NSF Learning Analytics Workshop

March 18-19, 2019

University of Michigan, Ann Arbor

Discussion Topics

The workshop will focus on defining research priorities in three areas:

1. How can we define the educational outcomes, competencies, and habits of mind that should serve as the goals of post-secondary institutions?

The core goal of educational institutions will always be communicating the richness of human cultures and values, creating a love of learning, building an understanding of the majesty the physical world, and facilitating constructive dialogue and debate. But the enormous growth in the percentage of people needing access to higher education for employment, and the growing need to refresh skills and learn new ones throughout a career, translates into a growing interest in the economic benefits of an education.

A survey of college freshman found that between 1971 and 2016 the percent of freshman saying that getting a better job was a "very important" reason for going to college increased from 70 to 84 and the percent saying that a "very important reason" was "to make more money" increased from 45% to 73%. Interest in credentials is clearly paramount for people in non-degree granting institutions and older students returning to degree granting institutions to obtain credentials other than a degree. Only about a third of post-secondary spending goes to acquire traditional degrees (Carnevale, Strohl, & Gulish, 2015) and only about half of the people in post-secondary education are in a program to get credits for a degree (Ganzglass, Bird, & Prince, 2011). Forty-seven percent of college students are now more than 24 years old (National Center for Education Statistics, n.d.).

Defining the competencies needed by employers is increasingly difficult. Studies of job requirements show a steady increase in the level of "substantive complexity" of jobs (cognitive demand, analytical reasoning, and synthetic reasoning) and an increasing demand for "interactive skills" (negotiating, instructing, persuading, speaking, taking instructions). About half of the increases resulted from changes in employment by industry type and half from changes in demand for different skill levels within industry groupings (Wolff, 2006). Three quarters of the fastest growing occupations in the US required some form of credential, half required a BA or higher, and a quarter required a graduate or professional degree (Baker, 2009). Thirty-four percent of working American adults reported that their occupation had legal or professional requirements for continuing education and 20 to 30% of people with a high school degree or less have some form of credential or license (US Dept. of Education, National Center for Education Statistics, 2013).

Employers are looking for more than mastery of specific bodies of knowledge or technical expertise. A recent survey of employers found that "Nearly all those surveyed (93%) say that "a demonstrated capacity to think critically, communicate clearly, and solve complex problems is more important than [a candidate's] undergraduate major" (Association of American Colleges and Universities and Hart Research Associates, 2013). Employers have a strong interest in non-cognitive skills or "soft

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skills" such as integrity, personal initiative, professionalism (Lumina Foundation, 2014). Since the specific skills needed for employment are almost certain to change over the course of a person's career, there is also a clear need to define the foundation needed lifelong learning (Lee, 2014). An ability to learn quickly, to find information quickly, to adapt, to function in situations of great ambiguity are often much more important than the ability to regurgitate an array of facts.

The need to modernize and rationalize learning goals in post-secondary educational has launched a number of projects and studies (Fain, 2014; U.S. Department of Education, n.d.; King-Collins & Baylor, 2013; Malan, 2000; King-Collins & Baylor, 2013; AACU, 2015; Lumina Foundation, 2014; Association of American Colleges & Universities, 2005; Maki, 2015; The Social Science Research Council, 2016; Klein-Collins, 2012; Manufacturing Institute, n.d.). These reports all appear to be in agreement on a key innovation: goals should be specified in terms of outcomes – what the individual actually knows and can do – rather than in terms of inputs such as credit hours or seat time.

Ignoring most of the efforts driven by university groups and other traditional sources of information about skills, , private employers are beginning to develop their own definitions of competency using new sources of data and new analytic methods to better understand the characteristics of most effective employees. The rapidly growing field of "People Analytics" is producing a variety of strategies for both to understand the characteristics of highly successful performers and to try to identify these competencies in job applicants (Craig, 2016; Software Advice, 2016; Capterra, 2017; Peck, 2013). This practice is made possible by the enormous amount of information generated as an integral part of a workplace using modern information processing and communication tools – virtually every occupation. This data is often supplemented with data gathered with the explicit goal of tracking employees. A recent review found that employees in a third of firms interviewed had some form of wearable devices to monitor employees (Sinar, 2015; Marr, 2015).

Analytics tools are being applied across a very broad set of competencies, including finding ways to define skills of recognized experts. This has been tried in defining the skills needed to maintain complex equipment and the even the characteristics of highly rated professors. (Azab, 2016). The tools are also being used to define and measure desirable competencies in social skills such as the characteristics of effective teams and work groups (Woolley, Chabris, Pentland, Hashmi, & Malone, 2010; Olguin-Olguin & Pentland, 2010; MacMillan, 2013).

Possible Related Research Questions:

- Can post-secondary institutions get access to data on employee activities and use it to gain insights into the competencies and expertise actually valued in the workforce?
- How can collaborations between academic research and corporate "people analytics" research best be managed?
- Can the tools of "people analytics" be expanded to help define the habits of thought and the problem solving skills of experts in academic disciplines (what does it mean to "think like an engineer"?)
- How can privacy be ensured without compromising the utility of the data?

2. How can we measure an individual's competence?

Even if it is possible to describe the kinds of expertise an educational institution aspires to help their students build, measuring actual attainment of those competencies can be challenging. Creative

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solutions have been proposed, but difficult to implement at scale (Messick, 1994; Mislevey, 2003). Unfortunately, the default approach continues to be a measure of knowledge that is easily assessed as a paper and pencil test (or an online form thereof). New technologies, however, open new opportunities.

There are two core practical challenges in measuring competence: (1) can measurements in a formal learning environment correlate well with competence in future jobs or courses, and (2) can we find ways to evaluate and credential competence gained outside of a formal learning environment?

The flaws in conventional test designs is becoming increasingly apparent: "Many existing standardized tools, because they were developed decades ago, are misaligned with contemporary priorities for student learning, not to mention being out of step with modern assessment technology" (The Social Science Research Council, 2016). One obvious problem is that these tests measure the performance of a person an environment unlikely to be experienced in the world outside the classroom only by anchorites -- isolated from external sources of information and conversations with colleagues (Bransford, 2001). Although there are a number of promising instruments being developed to measure characteristics like "growth mindset" (Dweck, 2006) and "grit" (Duckworth, Peterson & Mathews, 2007), there are no clear methods for evaluating "soft skills" using standardized metrics.

Employers are frustrated by the lack of progress. Large corporations like Ernst & Young and Penguin Random House have lost faith "that success at university correlates with achievement in later life" (Sherriff, 2016) and two thirds of employers did not ask recent college graduates for their transcripts (Arum, 2011). A data-driven study of success in a major corporate sales division found no correlation between success as an employee and the school the candidate attended, their GPA, or references (Bersin, 2003). In a recent series of interviews, Peck (2013) found that many companies using advanced analytic methods were hiring people who didn't attend college for technology jobs, high end sales jobs, and some managers (Peck, 2013).

Many employers have become less interested in formal degrees and more interested in a portfolio of credentials that demonstrate specific areas of competence. It is certainly possible that for all but the most elite institutions, degrees will be replaced with a set of "unbundled" credentials (representing competencies) that are constantly being refreshed (Craig, 2016). Data science may contribute to this shift by providing a set of tools for establishing verifiable credentials outside conventional instructional settings.

A variety of new technologies have opened the door to innovations that can make it practical to provide measures of competence that can both motivate students and provide a useful guide to future employers (or future instructors). Evaluations, for example, can make use of new tools for presenting challenges in simulated environments that imitate employment challenges, including such things as the practice of nursing, machine operation, and working with sophisticate scientific equipment – approaches that would be prohibitively expensive given traditional methods of instruction. But new information tools have changed this equation by supporting continuous evaluation as an integral, and accepted, part of the learning process. Sophisticated computer games, for example, encourage players to move to the next game level only when they have demonstrated competence at the previous level (National Research Council, 2011; Oblinger, 2015). In a well-designed game, players use the knowledge that they are not prepared not as failure, but an incentive to master the skills needed (Holman, Aguilar & Fishman, 2013). The games can provide highly sophisticated challenges, including challenges involving teamwork and timely communication. People who may take more time to master some competencies need not be penalized if the goal is to demonstrate real competence. The concept of "freedom to fail" is

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key in entrepreneurship and is a growing concept in education as well (Dicheva, Dichev, Agre, & Angelova, 2015).

Education technology now generates an enormous amount of data that can be captured – including which materials an individual watches, how they behave in simulations and games, and how they communicate with each other and instructors. But extracting useful information from this heterogeneous data is heroically difficult (Computing Research Association, 2015) and "data wrangling" has become an important skill for conducting learning analytics research (Clow, 2014). It is clear that powerful statistical tools will be needed to make these large datasets meaningful (Mislevey, 2003; Owen, Ramirez, Salmon, & Halverson, 2014). Machine learning and deep learning, for example, may prove to be useful in both identifying skills actually used in the work environment and assessing them in a learning environment. Methods like multi-modal analytics (e.g., Kahn, 2017) and social network analyses (Scott, 2017) can begin to make sense of the massive amounts of data becoming available.

Possible Research Questions

- How can we discover whether the competence measured in an educational setting translates into competence in employment?
- Can analytic tools employed by businesses to measure employee performance be used to determine how well credentials correlate with demonstrated competence?
- What tools can be developed to learn from the increasingly rich set of data trails generated by students – including use of instructional technologies, online-discussions with colleagues and instructors – to understand their approach to desired levels of competence.
- Can this include both subject area competence and skills such as critical thinking, team participation, and communication?
- Can the tools of "people analytics" be applied to capture a richer measure of each student's approach to meeting achievement goals?
- Can tools be developed that correlate information gathered on a student's performance in a school setting with actual on-the-job performance? Can this be used to measure the performance of different strategies of instruction? Different competency goals?
- If simulations, including team-based simulations, are used, can automated tools be developed to mine the multi-dimensional data generated by them.
- Can an individual's competence be measured with information derived from employment data and sophisticated "prior learning assessments"?

3. How can innovations in approaches to learning (both technologies and instructional strategies) be evaluated?

New information technologies open many new opportunities for building competence and driven a wide range of experiments. The experiments include how information can be conveyed – using video, simulations, augmented and virtual reality, games, and other tools; and the role that instructors, counselors, and other specialists can play; and, the overall management of instruction is managed (e.g. multi-modal learning, flipped classrooms, peer evaluation) (Christiensen, 2011). These opportunities have spawned an enormous international market, much of it not a part of conventional instructional institutions. In 2016, the global market for learning technology was $76 billion (Adkins, 2017). The challenge, of course, is finding out whether these innovations are actually improving learning by increasing the efficiency of mastering topics, the quality and durability of what is learned, and the extent

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to which the systems can serve the widest possible range of students. The possibilities and pace of change have outpaced the research base needed to sort all of this out.

Many parts of the economy would rely on market forces, but markets in education and training work poorly and there is essentially no tradition of innovation. The most obvious deficiency is the absence of any agreed way to measure quality (problems addressed in RQs 1 & 2). But even if there were clear metrics of success, few post-secondary institutions have either the funds or mechanisms for rewarding major process innovations.

One problem faced in finding the true potential of new technologies in education is that the kinds of transformations created by these technologies in other parts of the economy (e.g., business services, entertainment, and retailing) required huge investments and fundamentally new business models. A major video game production can, for example, involve a 700 person team and cost $400 million to complete (Theodore, 2017) – orders of magnitude more than even the largest course development. This kind of investment appears unreachable for education even though post-secondary education is an enormous enterprise.

There is, however, compelling evidence that the new tools can dramatically improve the quality and reduce the cost of learning if they are carefully designed by a competent team. A recent DARPA project reported by Fletcher (2012), cost $40 million and cut the time spent training shipboard IT systems personnel in half. In a careful assessment, the people trained on the new system not only attempted more tasks, and more difficult tasks, but succeeded at a much higher rate people trained on the new system not only attempted more tasks, and more difficult tasks, but succeeded at a much higher rate (Fletcher J. J., 2012). Other studies also provide hints that new systems can cut learning times 24-54% without sacrificing quality (Fletcher J. , 2009). Bowen (2012) conducted a carefully constructed randomized trial comparing a hybrid (computer training with some classroom time) system for learning statistics compared with standard classroom instruction. This project showed that student outcomes were the same although the hybrid course cost 67-75% less per student (Bowen, 2012). Other work has shown that skills gained in simulation-based training transferred successfully into real skills on the job (Stanton, 2015; Sheftick, 2014). Simulations can cost much less than traditional classroom approaches and let students experience a far wider range of experiences – including emergency situations that someone on the job encounters very infrequently.

The tools used to assess an individual's approach to a desired level of competence can also be useful in measuring an individual's emotional state, motivation, or other factors that would be useful to the people (and software) involved in instruction and counseling. (Pardo, 2015; Lonn S. T., 2014) Tools are being developed to understand how existing data from students can tailor instruction to increase the likelihood of success for the widest range of students. These can include improving counseling and advising (Perez-Rosas, 2017; Lonn S. T., 2014).

Tools developed to define and measure competence and the rich set of data continuously available from individual students should provide the resources needed to evaluate the massive number of natural experiments in innovative approaches to instruction now underway and to design A-B and other experiments that can rapidly gather additional insights.

Possible Research Questions

- Can tools such as adaptive rapid experimental design be used to evaluate the impact of innovations in instructional design?

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- How can individual student data be used to guide instruction tailored to each student and provide individualized advice, and counseling?
- What data should be collected about each student (demographics, fine grained indicators of mastery and deficiencies, skills in online and other interactions including team performance and ability to communicate, English language skills, other measures)?
- Can this portfolio be built and curated like personal medical records (e.g. distinct access and consent rules for instructors, instructional software, and researchers)?
- How can the data best be presented to instructors?
- How can students control access to this data?
- How can the records be secured? How can privacy be maintained? Can blockchain systems be useful? (Tapscott, 2017).

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