

Article

The Deskilling of Teaching and the Case for Intelligent Tutoring Systems

James Hughes ¹¹ University of Massachusetts Boston, jamesj.hughes@umb.edu

Abstract: This essay describes trends in the organization of work that have laid the groundwork for the adoption of interactive AI-driven instruction tools, and the technological innovations that will make intelligent tutoring systems truly competitive with human teachers. Since the origin of occupational specialization, the collection and transmission of knowledge have been tied to individual careers and job roles, specifically doctors, teachers, clergy, and lawyers, the paradigmatic knowledge professionals. But these roles have also been tied to texts and organizations that can disseminate knowledge independently from professionals. Professionals and organizations turn knowledge into texts and tools that enable lay people to access knowledge without the intermediation of professionals or organizations. In the 21st century, one emerging tool for transmitting knowledge is the intelligent tutoring system. This paper examines how technological, epistemic, and economic trends in education are supporting the routinization, proletarianization, and automation of the occupation of teaching, leading to the increasing substitution of intelligent tutoring systems for human instruction.

Some trends, such as standardized curricula and testing, both restrict teachers' professional autonomy and facilitate the creation of pedagogical tools. Other trends reduce teachers' ability to resist automation. The growth of adjunct teaching and paraprofessional roles in higher education allows organizations to take over and rationalize parts of the traditional teacher role. Faculty evaluations and learning outcomes assessment weaken professional claims to be the sole arbiters of instructional quality and student learning. The widespread use of intelligent tutoring systems also depends on the sophistication of software capable of performing the social-emotional and cognitive roles that educators perform. Eventually, pedagogical software will be able to interactively individualize curricula to the needs and interests of every learner, more cheaply, quickly, and accurately than any human teacher. Assessment of learning will be continuous, and certification of learning will be for specific skills instead of broad area competencies. Intelligent tutoring systems will help transition education from its medieval and industrial-era model to more accessible and flexible continuing education for employment and life enrichment.

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1. Introduction

Covid has forced an abrupt and radical reassessment of how we work, by both workers and employers. Many expect that one impact of Covid will be an acceleration of automation (Anderson et al., 2021; Autor & Reynolds, 2020; Lund et al., 2021). Studying the impacts of epidemics from 2003's SARS to 2014's Ebola outbreak, Sedik and Yoo found that these previous epidemics increased the rate of work automation for at least four years, across 18 industries and 40 countries and controlling for GDP, trade, and demographics (Sedik & Yoo, 2021). Of course, Covid has had a much more abrupt and profound impact on work than these previous epidemics. Covid accommodations made labor more

expensive, and workers more reluctant to return to work, creating an acute labor shortage in 2021. Employers have spent a year and a half experimenting with replacing face-to-face work with remote work and automation. Surveys suggest that firms may now allow a quarter of employees to continue working from home, and will shrink their office spaces accordingly (Lund et al., 2021). In a 2020 survey, 43% of employers were expecting to reduce their workforce (WEF, 2020).

While most economists have seen the little prospect of automation impacting teaching, Covid has had a dramatic impact on education. Parents and teachers have been concerned that their children have learned less online, while others have embraced online education. Teachers have chafed at the insistence that they risk their lives with unvaccinated students, but have struggled to keep students engaged online. In 2021 American K-12 schools faced a more acute teacher shortage than they did before Covid, with fewer college students choosing to enter education and the aging K-12 teacher population dropping out more quickly due to Covid burnout (Zamarro et al., 2021). There are more than half a million fewer public sector teachers in the United States in 2021 than there were in 2019, and the number of unfilled teacher jobs is now at a 20-year high (Hoff, 2021). What if, between Covid shocks, advances in artificial intelligence, and the deepening teacher shortage, automation is now poised to begin re-shaping education the way that it has begun impacting other white-collar occupations?

In his 1995 novel *The Diamond Age: Or, A Young Lady's Illustrated Primer* Neal Stephenson describes a dystopian future with persistent inequality. His protagonist is a poor Chinese girl, Nell, who comes to possess an experimental, interactive, AI-driven tutoring tool, the eponymous "illustrated primer." Through ordinary conversation, the AI assesses Nell's interests and knowledge and begins instructing her using personalized content appropriate to her context. The teaching software developed for the short-lived One-Laptop-Per-Child (OLPC) experiment in the 2000s was directly inspired by this device in *The Diamond Age* (Dodd, 2012).

The first examples of "intelligent tutoring systems" that interactively adapt to students began to be introduced back in the 1970s, however, well before recent breakthroughs in machine learning and natural language processing. Meta-analyses of the effectiveness of these crude algorithmic tools found that students learned as much from them as from one-on-one tutoring, and *more* than from classroom instruction (Kulik & Fletcher, 2017; Ma et al., 2014; Xu et al., 2019) These tools are certain to become more sophisticated and be applied to more educational domains. What is less certain is their impact on the profession of teaching and the organization of education. Technology futurism has a poor track record predicting the speed or form of technology adoption. Will AI-guided instruction supplant human instruction, or be used as a labor-extending tool by teachers who then focus on the other, less automatable parts of their work? Will personalized, self-paced instruction replace age-based classrooms and the four-year college degree, or will school gradually incorporate the new tools without major reform?

Much of the debate assumes that once a tool is available that it will be widely adopted, destroying jobs and whole sectors in its wake. Many technologies with disruptive potentials are never widely adopted and the literature on work has long noted how firms and workers, especially professionals, resist automation. This essay will combine the sociology of work with a discussion of the technical hurdles to developing teaching software to explore how and when new teaching technologies will be disruptive. The essay attempts to show how the systematization of knowledge necessary for the automation of occupational roles supports and is accelerated by capitalist rationalization, deskilling, and proletarianization.

The two oldest and strongest professions, teaching and healing, are based on the need for ordinary people to turn to specialists who have mastered esoteric bodies of knowledge. These fields of knowledge require a lifetime of investment, and in turn, they assert that only other experts can gauge the quality of their service. Both healing and teaching emphasize the importance of personal relationships – doctor-patient and teacher-student – and discourage attempts to measure and systematize their work. Mandated clinical pathways based on medical outcomes data are derided as “cookbook medicine,” and curricular guidelines measured by standardized exams are condemned for encouraging “teaching to the test.” The slow pace of automation in health care and education is also explained by the complexity of medical and educational knowledge, and the skills needed to deploy knowledge effectively. The work process in a hospital or a university is an order of magnitude more complex than in most factories. Determining the most cost-effective way to produce a widget is far simpler than identifying the best way to produce a cancer remission or an English major.

One result of the slow pace of automation in medicine and education is that their costs have inflated faster than other products and services, leading to growing pressures from the market and state to ensure that consumers are receiving valid, quality services. The uncertain relationship of medical services to health outcomes and higher education to actual learning and careers has led to growing skepticism of both professions. Now the rapid improvement in machine learning, predictive analytics, and natural language processing may accelerate a century of efforts at routinization and automation.

How Do Societies Organize and Transmit Knowledge?

In *The System of Professions*, Andrew Abbott (Abbott, 1988, 1991) proposes that there are three ways to organize expert knowledge, into professions, organizations, or commodities. Each way of accessing expert knowledge has its advantages and disadvantages. Professions offer strong financial and prestige rewards for those who endure the necessary training and challenging work. Organizations can divide up knowledge among specialized, interchangeable parts of a bureaucracy, lowering costs and improving quality control. The most routine forms of knowledge can become inexpensive commodities, e.g. textbooks. The medical texts of the 2nd-century Greek physician Galen – three million words of which have survived – were relied on as canonical medical knowledge for more than a thousand years.

In 19th century America, where doctors were difficult to find, books purporting to allow self-diagnosis and self-treatment were popular. As physicians professionalized in the 19th-century pressure grew to standardize medical education, suppressing heterodox theories like homeopathy, and codifying medicine into certification exams overseen by state-appointed licensure boards and administered by medical schools. As physicians adopted the legitimacy of scientific empiricism consumers increasingly turned to them as independent contractors.

In the 20th century, however, the proliferation of medical knowledge drove the growth of hospitals, medical specialties, paraprofessionals and larger systems of care. Today consumers can seek a self-diagnosis online, or turn to nurses using standardized diagnostic protocols provided by their healthcare organization, or make an appointment for a personalized assessment by a physician. In other words, medical knowledge is increasingly created, codified, and transmitted by organizations and software. While many consumers may prefer medical knowledge from their trusted professional, medical advice from an organization or algorithm allows much wider, faster, cheaper, and often more accurate, access (Walker, 2009).

Likewise, the teaching role began in prehistory and has been co-evolving with knowledge in books and organizations ever since. The first schools were established 5000 years ago in Sumer and Egypt after the invention of cuneiform and hieroglyphics required students to be formally instructed in reading, writing, and numeracy. Religious schools to train clergy to read and teach are at least 3000 years old. Roughly 2500 years ago schools emerged in the Greek city-states and Confucian academies were established in China. The Chinese schools were probably the first to be open to all social classes, and their integration into the civil service system made philosophical texts, scholars, schools, and standardized exams the basis of Chinese imperial authority into the 20th century.

Formal education for children and adolescents in Europe emerged in the 11th century out of the tutoring of elite boys preparing for the university or clergy. Before the emergence of universities in medieval Europe education was only accessible to those who could buy hand-copied books and hire tutors. The university structure allowed wider access to standardized knowledge and the validation of professional credentials. After the Renaissance, and especially after the invention of the printing press, secondary education for rich European boys expanded until states began organizing and providing universal public education in the 19th century. Even in the most egalitarian countries, however, schooling reflects the class of their students, with private schools for elites modeled on universities, and the children of laborers receiving standardized, age-based instruction in disciplined classrooms that prepare them for the factory.

While K-12 education reflects the industrial era in which it emerged, higher education is still shaped by the medieval system - departments focusing on specific disciplines, granting degrees, taught by relatively autonomous faculty who are also expected to generate new knowledge. With these ancient origins, the organized transmission of knowledge through teachers and schools has enormous cultural and political inertia. If teachers as a profession and schools as an organizational form face challenges today it will not be just from new teaching technologies, but their convergence with sociological trends that are finally re-shaping education a century after they transformed much of the rest of the economy.

Deskilling and Rationalization of Professional Jobs

"The bourgeoisie has stripped of its halo every occupation hitherto honoured and looked up to with reverent awe. It has converted the physician, the lawyer, the priest, the poet, the man of science, into its paid wage labourers." (Marx & Engels, 1847)

In the 1970s labor economist Harry Braverman (Braverman, 1998) proposed that all firms under capitalism are incentivized to deskill tasks that require expensive, skilled labor. This theory suggested that competition and profits will push most firms towards "scientific management" (Taylor, 1915) dividing and re-organizing discrete tasks into assembly lines to maximize efficiency. This theory fit the Marxian prediction that capitalism would rationalize the work of the petit bourgeoisie, making them more like wage laborers. Having a group of skilled workers in a firm is not only more expensive but a challenge to the rational, hierarchical management of the firm. In healthcare, this dual authority structure can be seen in the tension between medical staff and hospital administration, and in universities between tenured faculty and university administration. Unlike factories, neither hospitals nor universities can as effectively divide up, reorganize and deskill the central skills of their professionals, diagnostic and treatment decision-making in the case of medicine, and instruction and research for teachers. But with rationalized accountability structures and productivity pressures, such as larger classrooms, student course

evaluations, and standardized student learning assessment in the case of education, professionals do begin to feel more like proletarian industrial workers.

Braverman's thesis fell out of favor when the evidence for deskilling was found to be mixed, and studies showed industries creating new skilled occupations. Another problem for the application of Braverman's deskilling thesis in education is that much of the sector is public and not private, and the competitive and fiscal pressures forcing work rationalization in the public sector are more diffuse. Nonetheless, private sector work organization and managerial methods bleed over into the public sector when state and local budgets squeeze schools and universities. Politicians demand the measurement of educational productivity on the behalf of taxpayers. Schools are pressured to gear education more to the labor market, and less to education for its own sake or to prepare critical citizens. Fiscal pressures in higher education encourage hiring cheap adjunct instructors and fewer tenured faculty.

While the proletarianization of teaching reduces labor costs, teachers have been able to resist work rationalization, intensification, and automation because schools cannot yet substitute technology for their core skills. For schools and pedagogical software to seriously challenge teaching teachers' core skills and tasks need to be decomposed into standardized, interchangeable parts.

What are Teachers' Core Tasks?

Most occupations require multiple skills, but the specific skills and their importance vary within occupations. The core skill of primary care physicians is diagnosis and treatment decision-making, but they are also expected to have social-emotional skills to understand and educate their patients. If physicians employ physician assistants and nurse practitioners, then they can outsource some of the preliminary diagnostics, history-taking, and patient education, and spend more time on a larger patient load using just their core skills. Social workers, therapists, and dozens of other specialties now cooperate in providing patient care, organized around electronic medical records, with the physicians as the central decision-makers. Physicians can maintain their dominant role so long as their core skill is immune to industrial de-skilling and automation.

A decade ago Frey and Osborne (Frey & Osborne, 2013) used a classification of the tasks and skills involved in 702 occupations to estimate each occupations' vulnerability to automation. Their study suggested that about half of American jobs were vulnerable to automation in the next decade or two. Replication of this analysis in many industrialized countries found roughly the same results. They argued that highly educated occupations in general, and K-12 and postsecondary teachers in particular, were among the *least* vulnerable to automation. Nonetheless "Even education, one of the most labor-intensive sectors, will most likely be significantly impacted by improved user interfaces and algorithms building upon big data" (Frey & Osborne, 2013).

As with Braverman's deskilling theory, labor economists have pushed back on the Frey and Osborne analysis by pointing to the flexibility within occupations to re-focus on un-automatable skills and to use automation to extend an occupation's productivity instead of replacing their jobs (Arntz et al., 2016). Assuming that workers can adapt to automation by reallocating their time, critics estimate that far fewer occupations are vulnerable to automation. Workers with more power and prestige, like professionals, are more able to redefine their role and prevent their occupation from being eroded by technology. Occupations that require higher education are not only less likely to be replaced by

automation because of the difficulty in automating their tasks but also because they can use their professional authority to defend their core skills and use new technologies as labor extenders.

In 2020 the McKinsey consulting firm published a study of the impact that technology can have on the reallocation of K-12 teachers' work time (Bryant et al., 2020). They asked K-12 teachers in Canada, Singapore, the United Kingdom, and the United States how much time they spent on 37 different activities. They found that, on average, teachers spent half (49%) of their 50-hour workweek in direct interactions with students, including instruction, coaching, and "behavioral, social and emotional skill development." The other half of their week was spent on preparation, grading, professional development, and administration. McKinsey then estimated the impacts of new technologies on the time demands in these various tasks, concluding that the biggest time savers would be on tasks like curricular preparation, grading, evaluation, feedback, and administration, with the smallest impacts on student interaction. For instance, software "packages to help teachers assess the current level of their students' understanding, group students according to learning needs, and suggest lesson plans, materials, and problem sets for each group" could cut the time spent on these tasks in half. The roughly 13 hours saved could then be spent on more personalized, individual instruction (or having a better work-life balance).

McKinsey's analysis is presented as an optimistic vision that K-12 teachers can embrace, rather than a rationale for fewer teachers and larger classes. But K-12 teachers are less powerful than university faculty, and their skills, which require less education, are more amenable to standardization and rationalization. One way K-12 teaching has been prepared for deprofessionalization is through the standardization of K-12 curricula.

Curricular Rationalization and Standardization

In this section, I review how trends in curricular standardization, learning outcomes assessment, competency-based learning, and online education are contributing to the rationalization of instructional work and its gradual displacement by intelligent tutoring systems.

The Standardization of K-12 Curricula and Assessment

In their 2016 book *The Future of the Professions: How Technology Will Transform the Work of Human Experts* Richard and Daniel Susskind (Susskind & Susskind, 2016b) argue that the standardization and systematization of knowledge is the key prerequisite for the deconstruction of the professions. The degree to which a body of knowledge has been standardized is also the degree to which consumers can access it from non-professionals in an organization, or as a commodity.

Within professional organizations (firms, schools, hospitals), we are seeing a move away from tailored, unique solutions for each client or patient towards the standardization of service. Increasingly, doctors are using checklists, lawyers rely on precedents, and consultants work with methodologies. More recently, there has been a shift to systematization, the use of technology to automate and sometimes transform the way that professional work is done — from workflow systems through to AI-based problem-solving. More fundamentally, once professional knowledge and expertise is systematized, it will then be made available online, often as a chargeable service... when professional work is broken down into component parts, many of the tasks involved turn out to be routine and process-based. (Susskind & Susskind, 2016a)

In the case of education, a detailed standardized curricula is a prerequisite for intelligent tutoring systems to actually challenge the professional role of teachers rather than simply be instructional tools used for limited purposes. So far most intelligent tutoring systems have been developed in STEM fields which have more standardized curricula than the social sciences and humanities. There have also been more tools developed for K-12 education than for more complex higher education. While there are pressures towards curricular standardization in higher education, such as from learning outcomes assessment and discipline-specific accreditation, the process is more advanced at the primary and secondary level.

National curricula for K-12 education are common in many countries, albeit not in the United States where K-12 education is under state and local control. Over the last two decades, however, there have also been moves in the U.S. towards national educational standards starting with the Bush-era No Child Left Behind policies which financially punished schools found “underperforming” on standardized testing. Since the racial and class background of students is the principal driver of their aggregate achievement, this policy was widely perceived as a way to defund already struggling public schools and encourage private education. Teachers and schools complained that No Child Left Behind encouraged “teaching to the test” and cutting programs like art and music to spend more time on exam preparation.

During the Obama era, the fight over K-12 standardization shifted to the Common Core State Standards Initiative. The proposed Common Core was a comprehensive elaboration of competencies in each field that should be achieved at each grade level. Originally proposed by conservatives, and embraced as a bipartisan initiative, many states signed on. As the Tea Party mobilized against all Obama policies, the Common Core was demonized as a federal takeover of local education, and eventually shelved.

China, by contrast, with the world’s largest education system, adopted national curricular standards for K-12 education in 2003, and in 2018 announced updated standards for high schools. The Chinese enthusiasm for national curricular standards and the use of standardized testing as a meritocratic gatekeeper to class mobility is often attributed to the reliance on national civil service exams since the 6th century Sui dynasty. Today Chinese education is singularly focused on the university entrance exam or GaoKao, implemented in 1952. While 90% of Chinese high school students scored well enough on the 2020 GaoKao to attend some form of higher education, scores strictly determine the prestige of the university that a student can attend. China’s long history with curricular standardization and testing-based meritocracy was a strong influence on education in Vietnam, South Korea, Taiwan, and Japan, all of whom are in the top ten in international comparisons of learning (Jones and Whiting, 2020).

Countries like China that have adopted national curricula probably will have a head start in the widespread adoption of interactive instructional tools compared to countries that allow localities to determine curricula. Investments in an intelligent tutoring system, and programming the curricular goals to be achieved, will be a much more attractive investment with these larger markets. On the other hand, the local autonomy and diversity of curricula in places like the United States could also encourage more curricular experimentation, and the creation of intelligent tutoring systems for basic math and reading comprehension could be widely applicable without uniform curricula. We will have to see which kinds of systems implement more widespread use of intelligent tutoring.

The key to rationalizing a work process is measuring the time and cost of the labor inputs, and the quantity and quality of the outputs, to determine the most efficient methods for maximizing production at an adequate level of quality. As noted above, curricular standardization is more advanced in K-12 instruction than in higher education, and K-12 teachers have less autonomy over what they teach than higher education instructors. But the pressures in higher education to measure and redesign teaching have been increasing for decades, from accreditors, Board of Trustees, politicians, parents, and students. Universities are obliged to demonstrate that they are measuring both general educational skills, literacy, and numeracy, as well as the specific skills and knowledge promised within college majors. They are also being asked to demonstrate that they use these ongoing assessments to map and redesign their curriculum to improve learning outcomes.

Using learning assessments to guide curricular re-design is one aspect of the rationalization of teaching. Or as Ovetz (Ovetz, 2015) puts it “faculty autonomy over course design, content, delivery, and student assessment have been challenged, and even displaced, by the efforts to replace content-based assessment of learning, represented by the grade and degree, with competency-based standards, rubrics, departmental and student learning objectives, badges, micro-credentials, pathways, and certifications.” Learning assessment pushes education from relying on faculty grading and the granting of degrees to external assessment and to the “the differentiation of instructional duties that were once typically performed by a single faculty member into distinct activities performed by various professionals, such as course design, curriculum development, delivery of instruction, and assessment of student learning” (Gehrke & Kezar, 2015). Intelligent tutoring systems can then be based on these validated curricular maps and pedagogies.

Unbundling, Badgification and Competency-Based Education

Just as learning outcomes assessment can be used to rationalize and redesign curricula, a focus on ensuring student competencies encourages the redesign of secondary education and university degrees. Competency-based education has competed with the credit-hour-based degree for a long time, with the degree always being more prestigious. Now the tide seems to be shifting back towards competency, as self-guided curricula and assessment become more sophisticated, and the inflexibility and expense of degrees becomes less attractive. At the secondary level, most US states have adopted policies facilitating the completion of high school degrees through testing, such as by reducing or waiving requirements for class time (Brodersen et al., 2017; NASSP, 2021). For instance, the state of Ohio allows students to earn high school credit by demonstrating competency in a subject area rather than requiring a specific number of hours of classroom instruction (Deye, 2018).

The unbundling of education from a comprehensive transformative experience capped by a degree into a set of specific skills that can be assessed directly completes the process of curricular standardization and learning outcomes assessment. While understaffed secondary education may welcome competency-based pathways for the students who prefer them, the switch from time-based certification to competency-based assessment threatens the business model of higher education. For instance, more than 2 million US high school students take Advanced Placement tests each year. Advanced placement allows 8% of college freshmen to place out of an average of 10 credits, and up to a year’s worth, of introductory courses, shortening time-to-degree and costing their schools tens of thousands of dollars per enrollment (Evans, 2018). Extending competency testing to the rest of the curriculum could cut the time and cost of a college degree in half (Craig & Williams, 2015).

Brief curricula designed to confer badges for specific competencies can also adapt more agilely to labor market expectations. Instead of hiring a graduate with a computer science degree, employers might require competency badges for ten key skills, each requiring an intensive month of instruction. A competency-based model would also lend itself to life-long learning, drawing adults back for short, just-in-time training in skills that are immediately applicable to their work rather than to a two-year Master's degree. Badgification and competency-based education in turn simplifies the programming of intelligent tutoring systems to impart these streamlined and standardized skill sets.

Online Education and MOOCs

Online education is also contributing to the emergence of intelligent tutoring by encouraging curricular standardization and reducing instructor autonomy. Distance learning actually began in the 19th century with experiments in education through correspondence, followed by experiments in recording lectures for broadcast on the radio, television, or on film strips (Mirrlees & Alvi, 2014). By 1958 there were 31 educational television stations and 150 university closed-circuit television experiments in the United States. While administrators and reformers promoted distance learning as a way to educate more students and reduce costs, faculty saw televised education as “the threat of technological unemployment, the degradation of the teacher's status and role, and the dehumanizing of the teacher-pupil relationship” (Zorbaugh, 1958). Critics like David Noble charged that new instructional technologies “like the automation of other industries, rob faculty of their knowledge and skills, their control over their working lives, the product of their labor, and ultimately, the means of their livelihood” (Noble, 1998).

Since online education dispenses with the expensive infrastructure of schools and universities it is already significantly cheaper than the traditional model. Online services increase price competition and shift the balance of power from the provider of services to the owners of the curricular product and its consumers. Online education is a potentially global marketplace, far more price-competitive than public schools or local universities. Following this logic, there has been widespread attention to the potential of online education and massive open online courses (MOOCs) as a solution to the rapidly inflating cost of education. Even before Covid a third of American students in higher education were enrolled in distance learning, with about 15% exclusively taking online courses (Lederman, 2018) that are disproportionately taught by contingent faculty.

While many American universities have established their own online offerings, MOOCs grew quickly by offering universities partnerships with the technology and marketing expertise of companies like Coursera, edX, and Udacity. The carefully designed MOOC is the joint property of the university and external firm, with the teacher as a contracted content provider. By 2019 five companies accounted for 90% of the MOOC market (Shah, 2019). While a student in rural Oklahoma or Bangladesh might have previously taken a small continuing education course at a local community college, they now had the option of receiving a more prestigious MOOC certification from Harvard or MIT alongside several thousand other students. Businesses are increasingly open to accepting MOOC certification as a credential for hiring and promotion. For instance, the Information Technology Certificate Program offered by Google through Coursera involves courses in system administration, operating systems, and network security, resulting in a Google badge at a fraction of the cost of a comparable community college degree. While MOOCs have not drawn many students away from traditional curricula or degrees, during the Covid crisis of 2020-2021 participation in distance learning was closer to 100% and online education is poised to grow quickly.

Deprofessionalization

Perversely K-12 teachers have been simultaneously professionalized and proletarianized. The educational requirements for American K-12 teachers have increased over the last century, and most now have a college degree. But their salaries have remained 10% to 25% lower than comparably educated occupations for decades (Strauss, 2016). In 2019 dollars the average annual salary for American K-12 teachers reached a high of \$63,000 per year in 1990 and has stagnated since then (NCES, 2021). In response to declining wages, the number of American students training to be K-12 teachers has also been declining for decades, and those who remain in the field have turned to unprecedented labor militancy (Camera, 2019). With schools restricted from paying higher wages by austerity budgets, or from hiring more teachers by the growing teacher shortage, public education in the United States is primed to embrace intelligent tutoring systems and labor-extending software as proposed by McKinsey. While this essay has mostly focused on the trends in the United States, the shortage of teachers in the developing world is generally even more acute. Once the cost of automated teaching tools declines it may be even more attractive in poor countries without enough teachers (Edwards & Cheok, 2018).

As with the proletarianization of K-12 teachers, the decline in professional status and autonomy of university faculty is making it easier to adopt intelligent tutoring systems in higher education. In the United States in 1969 about four out of five (78%) higher education faculty were tenured. By 2018 that had fallen to only one out of four (27%) (Flaherty, 2018). Contingent faculty may have multi-year contracts or may be hired course-by-course, and include post-doctoral fellows, clinical faculty, and visiting professors. What they have in common is lower salaries and considerably less political influence within universities compared to tenured faculty. While higher education administrators and tenured faculty generally agree that hiring tenure-track faculty should be prioritized, financial pressures on universities make adjunctification hard to avoid. For-profit educational institutions in the U.S. rely even more heavily on adjunct faculty, with 90% of instructors being contingent (Proper, 2017). Even adjuncts on full-time, multi-year contracts earn less than comparable tenure-track positions. Reliance on adjuncts is also a boon to administrative flexibility since many adjuncts are hired weeks before courses begin, and their classes can be canceled if they don't fill (Kezar et al., 2019).

Adjuncts represent the unbundling of teaching from research, governance, and service expectations. While tenure-track faculty condemn the exploitation of adjuncts in aggregate, they also benefit from it since they have been able to shift the teaching of large introductory courses to adjuncts so they can spend more time on research or on teaching smaller classes for advanced students. Since adjuncts do not participate in governance and are doing more of the teaching, they are less able to resist attempts to measure and standardize curricula. The next stage of unbundling is when for-profit schools, like University of Phoenix, hire experts to design curricula and hire adjuncts to teach them. Finally, the university itself can be unbundled into stand-alone online programs, microdegrees, and badges (McCowan, 2017).

Automation of Teaching

The proletarianization of teaching and the subordination of teachers to planned curricula and learning assessment do not in themselves threaten the occupation, only its professional autonomy, prestige, and compensation. For capitalist rationalization to fully commodify the occupation it needs to turn the core skills of the profession into software. The technologies to automate these core skills have been in development for decades.

One of the first “intelligent tutoring systems” was called SCHOLAR, introduced in 1970 to teach South American geography. Tools for teaching STEM fields in general, and computer science in particular, have been over-represented, both because of the expertise of the developers, and the more objective, rule-based nature of STEM disciplines (Mousavinasab et al., 2021). After fifty years of development, these interactive learning tools now incorporate Bayesian logic, data mining, machine learning, and natural language processing. A 2019 meta-analysis of 19 studies of intelligent tutoring systems in K-12 education found that students who used them had higher test scores than students in teacher-led classroom instruction, with learning comparable to one-on-one instruction (Xu et al., 2019). These results were the same as those of two previous meta-analyses of more than 50 intelligent tutoring systems in K-12 and higher education (Kulik & Fletcher, 2017; Ma et al., 2014): “These results held across grade levels (elementary through higher education), content domains, and study quality (e.g., randomized controlled trials and quasi-experiments)” (Ma et al., 2014).

Chatbot Advisors and Tutors

A core teaching skill is the ability to talk to students about the material and to give them context-appropriate advice about what and how to study. Until now intelligent tutoring systems are incapable of understanding and generating conversational speech, and instructional chatbots have been limited interfaces to “frequently asked questions.” For instance, universities have experimented with interactive chatbots to guide students through routine inquiries about admissions or course registration (Engati Team, 2021). Admithub and Pounce are chatbots that schools offer to admitted students to steer them towards putting down a deposit. Beacon, a “digital friend” developed by Staffordshire University, recommends readings and makes connections with tutors (Newton, 2021).

Now intelligent tutoring systems are beginning to use natural language programming (NLP) for open-ended conversational interactions with students (Pérez et al., 2020). NLP models have achieved startling breakthroughs, as with the GPT-3 system introduced by OpenAI in 2020 (Heaven, 2020), ensuring more incorporation into tutoring systems. A team at the University of Bath found a significant increase in learning after incorporating the ability to parse natural language queries and provide hints and links into their intelligent tutoring system Korbit. Their system personalizes the answers and hints based both on previous student queries and their ongoing performance in the course (Kochmar et al., 2021). A GPT-3 system from Open AI can summarize books of any length (Wu et al., 2021), and Google, Facebook, and Microsoft have developed their own document summarizing tools (Wiggers, 2021). A GPT-3-based system called Learn From Anyone allows a student to assign any well-known public figure as “teacher” - such as Aristotle for philosophy or Einstein for physics - and the system responds to students’ queries in that person’s style (Gandhi, 2020).

Robot Graders

Multiple-choice exams scored by computers have been in use for fifty years. The much more difficult job is the assessment of text, which researchers have been attempting since the 1960s (Page, 1966). Auto-grading of tests and papers is advancing rapidly, and can now not only gauge spelling and grammar, but also the coherence of an argument, its relevance to the prompt, and the complexity of words and syntax. Software can then report on the

specific strengths and weaknesses of a student's writing. Essays with unusual features can be flagged for human review (Hussein et al., 2019).

These systems can be gamed by students who understand what is being scored, by including a lot of big words for instance, and the systems can't yet judge the accuracy of factual claims. But it is almost as much work to write convincing gibberish as it is to write actual prose. As a scientist at the Educational Testing Service, Nitin Madnani, noted "If someone is smart enough to pay attention to all the things that an automated system pays attention to, and to incorporate them in their writing, that's no longer gaming, that's good writing" (Smith, 2018).

The main form of cheating in writing assignments however is plagiarism, and automated plagiarism detection tools like TurnItIn have made catching work copied from the Internet painless. Students can also use these new tools to improve their own writing and check for accidental plagiarism. The tool Grammarly for instance gives students suggestions to improve word choice and tone, clarity, formality, and fluency, as well as flagging potential plagiarism. In other words, these tools already provide much of the feedback on writing that a teacher would. The next step is to have an AI help write your paper. The Rytr AI Writing Tool for instance can produce thousands of words of passable prose in 40 different styles given just a few prompts, and more "intelligent authoring" tools are coming to market (Dale & Viethen, 2021).

Predictive Analytics for Student Success

Teachers' largely intuitive sense of students' capacities and struggles is now being complemented by data analytics. Big data and machine learning provide rapid, quantitative assessment, using multiple factors to predict who will be in academic difficulty or require additional attention. Many universities now have data analytics platforms that use dozens of student characteristics to predict whether prospective students will enroll, how successful they will be, what courses they should take, and when they need an intervention to remain enrolled. Online learning management systems (LMSs) like Blackboard provide a moment-to-moment picture of student engagement, study habits, and performance that, combined with hundreds of other predictive facts, give instructors and advisors a clear idea of who needs help and with what. For instance, Solutionpath's Student Retention, Engagement, Attainment and Monitoring (StREAM) platform gives teachers and advisors a real-time dashboard of students' 'engagement score' that combines class attendance and the timeliness and quality of assignments and tests with LMS records of interactions with course materials, peers, and the library.

The next step in applying these Big Data approaches to education are personalized learning recommendations, with a "learning experience platform" (LXP) offering up texts, videos, podcasts, exercises, or course recommendations like Netflix or Youtube videos (Williamson et al., 2020). Intelligent tutoring system informed by this kind of real-time Big Data will be far better at tracking and motivating student learning than any one instructor could be (Kaklij et al., 2019). What kinds of instructional content or exercises should be suggested for an 18-year-old Latina would-be computer scientist who did well in high school but is juggling a second job, versus the 30-year-old Vietnamese adult male with dyslexia who commutes to take night classes to be a nurse? When and for which students does a bad grade on a paper raise a red flag? Are learning problems and successes tied to specific courses, instructors, or pedagogies rather than student characteristics? To the extent that teachers attempt to weigh these kinds of factors, they can be prone to biases that Big Data generally should not be.

Robots and Social-Emotional Labor

Social-emotional skills have been considered the most difficult to automate, and these skills are also central to the teacher's role. Ironically, the legendary ELIZA software developed by Joseph Weizenbaum at MIT in the 1960s to simulate Rogerian therapy demonstrated that very simple code, repeating the patient's statements as questions, could elicit trust and deep emotional sharing. Today, rapid progress in natural language processing has been accompanied by improvement in recognizing human emotions from verbal and nonverbal cues. Chatbots that can detect depression and other mental health issues are widely available (Ahmed et al., 2021; Jovanović et al., 2021), and there is accumulating evidence that interacting with mental health chatbots can improve symptoms of depression and anxiety (Abd-Alrazaq et al., 2020).

Education researchers are now incorporating emotion recognition into intelligent tutoring systems to gauge student engagement, frustration, and mental health (Khadimallah et al., 2020; Newton, 2021). Chinese educators are experimenting with real-time monitoring of students' faces in the classroom to generate an engagement dashboard for the teacher (Waltz, 2020). Researchers are developing similar tools to gauge student engagement in the online classroom, at least when students have their cameras on (Sharma et al., 2019). Incorporating emotion recognition into intelligent tutoring systems will allow the software to learn what the student finds engaging or boring, and adjust the content and pace of instruction accordingly.

Conclusions

Futurists have a poor track record in predicting how new technologies will impact employment and occupations, and predictions of rapid automation have often been wrong. Powerful occupations can resist the implementation of technologies that threaten their autonomy, or selectively adopt technologies to extend their productivity and authority. Subordinating professions to organizational rationalization is a political project which co-evolves with their social and occupational power, the systematization of their skills, the subdivision and outsourcing of their tasks, and the capacity of automation technologies. This essay has situated the development of intelligent tutoring systems within the standardization of curricula, the growing use of learning outcomes assessment and online learning, and the declining autonomy of the teaching profession. These social dynamics will shape how quickly intelligent tutoring systems are created and deployed.

For more than a century education at all levels has gradually attempted to measure and redesign teaching to maximize productivity and quality. As skills and tasks were re-assigned to specialists, they were also subjected to the monitoring and control of school administrators. Standardized curricula and external testing challenged curricular autonomy and grading. In higher education the most privileged professionals, tenured faculty, are being supplanted by contingent instructors, further enabling the standardization and commodification of instruction. The distillation of instruction into knowledge products, such as texts and online courses, complemented efforts to measure learning outcomes and standardize curricula. The principal obstacle to these efforts, the basis of professionals' occupational autonomy, was the irreducibility of their core bundle of skills. For teachers, those skills are the ability to assess students' learning and emotional state and to structure curricula and communicate with students in ways that illuminate and advance their learning. The decades-long gestation of intelligent tutoring systems is now poised to whittle

away at these core skills with natural language processing, predictive analytics, adaptive responses, and affective intelligence.

The expanded use of intelligent tutoring systems has the potential to address the shortage of teachers in many countries, reducing the cost of education, personalizing learning, and enabling access to life-long learning. Many of the problems with education will remain, however. The algorithmic data used to inform predictive analytics and learning systems will inherit biases from historical educational data in the same way criminal justice or natural language algorithms inherit biases from their training data. There will be better and worse intelligent tutoring systems, and presumably the better ones will be more accessible to the affluent. The content and pedagogical goals of intelligent tutoring systems will remain as political as curricula have always been. Will religious ideas about evolution be included? How will education about sexuality, imperialism, and racism be framed? Will the curricula for the children of the affluent stress creativity, leadership, and civic character development, while systems for the working class focus on marketable skills? Centralizing curricula and pedagogy into intelligent tutoring systems will reduce both good and bad forms of diversity, and give corporations and the state even more influence than they had over millions of human instructors, making these systems a new terrain of political struggle. As with the debate over automation of other fields, it is time to move past debating whether there should be intelligent tutoring systems to how they should be used.

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