Personalized Learning
A History of the Present

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A SERIES OF 21ST CENTURY EDUCATION REFORMS laid the groundwork for personalized learning to supplement and supplant face-to-face teaching in the United States (Duncan, 2010). Personalized learning includes a range of web-based learning and assessment technologies, including those that use data analytics to "personalize" online instruction, much like Facebook, Pandora, Amazon, and Netflix mine personal data and use algorithms to tailor advertisements, musical playlists, and product recommendations. Not surprisingly, technology companies and tech industry billionaires have played key roles in developing personalized learning, including Bill Gates (Microsoft), Mark Zuckerberg (Facebook), and Reed Hastings (Netflix). Over the last decade, a network of corporations, philanthropies, venture capital firms, and governments have funneled billions of dollars into personalized learning platforms, such as Summit Learning, K12, Khan Academy, Pearson's MyLab, McGraw Hill's ALEKS, DreamBox Learning, Altschool, IXL Learning, and Teach to One. In 2020, these non-profit and for-profit providers are well positioned to capitalize on the surge in online education brought about by the COVID-19 pandemic.

Popular critiques of personalized learning have emphasized how it ironically "de-personalizes" learning with technology and serves the interests of corporate education reform. This article opens up additional lines of critique by problematizing personalized learning through "a history of the present" (Foucault, 1977).

Foucault's historiography aimed to interrupt assumptions of historical progress and to make the present seem less neutral, natural, or inevitable (Foucault, 1991b). Histories of the present often start with "questions posed in the present and seek to make the terms through which those problems are currently understood an object of inquiry" (Meredyth & Tyler, 1993, p. 2). Accordingly, our first section has outlined language and practices that constitute "personalized learning" in the present. Our subsequent analysis then historicizes these terms and practices by tracing conditions of emergence and lines of descent that made them possible. This archival work has worn away at the self-evidence of personalized learning by documenting its "lowly beginnings" and "questionable ancestry" (Foucault, 1984) and unearthing "the accidents, the minute deviations—or conversely, the complete reversals—the errors, the false appraisals, and the faulty calculations that gave birth to those things that continue to exist and have value for us" (Foucault, 1984, p. 81). This mode of historical problematization may have the effect that personalized learning "can no longer be spoken so lightly…no longer so unhesitatingly performed" (Foucault, 1991b, p. 83). In this sense, Nikolas Rose notes, histories may be more unsettling and provocative than empirical critiques or ideological critiques, which dominate educational research:

> Foucault's own work shows us that we can question our present certainties—about what we know, who we are, and how we should act—by confronting them with their histories: this experience can prove more unsettling and provocative than either the exposure of empirical errors or the formulation of conceptual critiques. (Rose, 1999, p. x)

In this instance, personalized learning might confront its strange and dubious lineage, including its ironic debts to the 20th century industrial model of education and its unsettling links to rat psychology, pigeon-guided missiles, and a line of technologies that were largely panned as educational and commercial failures. At the same time, our curriculum history has also linked the (re-)emergence of personalized learning to new policy networks and novel technologies of government adapted from "big data" and social media that enable programmers, businesses, and philanthropies to assume educational roles that previously were considered anti-democratic, if not dystopian.

What is "Personalized Learning"?

"Personalized learning" represents a range of online platforms that track student data as they work through competency-based learning progressions based on the Common Core State Standards (CCSS) (Bill & Melinda Gates Foundation et al., 2014). The U.S. Department of Education has partnered with philanthropies, edu-businesses, think tanks, and policy entrepreneurs to promote personalized learning as the present—and future—of learning (Duncan, 2010). This self-described "network of innovators" (Bill & Melinda Gates Foundation, 2010) has held up the online platforms of Summit Learning and Teach to One as exemplars of personalized learning. A quick overview of these platforms highlights some of the languages and practices that constitute "personalized learning" in the present.

Summit Learning[1]

Summit Learning began as a partnership between Summit charter schools and the Chan-Zuckerberg Initiative (CZI)—the limited liability company launched by Facebook CEO Mark Zuckerberg and his wife, Priscilla Chan, to manage the couple's investments, philanthropy, and political activities. CZI contracted Facebook software engineers to develop the Summit Learning platform as an "online tool to power personalized learning."

Summit's personalized learning platform includes a pre-set "base curriculum" based on the CCSS and on-demand "content-area assessments" that students complete at their own pace. During "Personalized Learning Time," students log in to Summit's online platform to complete a "Playlist" of pre-set "Resources" sourced from non-profit and for-profit vendors, including: online study guides, videos, worksheets, slideshows, and graphic organizers. Students progress incrementally across a linear “learning continuum” as they “demonstrate mastery” of CCSS objectives by scoring 80% or better on short, multiple-choice quizzes. Summit’s “Data Dashboard” tracks students’ mastery of CCSS learning objectives and compares individuals’ achievement data against their short-term and long-term goals for GPA, test scores, college, and careers.

Summit Learning is “personalized” in the sense that individuals work at their own pace to complete pre-set resources and assessments. Summit teachers do not make curricular decisions, nor do they teach academic content during Personalized Learning Time. Rather, their primary roles are to monitor student assessment data and teach generic “academic literacy strategies” to help students “extract and retain information” from playlist resources, such as modeling how to take Cornell Notes or how to apply reading strategies (e.g., chunking, skimming, reading charts). Teachers “develop personal connections” with students during weekly “mentoring time”—ten-minute meetings in which they discuss performance data and coach students to set measurable performance goals and embody Summit’s “Habits of Success.” This is how Summit Learning “empowers instructors to customize instruction to meet students’ individual needs and interests, while putting students in charge of their own learning.”

Teach To One[2]

In a 2016 keynote to entrepreneurs, Bill Gates named Teach to One “the future of math.” Teach to One started out as School of One, the New York City Department of Education’s personalized education program. In 2011, however, School of One founders partnered with philanthropies and investors to form New Classrooms, a non-profit company that scaled the platform up to the national market by aligning it with the Common Core and re-branding it Teach to One.

New Classrooms’ flagship product is Teach to One: Math. Like Summit Learning, Teach to One: Math has organized CCSS-aligned playlists and on-demand assessments in a browser-based platform, and it tracks students’ mastery of CCSS skills and objectives through online, competency-based assessments. Again, “learning” is the practice of demonstrating competence or mastery of standardized objectives and skills. In contrast to Summit Learning, however, Teach to One mediates *non-linear* routes to skills mastery (New Classrooms, 2015) by using *algorithms* to assign lessons from an online Lesson Bank using data on (1) Historical Learner Patterns, (2) Individual Learner Attributes, and (3) Lesson Characteristics.

In personalized math, students check a monitor for their assigned physical location(s), instructor(s), and lesson modalities as determined by algorithms. They complete online or print resources sourced from McGraw-Hill, Pearson, Houghton Mifflin Harcourt, LearnZillion, IXL Learning, or Khan Academy. After each lesson, students complete an online “Exit Ticket”—a 4-6 question quiz to assess competency of a CCSS skill or objective. Learning is “personalized” in the sense that computers process exit ticket data to update learner profiles and algorithmically generate the next day’s schedule for students and teachers.

Ultimately, software engineers determine what, when, where, and how students learn math. Teach to One: Math teachers have neither their own students nor their own classrooms. Instead, they monitor online lessons or implement externally sourced lessons for variable groups of students determined by software algorithms. According to Teach to One, this is how the program “empowers students to accelerate their own learning through a personalized curriculum that meets them where they are, allows them to progress at their own pace, and incorporates a combination of approaches aligned to the ways they best learn."

Historicizing Grand Claims of Personalized Learning

Many of the world's leading corporations, philanthropies, think tanks, NGOs, and venture capital firms take for granted that personalized learning constitutes a fundamentally new model of "next-generation learning" (e.g., Bill & Melinda Gates Foundation, 2010). Likewise, Summit Learning and Teach to One have branded themselves the 21st century alternatives to the industrial model of education:

> We are living in a post-industrial age, but our public education system still reflects the careful design of an earlier era. Summit Public Schools…and its personalized approach to teaching and learning, Summit Learning, represent an alternative to the industrial model of education. (Summit Public Schools, 2018, p. 11)

> The rigidity of the traditional school model…makes it nearly impossible for teachers to meet each student's unique needs. Instead of being based on research on how students best learn, it is instead a reflection of industrial era thinking, where factories provided the template for mass education. (New Classrooms, n.d., p. 1)

However, these historical claims obscure how personalized learning has recycled early 20th century learning theory and industrial era thinking. They also overlook how 21st century platforms have descended from 20th century technologies that were deemed commercial and educational failures. These historical ironies come into view by revisiting the rise and fall of Sidney Pressey's "Automatic Teacher" and B. F. Skinner's "teaching machines."

Pressey's Automatic Teacher

This country's faith in technological solutions to educational and social problems is at least as old as the Puritans (McKnight & Triche, 2011). However, Sidney Pressey's invention of the Automatic Teacher in the 1920s arguably marked the first personalized learning technology (Benjamin, 1988). Pressey was a psychologist from The Ohio State University who launched his own testing business a hundred years ago as intelligence testing went mainstream. He not only created standardized tests and sold testing blanks, but also set out to invent an inexpensive "labor-saving device" that would spare psychologists and educators from the "drudgery" of administering and scoring standardized tests (Pressey, 1926).

Pressey sought to solve two overlapping problems of mass education that were made worse by the invention of the modern objective test. In his view, teachers were "woefully burdened" by the time they wasted on (1) the clerical demands of standardized testing and (2) mechanical teaching routines associated with "the mastery of drill and informational material" assessed by standardized tests (Pressey, 1926, p. 373–374). He hoped his labor-saving device would spare teachers from these "unnecessarily labored and enthusiasm-killing routines" to free them to "do very much more than at present in the way of class discussions, special help on difficulties, and so on . . . [and] much more real teaching, of the thought-stimulating and ideal-developing type, than is now possible" (p. 376).

In 1926, Pressey filed his initial patent application for a "Machine for Intelligence Tests"—a desktop machine assembled from typewriter parts. In many ways, Pressey's "testing machine" was not far removed from the content assessments of Summit Learning and Teach to One: Math. It displayed multiple-choice questions in a window, and pupils pressed one of four keys to select answer A, B, C, or D. A mechanical counter scored the response, a drum-like device rotated to the next question, and the apparatus documented students' "mastery" of standardized objectives and skills with a printed receipt.

However, Pressey (1926) was explicit that his invention was merely a "testing machine" or "drill apparatus." It automated "clerical" and "mechanical" routines of standardized assessment that were distinct from "those inspirational and thought-stimulating activities which are, presumably, the real function of the teacher" (p. 374). With the addition of a simple locking mechanism, however, his labor-saving device could be understood as "a simple apparatus which gives tests and scores—*and teaches*" (Pressey, 1926). His updated model—the "Automatic Teacher"—not only came equipped with a "test" mode, but also a "teach" mode, where

> the subject *must* get the correct answer to each question before he can go on to the next. When he [sic] does give the right answer, the apparatus informs him, immediately, to that effect. In short, the apparatus provides for…efficient learning. (Pressey, 1926, p. 374–375)

This notion of efficient learning gained popularity with the "social efficiency" reforms of the early 20th century. As education was linked to Edward Thorndike's behavioral psychology and Frederick Winslow Taylor's science of industrial management, it became possible for a simple machine to teach rudimentary "drill and informational material." The behaviorists' invention of the modern objective test had reduced learning to observable and measurable responses that were "simple and definite enough to permit handling of much routine teaching by mechanical means" (Pressey, 1926, p. 374). At the same time, Thorndike's psychology constituted a radical break in the history of learning theories when he argued that laws of human learning could be extrapolated from experiments on animals.

Pressey designed his apparatus in accordance with Thorndike's Laws of Learning—learning theory primarily derived from rats. Much like Thorndike had trained lab rats to run through mazes, Pressey's apparatus taught in the sense that it "tells the subject at once when he [sic] makes a mistake (there is no waiting several days, until a corrected paper is returned, before he knows where he is right and where wrong)" (Pressey, 1926, p. 374). It also incorporated a "reward dial" that could be set to dispense rewards, such as candy, to reinforce test-subjects when they met predetermined performance goals.

Pressey's apparatus also automated scientific curriculum-making processes that social efficiency educators had recently adapted from F. W. Taylor's model of industrial management. Taylorism had inspired scientific curriculum-makers, such as Franklin Bobbitt, to disaggregate fields of study into discrete "objectives" and "skills" and to employ scientific analysis to focus instruction on the sub-set of objectives and skills over which individuals had not demonstrated mastery (Au, 2011; Kliebard, 2004). Accordingly, the Automatic Teacher administered modern objective tests and utilized a mechanical counter to tally correct and incorrect responses to "*omit a question from further presentation as soon as the subject has attained the correct answer twice in succession*" (Pressey, 1926, p. 376, italics in original). In the 1920s, "mastery" represented

100% correct responses on all test items in two successive assessment cycles—much more stringent than today's personalized learning (80% on a short quiz). This level of "mastery" would (a) not reward lucky guesses and (b) reinforce correct responses. This (industrial) mode of automated teaching was thought to be "efficient" in the sense that it "eliminated overlearning" and secured an "individual and exact adjustment to difficulty" along each rotation through the assessment cycle (Pressey, 1926, p. 376). Thus, the Automatic Teacher was thought to "teach informational and drill material more efficiently, in certain respects, than the 'human machine'" (Pressey, 1926, p. 374) and to "adjust to the detail of each child's needs" (Pressey, 1926, p. 376).

Like present acolytes of personalized learning, Pressey positioned this automated teaching and learning at the forefront of an educational revolution. However, 21st century reforms have inverted his line of thought. For example, personalized learning has been branded a "shifting paradigm of teaching" in which curriculum and content-area instruction have been delegated to computers to free time for teachers to "assess metacognitive skills, standards, and learning targets…and continually monitor and respond to students' data" (Jenkins, Williams, Moyer, George, & Foster, 2016). Ironically, this paradigmatic shift has (re)centered 21st century teaching on the ("mechanical" and "clerical") assessment tasks that Pressey positioned as opposed to *real* teaching and learning in the early 20th century: "What the writer is urging is the freeing of the teacher from the mechanical tasks of her[3] profession—the burden of paper work and routine drill—so that she may be a real teacher, not largely a clerical worker" (Pressey, 1926, p. 376).

In another irony, personalized learning is now branded the 21st century alternative to the industrial model of education. In the early 20th century, however, technologies that adapted automatically to individuals' performance were recognized as desired instruments and effects of the industrial revolution:

> There must be an "industrial revolution" in education, in which educational science and the ingenuity of educational technology combine to modernize the grossly inefficient and clumsy procedures of conventional education. Work in the schools of the future will be marvelously though simply organized, so as to adjust almost automatically to individual differences and the characteristics of the learning process. (Pressey, 1933, p. 582–583)

In this sense, personalized learning clearly is derived in part from an old strain of (efficient) learning and scientific management that is inextricably linked to F. W. Taylor's industrial model.

Ultimately, Sidney Pressey failed to bring about the industrial revolution in education. In the early 1930s, he hoped the crisis of the Great Depression would force schools to adopt his machines as a cost-saving measure (Pressey, 1932). After years of financial losses and a nervous breakdown, however, he acknowledged that the Automatic Teacher was a commercial and educational failure (Petrina, 2004). Pressey attributed this failure to his manufacturer (Petrina, 2004) and to teachers' resistance to the industrial model of education (Pressey, 1932). Whatever the reasons, Pressey's work fell into obscurity—until the eminent psychologist B. F. Skinner resurrected the dream of teaching by machine.

Skinner's "Teaching Machines" & "Programmed Instruction"

In 1953, Burrhus Frederic Skinner brought machine-based teaching back to life after a visit to his daughter's elementary school. The Harvard psychologist was horrified to observe a 4th grade math lesson where students had to (1) proceed at the same pace and (2) sometimes wait more than a few seconds for the teacher to reinforce correct responses. Within days, Skinner developed his first "teaching machine" for arithmetic—one that would "restore important features of *personalized instruction*…by enabl[ing] students to profit from an immediate evaluation of what they have learned and to move forward at their own pace" (Skinner, 1986, p. 103, italics added).

Today's personalized learning echoes Skinner's "personalized" instruction—a model of learning he previously outlined in *How to Teach Animals* (Skinner, 1951). Like Thorndike, Skinner reasoned that a universal learning process could extrapolated from laboratory studies of "lower organisms," such as "pigeons, rats, dogs, monkeys, human children, and psychotic subjects" (Skinner, 1968, p. 33). Thorndike had his rats. Skinner was partial to pigeons.

Indeed, Skinner's teaching machine rose from the ashes of Project Pigeon—a federally funded project to train pigeons to pilot Pelican missiles for the U.S. military (Skinner, 1960). During World War II, Skinner worked with engineers from General Mills to develop a missile nose-cone equipped with bird-sized windows and a missile guidance system that three pigeons controlled by pecking on navigation screens. Using operant conditioning, Skinner successfully trained pigeons to fly missiles in flight simulation experiments; however, the military shut down Project Pigeon in 1944, recommending that Skinner give up on his "crackpot idea" and "go out and get drunk!" (Skinner, 1960, p. 34). The Navy later resumed Skinner's experiments in Project ORCON before scrapping pigeon-guided missiles for good in 1953. However, not all was lost. That same year, Skinner applied the science of pigeon training to a machine that would teach his daughter math:

> there is a direct genetic connection between teaching machines and Project Pigeon…. [Those] techniques of shaping behavior and of bringing it under stimulus control can be…directly applicable to education…. Call it a crackpot idea if you will; it is one in which I have never lost faith. (Skinner, 1960, p. 36–37)

Skinner's teaching machine worked much like the Automatic Teacher. Both "taught" by (1) presenting a stimulus prompt, (2) providing means for response, and (3) providing immediate feedback on the correctness of each response (Benjamin, 1988). Indeed, these similarities prompted Pressey's former students to accuse Skinner of ignoring their work, if not plagiarizing it. Skinner (1968) countered that he had never heard of Pressey's forgotten work—and later highlighted three key differences between teaching machines and the Automatic Teacher. The most important distinction, Skinner wrote, was that Pressey's invention "lack[ed] a skillful program which moves forward through a series of progressive approximations to the final complex behavior desired" (Skinner, 1968, p. 35). In contrast, Skinnerian teaching machines arranged discrete learning tasks into a linear sequence called "Programmed Instruction."

Programmed Instruction organized school subjects into a series of instructional "frames" that divided (or "programmed") a field of study into incremental steps that built up to a complex, terminal behavior. Skinnerian teaching machines then "taught" these programs by ordering contingencies of positive reinforcement to reinforce correct displays of observable behaviors and sub-skills that operationally defined mathematics. Much like Skinner had trained dogs to stand on their hind legs (Skinner, 1951) and pigeons to play ping-pong (Skinner, 1968), teaching machines conditioned children to demonstrate mathematical competence—step by step, subskill by subskill, positive reinforcement by positive reinforcement.

The conditions necessary for programmed instruction were simple: "A first step is to define the field. A second is to collect technical terms, facts, laws, principles, and cases. These must then be arranged in a plausible developmental order—linear if possible, branching if necessary" (Skinner, 1968, p. 64).

Skinner's (1968) "linear programming"—adapted from animal training and the treatment of human psychoses—was (and remains) a prominent design of educational technology:

> In acquiring complex behavior the student must pass through a carefully designed sequence of steps, often of considerable length. Each step must be so small that it can always be taken, yet in taking it the student moves somewhat closer to fully competent behavior. The machine must make sure that these steps are taken in a carefully prescribed order. (p. 51)

In contrast, Norman Crowder's (1963) "intrinsic programming," or "branching programs"—first developed for military training—structured non-linear ("branching") routes to skills mastery:

> A linear program is self-pacing in the sense that some students read faster than others, but all must read the same material. An intrinsic program provides different amounts and kinds of material for individual students, based not on prior estimates of the student's needs or on his self-evaluation as he goes through the program, but on his demonstrated performance in choosing answers to the questions. (p. 253)

Skinner's linear programming was the dominant model of programmed instruction into the 1960s (Benjamin, 1988). However, Crowder's intrinsic programming was more "diagnostic" and "remedial" in the sense that his devices assessed each response in real time

> to control the material that the student sees next. If the student passes the test question, he is automatically given the next unit of information and the next question. If he fails the question, the preceding unit of information is reviewed, the nature of his error is explained to him and he is retested. (Crowder, 1959, p. 109)

Much of this old distinction between "linear" and " intrinsic" programming has carried into present distinctions between "responsive" and "adaptive" systems of learning personalization (e.g., Bulger, 2016). Responsive systems, such as Summit Learning, mirror linear programming in the sense that they primarily monitor students' mastery of a linear sequence of pre-determined content and assessments. Likewise, Crowder's intrinsic programs did not use algorithms; however, their "branching" design and capacity to adapt to students' demonstrated performance bear a family resemblance to today's adaptive systems, such as Teach to One: Math (New Classrooms, 2015), which adapt online content and assessments based on user performance data and competency measures.

These historical continuities suggest that personalized learning is not a fundamentally new model of "Next Gen Learning" (Bill & Melinda Gates Foundation, 2010). Indeed, Crowder (1963) argued almost sixty years ago that programmed instruction was not new—it simply automated "educational functions that have previously required a live teacher or tutor…to allow *some rather* *old ideas about teaching* to be more effectively implemented" (p.250–251, italics added). Indeed, 1960s instructional designers explicitly linked learning principles of programmed instruction to Taylor's principles of scientific management (Richmond, 1963, p. 36):

> (1) The subject matter, process, or skill to be taught is first defined, then analysed and broken down into its elements.
> (2) The material is then presented step by step in a carefully prearranged sequence.
> (3) At each step, the learner is given just enough information to ensure that he can make an active response before going on to the next.
> (4) The learner receives immediate confirmation of the results of his responses, works at his own rate, and checks his own progress.

These four learning principles continue to operate in Summit Learning and Teach to One: Math. Thus, personalized learning clearly has re-inscribed industrial-era thinking and behavioral learning theory. Over time, however, people have forgotten how this understanding of learning was made possible when education was linked to Taylorism and the behaviorism of the modern objective test, rat psychology, and pigeon-guided missiles.

The Rise and Fall of Programmed Instruction

Our history has drawn attention to personalized learning's "lowly beginnings" and "questionable ancestry" (Foucault, 1984) to wear away at grand claims of "innovation" and change. In addition, examining the rise—and fall—of personalized learning's 20th century ancestors may have tactical use in reassessing the present movement to personalize education through technology (Foucault, 1984).

Pigeon-guided missiles may have been too eccentric for the U.S. military, but Skinner's "crackpot idea" launched teaching machines and programmed instruction into the educational spotlight during the Sputnik-era reforms of the late 1950s and early 1960s. Teaching machines made the front page of the New York Times in 1957, and IBM developed teaching machines for commercial distribution (Skinner, 1986). By 1962, approximately 200 companies were producing machine-based and print-based systems of programmed instruction, and hundreds of programmed instruction courses were available for elementary and secondary students, especially in mathematics (Benjamin, 1988). This included desktop teaching machines, programmed instruction workbooks, and the first computerized self-instruction systems, such as PLATO at the University of Illinois.

Military and industrial trainers embraced these technologies; however, teaching machines and programmed instruction quickly fell out of favor with educators and researchers. By the end of the 1960s, they had all but disappeared from education (Benjamin, 1988). Psychologists and entrepreneurs would later exhume programmed instruction and adapt it to desktop computers in the 1980s—only to see it fail again (Skinner, 1986). With personalized instruction technologies attempting yet another comeback, it's worth revisiting these controversies and failures from the past to reassess the present.

In previous generations, researchers challenged the empirical and conceptual bases of programmed instruction. Research associations, including the AERA and APA, critiqued how commercial companies were selling programmed instruction materials that had not been vetted by educational experts or empirical research (Benjamin, 1988). The few empirical studies of programmed instruction yielded inconsistent results and often challenged prominent claims about machine-based learning (Pressey, 1963). Even the most prominent scientists and instructional designers within the programmed instruction field found themselves working at cross purposes, forming rival factions, and assuming different positions on machine-based teaching and learning (De Grazia & Sohn, 1962).

At the K-12 level, teachers worried that teaching machines provided politicians and administrators a ready means to increase class sizes or replace them with technologies. Many educators and psychologists objected that "teaching machines" did not really "teach" and that "programmed learning" was not "real learning," since they were primarily used in *remedial* education and limited to *rote* learning—not "*human learning of meaningful matter*!" (Pressey, 1963, italics in original). These older machines were also considered "de-humanizing" in the sense that they reduced human interactions with teachers and peers and also subjected children to behavioral modification techniques designed for animals. As Benjamin (1988) noted, the media amplified these concerns with a series of provocative headlines that helped topple machine-based teaching and learning: *Can Machines Replace Teachers? Will Robots Teach Your Children? Do Teaching Machines Really Teach? Can People Be Taught Like Pigeons? Which Is It? New World of Teaching Machines or Brave New World of Teaching Machines?*

Much like today's reformers, Skinner blamed the "educational establishment" for its rejection of science and technological innovation. This was yet another example of educators resisting the industrial revolution, Skinner (1986) reasoned, as he compared teachers' fears of teaching machines to automobile workers' irrational fears that technology would make factories so efficient that they would lose their jobs to robots. Progressive educators were right to reject the "discipline of the birch rod," Skinner reasoned, but their dismissal of "skills mastery" as "rote learning" went too far: "Skills are minimized in favor of vague achievements—educating for democracy, educating the whole child, educating for life, and so on" (Skinner, 1958, p. 37). Likewise, cognitive psychologists undermined more efficient learning, Skinner argued, as they replaced operant conditioning and behavioral objectives with "vague" notions of "understanding" mathematical relationships (Skinner, 1968, p. 44) and calls for children "to think, grasp concepts, explore, be creative" (Skinner, 1986, p. 106).

As cognitivism began to supplant behaviorism as psychology's dominant paradigm in the 1960s, however, psychologists increasingly rejected Skinner's radical behaviorism. Among them, Jerome Bruner (1963) argued that programmed instruction had been "derived willy nilly from a theory of learning which states that learning is incremental and goes in small steps" (p. 524). Even if learning were linear and incremental—which Bruner rejected—it did not necessarily follow that children needed learning to be reduced to "bite sized packets of information" or "organized in small steps [as if they were] lower primates" (p. 524).

Even Sidney Pressey—the so-called "grandfather of personalized learning" (Petrina, 2004)—came to reject learning theory derived from experimental analysis of animal behavior. Thirty years after pulling the plug on the Automatic Teacher, he argued "current animal-derived procedures in auto-instruction destroy meaningful structure to present fragments serially in programs and replace processes of cognitive clarification with largely rote reinforcings of bit learnings" (Pressey, 1963, p. 5). Given "the all-important fact that human [learning] has transcended animal learning," Pressey (1963) reasoned, it was remarkable that learning theorists would insist on teaching people as if they were pigeons:

> Far more remarkable than Skinner's pigeons playing ping pong is the average human scanning a newspaper—glancing about to find matter of interest to him [sic], judging, generalizing, reconstruing, all in silent reading without overt respondings or reinforcings. Most remarkable of all is it to see learning theorists, hypnotized by the plausibilities of a neat theory, trying to teach that human as if he [sic] were a pigeon—confining his glance to the rigid slow serial peep show viewing of innumerable "frames" each demanding that he respond and be reinforced. (p. 5)

Finally, the press fueled parents' fears that programmed instruction granted corporations and instructional programmers considerable powers of social engineering without public oversight (Benjamin, 1988). Many Americans feared how an anonymous programmer could shape thousands of lives from a distance with a single technology. At the height of the Cold War, the image of children sitting in automated classrooms, staring at screens, completing standardized programs struck many Americans as the dystopic education of Orwell's *1984* or Huxley's *Brave New World*—not a democratic society (Benjamin, 1988).

Personalized Learning: New Conditions of Possibility

At different points in the 20th century, entrepreneurial psychologists teamed with technology companies to sell self-paced learning and assessment machines to the public school market. In each instance, however, these technologies were deemed educational and commercial failures. One might assume that "personalized learning" might suffer a similar fate since it shares considerable lineage with these failed technologies from the past. However, personalized learning has (re)surfaced in a neoliberal context that's forged new connections among education, business, government, and philanthropy (Ball, 2012). These new conditions of possibility are much more conducive to Ed Tech and educational entrepreneurism.

In the 21st century, personalized learning platforms are not the side hustles of university psychologists turned entrepreneurs, such as Sidney Pressey or B. F. Skinner. Rather, personalized learning has been incubated, hatched, and nurtured by a network of businesses, philanthropies, and governments that have worked together to open the education market to for-profit and non-profit providers. Their aim is to disrupt, and provide market alternatives to, the public education system (e.g., Bill & Melinda Gates Foundation, 2010; Duncan, 2010). The personalized learning network is comprised of multinational corporations (e.g. Facebook, Google, Pearson), ed tech startups (Summit Learning, Knewton), government (U.S. Department of Education), philanthropies (Gates Foundation), think tanks (Brookings Institute), online learning and charter school advocacy organizations (EDUCAUSE, iNACOL), and venture capital groups (CEE Trust, Charter School Growth Fund, Global Silicon Valley) (Bill & Melinda Gates Foundation et al., 2014).

This self-described "network of innovators" (Bill & Melinda Gates Foundation, 2010) has also functioned as "new policy network" (Ball, 2012) in education. In the 21st century, Ball (2012) has noted, business, government, and philanthropy have assembled new networks to develop education policy on behalf of states and independent of states. For example, the Common Core was developed for the states by a network of trade groups, policy entrepreneurs, philanthropists, non-profits, and testing companies—in part to lay the groundwork for computer-adaptive testing and personalized learning (Brass, 2016). With the rise of "network governance," education policy-making increasingly has bypassed legislative bodies, blurred the boundaries between the "public" and “private” sectors, and circumvented democratic governance in the interest of reforming education through markets, entrepreneurism, and corporate managerialism (Ball, 2012). The personalized learning network’s “Policy Playbook” has recommended state and federal policies to (1) increase the supply of personalized learning models, (2) build demand for those models, and (3) “eliminate barriers” to private sector participation in education, such as relaxing student privacy laws to expand companies’ access to students’ personal data (Bellwether Education Partners, 2014). These policy “plays” have featured prominently in federal education policies and funding schemes since 2010 (e.g., Duncan, 2010; U. S. Department of Education, 2012).

Importantly, these new alignments of education, business, government, and philanthropy represent a global shift from social democratic to neoliberal governance of education (Rizvi & Lingard, 2010). In Foucault’s (1991a) terms, neoliberalism is a governmentality in which market principles have been adapted to social and political domains as means to govern people’s conduct. In neoliberal government, free markets are thought to be ideal mechanisms to coordinate thought and action, and individuals’ pursuit of their economic self-interests is thought to maximize their well-being and contribute to a more efficient, innovative, and productive society (Rose, 1999). Further, neoliberal governments are to limit interventions to secure social welfare; instead, they intervene to create and maintain markets, to inject market principles and managerial practices into public organizations, and to encourage the private sector to “partner” and compete with the public sector.

The ascendance of neoliberal governance has facilitated the (re)emergence of personalized learning in the early 21st century. In the 1960s, for example, the public demanded more government oversight of programmed instruction and commercial education vendors to protect the public interest (Benjamin, 1988). In the present discourse of education reform, however, public oversight and government regulations are considered outdated barriers to educational innovation (Bellwether Education Partners, 2014). According to this view, the role of state and federal government is to deregulate public education and partner with the private sector, venture philanthropy, and intermediary organizations “to design, develop, validate, and scale up new technology-based assessment resources” and “new business models” in education (Duncan, 2010, p. xxi). Thus, the U.S. Department of Education has funded and partnered with technology companies, corporate philanthropies, and their intermediary organizations to develop personalized learning systems to disrupt, and provide market alternatives to, public education.

Algorithmic Governance, Learning Analytics, Behavioral Economics

The (re)emergence of personalized learning is not only tied to neoliberal rationalities of government. It is also constitutively linked to new technologies of government—that is, “technologies imbued with aspirations for the shaping of conduct in the hope of producing certain desired effects and averting certain undesired ones” (Rose, 1999, p. 52). This includes a range of calculative technologies (e.g. algorithms), inscription devices (college and career readiness standards), and governmental practices adapted from the business, technology, and entertainment sectors:

> Education has not…incorporated many of the practices other sectors regularly use to improve productivity and manage costs, nor has it leveraged technology to enable or enhance them…. What education can learn from the experience of business is that we need

> to make the fundamental structural changes that technology enables if we are to see dramatic improvements in productivity. (Duncan, 2010, p. xiv)

Former Secretary of Education Arne Duncan seems oblivious that schools have contracted with private sector consultants and intermediary organizations for more than a hundred years to improve the efficiency and productivity of education (Trujillo, 2014). As Tina Trujillo (2014) has noted, much of the work of today's intermediary organizations has been derived from early 20th century "scientific management," such as "distilling work into discrete, quantifiable tasks; measuring observable outputs; exercising heavy managerial control over workers; and minimizing costs by appealing to workers' economic self-interests, as well as by engaging in systematically derived best practices and planning" (p. 208). At the same time, however, personalized learning is also part of technology-based reform movement that's explicitly modeled itself on venture capital (Williamson, 2017), Silicon Valley (Williamson, 2017), big business, and big data (Thompson, 2016; Thompson & Cook, 2016). It's these rationalities and technologies—adapted from "big data" and social media—that have created new possibilities for the business and technology sectors to extend their performance management systems and practices of social engineering into the education sector through personalized learning technologies.

In the 21st century, for example, personalized learning reflects the rise of "big data" and emergent practices of "datafication" adapted from multinational firms and technology companies (Thompson & Cook, 2016). Even as the school reform movement's "data-based" decision-making has deep roots in early 20th century Taylorism (Trujillo, 2014), today's "software-powered" platforms (Lynch, 2015) also have radically extended the volume, velocity, and variety of data collection, data sharing, and data analysis (Thompson, 2016). Personalized learning platforms not only collect demographic, curricular, and standardized testing data, for example; they can also track online behaviors and social interactions across their platform and third-party applications (e.g. clicks, response time, pauses, mouse movements, scroll rates, navigation patterns, email content, interactions with other users) and "off-put data" from students' social media profiles and web browsers (Williamson, 2015), such as age, geographic location, IP address, hardware specifications, reading and writing habits, searches, browsing history, and online purchases.

With interoperability the norm in the tech sector, this data can be collected, shared, analyzed, and used by a range of companies, third party vendors, and intermediary organizations. Most of this data sharing and data mining is invisible with Summit Learning, Teach to One, and other personalized learning platforms. Blurring the boundaries between the public and private sectors, these technologies are proprietary black boxes that obscure which data are collected and shared, with whom, and for what purposes. In addition, the U.S. government has relaxed student privacy protections (such as FERPA) over the last decade and explicitly supported personalized learning providers to share, aggregate, and mine personal data to develop educational products that exploit patterns in users' online activity:

> The interconnected feedback systems…rely on online learning systems collecting, aggregating, and analyzing large amounts of data and making the data available to many stakeholders. These online or adaptive learning systems will be able to exploit detailed learner activity data not only to recommend what the next learning activity for a particular student should be, but also to predict how that student will perform with future learning content, including high-stakes examinations. (U.S. Department of Education, 2012, p. 3)

At this point, it's clear that personalized learning is not only descended from behavioral psychology and Taylor's "scientific management." In adaptive platforms, such as Teach to One: Math, interventions upon the learner's thoughts and conduct are made possible by a range of statistical calculations and governed by an algorithmic governmentality not possible in the programmed instruction movements of the past. With personalized learning, it is reasoned that tracking and quantifying individuals' online behaviors and social relations renders them knowable—and, therefore, more amenable to being shaped, optimized, and controlled through technology (Thompson & Cook, 2016). Thus, educational thought and practice may be governed in novel ways by the algorithmic power of "big data" and by social media technologies underpinned by consumer psychology and behavioral economics.

On one hand, personalized learning platforms have adapted the "big data" techniques of multinational corporations to govern the child through "learning analytics" and "educational data mining" (Baker, 2016). Learning analytics mine demographic, performance, and behavioral data to profile users and build predictive models of individual and group conduct through practices of statistical correlation, inferencing, and probability. For example, Teach to One: Math mines individual and collective data to classify and cluster users into population groups for which algorithms predict which commercial resources in its lesson bank are statistically most likely to increase engagement and outcome measures. More broadly, large-scale and longitudinal data mining can identify demographic variables and user behaviors that are positively and negatively correlated with college and career outcomes. With these analytics, it becomes possible to steer youth towards schools, academic majors, and jobs (etc.) that are positively correlated with their demographic or behavioral classifications; conversely, certain data patterns can trigger software interventions to remediate problem populations and/or steer them away from life pathways for which their data profiles demonstrate statistical risk factors, negative correlations, or weak predictors of success (Baker, 2016). Importantly then, "the conduct of the learner is to become the target of decision making that is in part delegated to the automated and algorithmic power of database software" (Williamson, 2015, p. 100)—not to psychologists, teachers, parents, or students themselves. This social engineering goes well beyond the "social efficiency" reforms of the early 20th century and the programmed instruction of the mid-20th century that many Americans considered anti-democratic, if not dystopian.

On the other hand, personalized learning has also leveraged techniques from consumer psychology and behavioral economics that social media platforms use to predict and shape people's choices and social affiliations (Thompson & Cook, 2016; Williamson, 2017). The "Science of Summit Learning," for example, references "learning sciences" that have combined older behavioral and cognitive sciences with neuroscience, social psychology, and behavioral economics (New Classrooms, 2015). As Taubman (2009) noted, the learning sciences have popularized notions of learning that have facilitated the rise of standardized testing and outcomes-based performance management systems in education. Beyond this, personalized learning has also aligned educational governance with the expertise and governing practices of behavioral economics and consumer psychologies. Behavioral economics assumes that the habitual and predictable nature of human behavior makes it possible to manipulate consumer choices; thus, tracking, quantifying, and modeling user behavior in personalized learning platforms enables software to predict and shape people's future conduct through "hyper-nudging," persuasive computing, and "political hacking," and other techniques that Facebook and other social media have used to manipulate brand loyalty, consumer purchases, public sentiments, political opinions, and voting behaviors (Williamson, 2017). These behavioral controls are more intrusive and extensive than the classical conditioning (Pressey) and operant conditioning (Skinner) of personalized learning's 20th century predecessors. These governing practices are also highly controversial, given current debates about online privacy and the role that social media played in manipulating the 2016 presidential election.

In summary, the rise of personalized learning is constitutively linked to 21st century practices of educational commercialization and privatization, new policy networks, algorithmic power, and digital governance that are radically different from the market conditions, calculative technologies, and social-democratic governance of 20th century education (Ball, 2012; Williamson, 2017). Today's personalized learning platforms not only have reproduced older learning theories and industrial models of management, but also re-appropriated elements of Silicon Valley startup culture (Williamson, 2016), "big data" practices of multinational corporations and firms (Thompson & Cook, 2016), and the online consumer experiences of Netflix, Google, Amazon, and Pandora (U.S. Department of Education, 2012). All together, these networks of relations have enabled programmers, businesses, and philanthropies to infiltrate the education "market" in new ways and to align educational thought and practice with the logics, values, expertise, and performance management systems of the business, technology, and entertainment sectors (Ball, 2012; Thompson & Cook, 2016; Williamson, 2016).

Conclusion

It's largely taken for granted in philanthropic, government, and corporate circles that personalized learning represents the leading edge of technology-powered revolution in education. Our history of the present has worked against such faith in technology and market-based reforms by confronting personalized learning with its histories—histories that link 21st century learning personalization to Taylorism and behaviorism, "crackpot" experiments with pigeon-guided missiles, and at least three generations of technologies that were deemed educational and commercial failures. On one hand, this study has highlighted how personalized learning remains constrained by the industrial model of education and by dated learning theories long associated with the training of animals and treatment of human psychoses. On the other hand, personalized learning is not simply the online version of the "New Taylorism" (Au, 2011) or a 21st century "cult of efficiency" (Trujillo, 2014). Older notions of learning and industrial management now intermingle with practices borrowed from the commercial and entertainment sectors in a political and economic landscape that has dissolved traditional distinctions between public and private, non-profit and for-profit, government and business. Thus, personalized learning is also an instrument and effect of a radical shift from social democratic to neoliberal governance and the rise of a techno-economic model of education reform based on Silicon Valley venture capital and startup culture (Williamson, 2017).

Since the 1970s reconceptualization of curriculum, curriculum theorists have resisted technocratic models of educational reform and the commercialization, commodification, and privatization of education. At a time when venture philanthropists, tech companies, and software engineers increasingly assume the roles of educational policy-makers, curriculum-makers, and social engineers, curriculum workers should confront the rise of personalized learning platforms and the rise of new policy networks, algorithmic power, digital governance, and Global Silicon Valley in education (Ball, 2012; Thompson & Cook, 2016; Williamson, 2015, 2017). Toward this end, our curriculum history has highlighted the strange histories that have made it possible for personalized learning to re-emerge in the early 21st century as a possible supplement, or successor, to face-to-face teaching and learning. With a nod to Foucault (1991b), this mode of historical problematization might open new spaces of contestation and debate and help bring it about that "personalized learning" can no longer be spoken so lightly, no longer so unhesitatingly adopted.

Notes

1. This section draws on and quotes from Summit's official website: www.summitlearning.org (Summit Learning, n.d.), which has neither a cited author, date, nor page numbers. As such, this endnote serves as citation for the section in lieu of repeating a citation of limited information. In addition, Summit Learning recently announced the formation of a new organization, T.L.P. Education, which will lead the Chan Zuckerberg Initiative's efforts to scale their personalized learning platform nationally.

2. Similarly to the previous section, this section draws on and quotes from the official homepage of Teach to One: www.newclassrooms.org/ (New Classrooms, 2020).

3. This gendered construction of the teacher as female is instructive since the convention of the time was to represent third person singular with the masculine "he." Due to space constraints, we could not explore this and other gendered dimensions of machine-based teaching, past and present.

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