems, and it remains unclear that adopting a Netflix/Amazon model of recommendations is appropriate for the classroom. Reports generated by personalized learning systems provide details that are measurable, but not empirically proven as useful to improving students' learning outcomes. For example, most systems show the number of resources a student accessed, when they accessed them, and how much time they spent with each one. Yet learning studies find that *time* itself is not a significant indication of engagement, but rather how that time is spent (Berliner, 1990). The measures reported by the systems are serving as proxies for, but not accurate representations of, attentional focus; however, this gap is not made explicit. Instead, there seems to be an expectation that the onus is on the teacher to make the data useful, rather than designing systems that will produce recommendations useful for instruction.

Does Personalized Learning Introduce New Risks for Student Privacy?

As schooling moves toward the 'more data is better' model of tech startups and personalization, concerns continue to emerge around why the data is collected, with whom it will be shared, and how it will be used. Privacy advocates such as the Future of Privacy Forum and the Data Quality

campaign offer principles for responsible data collection and use, advising that data collection should be driven by critical education questions.[5]

Data-driven personalized learning algorithms depend upon data points. The subject of proposed national and state legislation is the lack of transparency and resulting confusion over what data points are collected from and about students, how they are used, and who is permitted access (EPIC Student Privacy project; Herold, 2014). There is limited discussion occurring around the re-use, or secondary use of student data and the distinction between primary and secondary uses of data (for what purposes are the data being re-used and by whom?). Education technology researcher Neil Selwyn finds that "many students and teachers remain largely unconscious of the extent and implications of their daily production of digital data traces and trails" (2015, p.8). Pairing a lack of training or understanding of the usefulness of student data with a lack of clarity about what is collected sets an unsteady foundation for personalized learning efforts.

Distinguishing what constitutes student-specific information is also unclear in both practice and policy. Further clarity is need on the role and process of creating de-identified aggregate data and the value and purpose of these processes.

Business models and technology development approaches to collect as much data as possible to determine what is useful clash with parents' and advocacy groups' desire to know what types of data are necessary. Much uncertainty and opacity surround the present and future use of these datasets. What data are necessary to develop effective personalized learning systems remains an open question. Data collection is not limited to proficiency assessments or demographic information provided by the schools, but is increasingly extending to students' personal lives via school-issued devices brought home, and the monitoring of students' social media accounts (Singer, 2015; Quinton, 2015). Researchers question when such student data collection shifts from instructional benefit to oversight and surveillance (Selwyn, 2014; Reddy, et al., 2015).

Lacking guidance, data interpretation has potential for serious misuse. Consider a scenario in which teachers have access to information about when students access assigned materials. Will a teacher treat differently a student who accesses the materials immediately before class versus one who

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[5] For more information, see the Data Quality Campaign Student Data Principles http://studentdataprinciples.org/ and Future of Privacy Forum recommendations for responsible use https://fpf.org/issues/k-12-education/

accessed them at the time of the assignment? If a student reports difficulty in understanding materials, will a teacher review the record of number of resources accessed and will this information be helpful or detrimental to the response the student receives? In cataloguing the timing and time spent on students' access and use of materials, student learning practices become data points, rather than a matter of private choice, or potentially part of a larger story. Students differ in motivation, aptitude, and approaches to learning. The number of resources accessed, time spent reading, and time accessed are not sufficient predictors of learning outcomes (Guthrie, 2001; Brophy, 1988). Students with highly sophisticated learning strategies may in fact use fewer resources because they identify the most critical points and drill down, whereas those who might be confused about the assignment or have weak learning strategies may read all of the resources, with lower outcomes (Dweck & Leggett, 1988).

There is a danger of false positives depending on how a system is programmed that can use data points to indicate disinterest or lack of engagement when the opposite is true. A concern expressed by advocacy groups is that students will be unnecessarily flagged for a cycle of remediation based on a faulty algorithm and a lack of understanding of how people learn. There is further concern that these small errors can result in students being tracked throughout their academic career and their opportunities limited.

For families, increased reporting by personalized learning systems, oftentimes via text messaging, may increase feelings of anxiety. A study of 40 mothers and their third grade children found that mothers who perceive a high stress situation tend to be more controlling of their children's homework (Gurland and Grolnick, 2005) and that higher levels of parent control result in lower student performance and creativity (Grolnick, et al., 2002). A 2014 *New York Times* article raised privacy concerns over ClassDojo, where teachers can input disciplinary and behavioral scoring that can be shared with parents (Singer). Likewise, learning app Kinvolved sends text messages to parents regarding attendance and lateness (Singer, 2016).

What Do Personalized Learning Systems Optimize For?

Underlying adaptive personalized learning systems are algorithms—analyses driving programs to serve content that increases the likelihood of reaching a desired end goal. But which goals are being encoded in the design of personalized learning systems? Multiple goals are described in marketing materials (e.g., improved scores on quizzes or preparation for Common Core), yet optimizing for multiple goals is ineffective. It is currently unclear from descriptions of personalized learning

systems, what goals each are optimizing for, and how they are differentiating between interim goals (e.g., testing to represent mastery) and larger end goals (progressing to the next grade level).

Here, the tech is surfacing a problem more broadly evident in education: it is difficult to measure for or optimize for success when success isn't clearly defined. For schools, if the end goal is unclear, it is difficult to evaluate what elements of the learning experience are contributing to reaching broader goals. Is the purpose of schools to train students for the workforce, to contribute to the national GDP? Is the purpose of schools to adequately prepare students for success in college and/or to contribute to a civil society? Is the purpose of schools to create a level playing field and remove the effects of economic and racial inequality? Is education supposed to result in a populace that critically engages with issues and events? Does happiness, well-being, or job satisfaction factor into success? What does success look like for the lifetime use of those subjects students are expected to master in schools, and how can this be measured? The expectations and promises of personalized learning are becoming as broad as the schooling system itself and therefore creating a climate in which success is unlikely even under ideal circumstances; technology is just a tool and cannot fix broader social issues alone. Many of the issues plaguing education stem from a lack of consensus over its purpose and these same uncertainties will impact the effectiveness of personalized learning systems. More notably, personalized learning systems will choose and implement these values, even as they are still being debated. This raises a fundamental question: who gets to decide what education should be optimizing for?

Conclusion

This primer highlights the tensions between what is being promised for personalized learning and the practical realities. The realities do not point to a binary conclusion of whether personalized learning is beneficial or not, but rather a complex story in which technology developers are applying successful marketing tactics (personalized content delivery and recommendation systems) to education, and start-up models to the learning experience (risk-taking, test in field), while administrators seek to improve efficiency and performance through formative testing and tailored learning modules. Although they also have a strong stake in the debate, the perspective of parents and teachers are not often included in these discussions. Potentially, personalized learning systems can empower teachers by providing scalable data on student performance, interests, and behaviors, yet they can also disempower through opaque processes and prescriptive formats. For parents, the systems potentially offer increased communication about their child's schooling. A key issue is that personalized learning currently isn't being used as well as it could be and the reason is that few, if

any, of these actors hold a complete picture of how to maximize use of student data to benefit learning. For example, should parents focus on incremental scoring or modular completion? Should their efforts to support their children focus on raising those numbers? Which data points are useful for teachers in real time, and how would they know? Do technology developers have a responsibility for testing learning programs before marketing to schools?

The rhetoric confounds what is important and should be a priority. Instead, it often focuses on the promise of technology as a fix for the education system. Discussions of student data privacy address both data and privacy, but rarely focus on students. What is missing from conversations around personalized learning is that the expectations and goals of personalized learning may not necessarily match the interests of students, parents, teachers, or even society.

The vision Asimov described, of students 'following their own bent' – the notion that not only can a learning plan adapt to a students' pacing, but also enable individualized pursuit of interest – is endlessly reiterated in promises of personalized learning. Positive as this possibility sounds, current infrastructures may not be prepared for the practical realities of students pursuing their own interests. What if students wish, for example, to not go to college, or to play games instead of completing assignments? To what extent do parents, school districts, or future employers really want students to pursue their own interests? Asimov (1988) uses the analogy of baseball to describe the pursuit of interests:

"You learn all you want about baseball, because the more you learn about baseball the more you might grow interested in mathematics to try to figure out what they mean by those earned run averages and the batting averages and so on. You might, in the end, become more interested in math than baseball if you follow your own bent, and you're not told."

There is an assumption that left to pursue their own interests, students will gravitate toward creative, fulfilling, socially valued intellectual pursuits. But what if an interest in baseball doesn't lead to an interest in math? What if an interest in baseball leads to a deeply satisfying sports hobby or playing baseball video games? Or what if an interest in baseball comes at the expense of an interest in math, literature, or other topics? Another possibility is that a student really fulfills this expectation, that a love of baseball does lead to a love of math and that love of math leads to a career exploring complex questions. How long will algorithmic measurement allow between the child's interest in baseball and her/his demonstrated interest in math before suggesting something else?

Schooling is a longitudinal endeavor, with outcomes often not realized until a child who may have started around age 3 in preschool completes her first few years of steady employment as an adult. How does a personalized learning system measure and predict success when there is no conceptual agreement among those responsible for schooling? Returning to Asimov's ideal of students following their interests, when would the algorithm declare the student's trajectory a success or failure? In the realities of an iterative world, which focuses on small gains, such as test scores, rather than larger ones, such as well-being or job satisfaction, how is the open-ended process of intellectual discovery accounted for? Algorithms can only measure what they are programmed to measure. Given the limitations of technologies in determining the success of an open-ended process with no clear outcomes until the outcomes are clear, how would progress be measured, or allowed, and what data or meta-data are available to be part of the calculation?

Appendix A: The Technology and Investment Landscape

While district-level adoption rates are difficult to determine, investments in personalized learning technologies tell an interesting story. In 2011, Rupert Murdoch declared the K-12 educational technology industry in the U.S. to be worth $500 billion annually (Adams, 2011). That same year, the Department of Education reported a much smaller figure: annual spending of $59.8 billion in educational technology expenditures for the U.S. K-12 schools (Department of Education, 2011). A year earlier, Murdoch's News Corp invested $360 million for a 90% share in Amplify (Wireless Generation). While descriptions of Amplify's adaptive offerings showed promise, by 2015 it reported $371 million in losses before its sale. Yet personalized learning remains a compelling promise: leading the buyout was Laurene Powell Jobs' Emerson Collective (Reuters, 2015). The moral of this story is that personalized learning remains a captivating goal for investors and technologists—even as its reach might still exceed its grasp.

To date, the Bill & Melinda Gates Foundation have funded the most active and aggressive campaign in this space. The Gates Foundation has invested $5 billion over the past decade on learning initiatives, with nearly $175 million going toward personalized learning development (Next Generation Courseware Challenge: CogBooks, Smart Sparrow, Open Learning Initiative, among others; Khan Academy), learning pilots (e.g., Personalized Learning Pilots), research (RAND Corporation, 2014; Pain, et al., 2015), and activism (e.g., Data Quality Campaign) (Bill & Melinda Gates Foundation, 2010 and 2016).

In November 2015, Mark Zuckerberg and his wife Priscilla Chan pledged $45 billion over their lifetimes to advance personalized learning, cure disease, connect people, and build communities. In an open letter (Facebook, 2015) to their newborn daughter, they asked "Can you learn and experience 100 times more than we do today?" and described the potential for personalized learning to equalize learning opportunities and enhance learning for all. They have since established the Chan Zuckerberg Education initiative. Facebook has partnered with Summit Public Schools to provide the Summit Personalized Learning platform in over 100 schools (Singer, 2015; Tavenner, 2016).[6]

Additional efforts to support districts in developing personalized learning programs have been funded by the William and Flora Hewlett Foundation, Rogers Family Foundation, Susan and Michael Dell Foundation, and the Eli and Edythe Broad Foundation (Garden, 2015).

As part of its Race to the Top initiative, between 2012 and 2015 the U.S. Department of Education awarded $510 million to 21 grantees to create "personalized, student-focused approaches to teaching and learning that will use collaborative, data-based strategies and 21st century tools to deliver instruction and supports tailored to the needs and goals of each student." In 2014, the Department of Education reported mixed results among the schools, mainly that while the technologies and teaching practices were promising, they faced resource challenges, including limited wifi, limited technical support, and state-level legislative hurdles that did not allow for salary incentives for teachers engaging in program (Sykes, et al., 2014). Most 'model' schools covered in the media as examples of personalized learning received funding either from the Gates Foundation's Personalized Learning Pilots program or the Department of Education's Race to the Top or both (Rand Corporation, 2014; Sykes, et al., 2014).

Early investors in personalized learning systems also include the large educational publishing houses, including Pearson, Houghton-Mifflin Harcourt, and McGraw Hill. Launched in 2012, the Knewton platform powers a majority of personalized learning systems offered by major publishing and technology companies, including Pearson, Houghton Mifflin Harcourt, Macmillan, Hewlett-Packard, Microsoft, and Sesame Workshop. Demonstration videos and marketing materials from Knewton describe it as adaptive, using "normed content" collected across a network of students. Amazon recently entered the fray with its acquisition of TenMarks, an adaptive math curriculum. Microsoft, Amazon and Google additionally play an indirect but significant role in providing web

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[6] Note: primer updated August 11, 2016 to add this news item.

services and hosting for school districts to power the delivery and support of tech-enabled personalized learning.

Mostly, these initiatives provide personalized learning systems delivered via laptops, desktops, or tablets and, as in the case of TenMarks or MyLab, consist of activities students complete individually, such as watching a demonstration of a math problem and then completing activities that test proficiency. Many of the systems offered by publishers are tied to the proprietary instructional resources across Mathematics and English Language Arts instruction. The systems report student performance to the instructor and recommend next steps, which the instructors can approve or modify.

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Acknowledgements

Data & Society is a research institute in New York City that is focused on social, cultural, and ethical issues arising from data-centric technological development. To provide frameworks that can help address emergent tensions, Data & Society is committed to identifying issues at the intersection of technology and society, providing research that can ground public debates, and building a network of researchers and practitioners that can offer insight and direction. To advance public understanding of the issues, Data & Society brings together diverse constituencies, hosts events, does directed research, creates policy frameworks, and builds demonstration projects that grapple with the challenges and opportunities of a data-saturated world.