Unleashing the Power of Data Analytics to Examine Engineering Students' Experiences and Outcomes

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Abstract

In this theory paper, we integrate literature from different fields. We argue that efforts to expand engineering education research through data analytics need to be grounded in the established literature and understanding of student development. We discuss the opportunities and challenges associated with using data analytics to examine engineering students' experiences and outcomes. We suggest that engineering schools should enhance data infrastructure, along with data governance policies, to foster a culture of collaboration among units and divisions, and better utilize existing student data sources through greater data integration. We also suggest that engineering education researchers equip themselves with knowledge on data science, in addition to knowledge about different types of student experiences, and actively explore a wider range of data sources for research. Thereby, we envision a new research landscape with expanded data sources, integrated data systems, and new analytical techniques to enable predictive analysis and more actionable findings.

Introduction

Engineering students develop competencies through classroom learning, work-integrated learning outside the classroom, and extra-curricular activities on and off campus [1-3]. In two ways, current engineering education research (EER) does not adequately reflect these multiple interlinked experiences that contribute to competency formation. Firstly, while much EER has been devoted to students' classroom learning [4, 5], less emphasis has been placed on work-integrated learning and the synergies arising from learning inside and outside classrooms. Secondly, the potential of existing data sources, such as administrative data, academic records and student surveys which engineering schools routinely collect, remains relatively untapped. These data sources are rarely cross-linked, significantly reducing the potential of building a rich holistic understanding of student experiences.

Lack of data linking and alignment is not just a missed opportunity within engineering education [6, 7]; there have been calls to use data analytics to leverage the explanatory and predictive power of student data broadly across postsecondary education [8, 9]. Hence, this theory paper aims to explore how a holistic view of student experiences and the rapidly emerging field of data analytics in postsecondary education can contribute to improved engineering education practice and research.

In the following sections, we will present concepts and insights from two bodies of literature: student development and data analytics in postsecondary education. Then, we will use examples from EER literature to discuss opportunities and challenges in applying data analytics to examine engineering students' experiences and outcomes. This paper aims to enhance methodologies in EER by integrating knowledge from different fields and engaging with the scholarship of integration according to Ernest Boyer's typology of scholarship [10].

Student Development Perspectives

The holistic view of student experiences is manifested in two interrelated concepts about student learning: lifewide learning and integrative learning.

Lifewide Learning

The notion of "lifewide learning" is often coupled with "lifelong learning" and is understood as all learning and personal development that emerges through activities in the multiple contexts and situations people inhabit contemporaneously at any point in life, with the aim of fulfilling roles and achieving specific goals, and continuously developing knowledge, understanding, skills, capabilities, dispositions and value for their personal, civic, social and/or employment-related contexts [11]. Lifewide learning can be self-directed and incidental (often unacknowledged and even unnoticed) [12].

Lifewide learning reflects the social dimension of learning; therefore, it is rooted in the sociocultural theory of situated learning and community of practice [12]. According to Lave and Wenger, learning is viewed as "a dimension of social practice" (p. 47) [13] and "a fundamentally social phenomenon" (p. 3) [14]. Through participation in a community of practice, learners go through a process of beginning to acquire knowledge and skills that prepare them to become full members of the community—a process of "legitimate peripheral participation" [13]. In order for a group of individuals to become a community of practice, they must enter into a process that features mutual engagement, joint enterprise, and shared repertoire [14]. Within this process *Mutual engagement* includes "engaged actions whose meanings [are] negotiated with one another" (p. 73). *Joint enterprise* involves a fluid process of negotiating and renegotiating actions, behaviours and participation that "reify standards and competent engagement in practice" as "important aspects of becoming an experienced member" (p. 92). *Shared repertoire* represents a marker of community in which, over time, community members develop "coherence" in which "they belong to the practice of a community pursuing an enterprise" (p. 82). When engineering students participate in different communities of practice on and off campus, they engage in these three areas of experience, which help them develop their technical and professional skills.

Integrative Learning

Integrative learning represents a desired learning outcome of postsecondary education. It is defined as "an understanding and a disposition that a student builds across the curriculum and co-curriculum, from making simple connections among ideas and experiences to synthesizing and transferring learning to new, complex situations within and beyond the campus"[15]. Integrative learning demonstrates a deep learning approach; other deep learning strategies include reflective learning (reflecting on how individual pieces of information relate to larger constructs or patterns) and higher-order learning (i.e., learning by analyzing information, synthesizing ideas, making judgments and applying theories to practical problems) [16-18]. In contrast, surface learning involves learning strategies such as rote learning memorization [16, 18].

Literature shows disciplinary differences in use of deep vs. surface learning approaches. One framework for examining disciplinary differences is Biglan's disciplinary classification [19], in which there is a divide between the physical science-related disciplines ("hard") and the arts and social science-related disciplines ("soft"); with the fields of engineering fall under the cluster of hard, applied, nonlife system. Empirical studies using Biglan's framework found that in general deep learning is used more frequently by students in "soft" disciplinary areas and less frequently in "hard" fields of study [17]. In particular, surface learning was found to dominate in engineering [20]; this finding appears to be related to the dominance of long-standing lecture-based learning in engineering education practice [21].

Implications

The concepts of lifewide learning and integrative learning have two implications for examining experiences and outcomes of engineering students. First, engineering education research needs to include data that reflect multiple dimensions of student experience, that is, classroom experiences, co-curricular and extra-curricular experiences. Grounded in different communities of practice, these experiences manifest the social interactions between engineering students and their learning environments. Therefore, it is important to integrate various data sources that were collected about different student experiences. Second, although engineering students learn from various social practices, integrative learning may not be happening as evidenced by existing literature on disciplinary differences of student engagement in deep learning. It seems that engineering students do not necessarily translate lifewide learning experiences into an integrative learning process.

Data Analytics in Postsecondary Education

Data Analytics is a term "devised to describe specialized processing techniques, software and systems aiming at extracting information from extensive data sets and enabling their users to draw conclusions, to make informed decisions, to support scientific theories and to manage hypotheses" (p. 2); it has emerged from scientific disciplines, such as engineering, natural, computer and information sciences, and life sciences [22]. Discussion about the role of data analytics in postsecondary education is a more recent phenomenon and this literature contains different definitions for data analytics in postsecondary education. In US-based EDUCAUSE publications, analytics is defined as "the use of data, statistical analysis, and explanatory and predictive models to gain insights and action on complex issues" (p. 6) [9]. This definition places particular emphasis on prediction and action.

Typology

US-based research has classified the use of analytics in postsecondary education into two complementary types: institutional analytics and learning analytics [23]. While institutional analytics is intended to improve existing services and practices across the institution, learning analytics is intended to enhance or improve student success (slightly modified from [23]), with indicators of student success such as student learning outcomes, retention, or course completion [24]. As core practice in postsecondary education is related to teaching and learning, these two dimensions of analytics overlap to a certain extent. In an Australian study [25], although there was no differentiation between institutional and learning analytics, two trajectories of learning analytics implementation were identified. One trajectory was focused on institutional concerns such as student retention and efficiency; the other trajectory was underpinned by a focus on student learning and understanding the learning process that precedes student retention and success. These foci appear to be reflected in the two types of analytics identified in the US-based research [23].

An often cited definition of learning analytics is offered by the Society for Learning Analytics Research. With a similar focus on student learning, this society defines learning analytics as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs."[1] Main data sources for learning analytics include data collected from virtual learning environments and student information system of postsecondary institutions [26]. While the definition does not make prediction and action explicit, these two purposes appear to be embedded in practice. This is illustrated by case studies in US, UK and Australia, which document how learning analytics has been used to identify at-risk students and reduce attrition rates, facilitate student advising, monitor or measure student progress, enhance teaching and help students plan their own pathways [24, 26].

Patterns in Current Development

Literature suggests three key patterns in the current development of analytics in postsecondary education. Firstly, data analytics is an emerging and rapidly evolving field of research and practice; secondly, professionals within the field tend to work in silos; and thirdly, there is significant variation in the type of data analysis performed within institutions.

Data analytics in education emerged as a field that is separate from educational data mining and academic analytics, with the first international Conference on Learning Analytics and Knowledge and the formation of the Society for Learning Analytics Research in 2011 [27]. The field of learning analytics has been influenced by a wide range of disciplines including education, psychology, philosophy, sociology, linguistics, learning sciences, statistics, intelligence and computer machine learning/artificial science; with the two most dominant disciplines being computer science and education [26]. Two Australian studies revealed that as of 2016, postsecondary institutions were at early and preparatory stages for learning analytics implementation as many of them reported no or nascent strategy development [25]; but there is growing investment in technologies that will effectively support the institutional uptake of learning analytics [28]. In the U.S., less than half of postsecondary institutions indicated they were making major investment in student data analytics as of 2018 [8]. A recent learning analytics survey in Ontario, Canada reveals the potential of developing a strategic framework to guild learning analytics activities at Ontario postsecondary institutions [29]. All these studies suggest that data analytics in postsecondary education is an emerging field that will continue to evolve and change.

It can be anticipated that this relatively new field will rapidly develop, and become a new driver for the development of postsecondary education. This is evidenced by two recent

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[1] https://www.solaresearch.org/about/what-is-learning-analytics/

publications. One is a book entitled The Analytics Revolution in Postsecondary education [30], calls for postsecondary institutions to harness the analytics revolution to improve student success. The other is a joint statement released in 2019 by three US organizations within U.S. postsecondary education communities (The Association for Institutional Research (AIR), EDUCAUSE, and the National Association of College and University Business Officers), expresses a strong sense of urgency to reaffirm postsecondary education's commitment to the use of data and analytics to make better strategic decisions [31].

Data analytics has arisen from existing, well-established practices within postsecondary institutions carried out by data-oriented professionals in the areas of institutional research (IR), information technology (IT), student life (or student affairs), and business intelligence [8, 9]; however, professionals from these areas do not necessarily work together or share data with each other. Two US-based analytics landscape assessment studies revealed that less than half of surveyed institutions deliver analytics services as a joint program run by IR and IT [23]. It has been argued that a successful analytics program require better communication and partnership among these data-oriented professionals [8, 9, 32].

Perhaps partly due to the existing practice of working in silos, some data sources collected by postsecondary institutions are not connected and integrated with other data sources, resulting in lost analytical opportunities . As shown in a US-based study [23], data collected from learning management system and integrated planning and advising services that inform learning analytics had a higher chance of being "collected but not connected", than data collected for student information system and admissions. These results suggest that postsecondary institutions have not been able to optimize their analysis t of the data they have available. An Australian study [25] took this further by recognizing the integration of actionable data with educator practices as an important implementation capability of postsecondary institutions that perform learning analytics.

There are considerable variations among postsecondary institutions in terms of what resources are in place for learning analytics. US-based research also reveals that learning analytics lags institutional analytics in terms of priority and investment [24]. It was also found that while more than four-fifths of surveyed institutions reported that they had data-oriented leaderships and had identified potential targets for analytics; and approximately half of them reported having the right data and storage capacity, the right data policies, and appropriate IT professionals; less than one fifth reported having adequate funding or adequate number of analysts [9]. These variations have introduced the concept of measuring "analytics maturity" of institutions. EDUCAUSE has developed an analytics maturity index that consists of 32 factors on a five-point scale being organized into six dimensions [23]:

- decision-making culture;
- policies for data collection access and use;
- data efficacy relating to quality, standardization and "rightness" data and reports and the availability of tools and software for analytics;
- investment/resource;
- technical infrastructure; and
- IT involvement.

Along a similar line of research, an Australia-based study [25] has identified a number of "readiness" factors (i.e., leadership, strategy, organizational culture, organizational capacity and technology) that mediate outcomes of learning analytics implementation.

Implications

Literature on data analytics in postsecondary education has three implications on engineering education and practice. First, as an emerging field, the development of data analytics in postsecondary education lags behind analytics used in other fields; and hence there is considerable potential to explore how the use of analytics can inform engineering education and practice. Second, data-related activities within engineering schools can be viewed from two perspectives: institutional analytics and learning analytics, which have different objectives and can use different analytical methods. Third, engineering schools may achieve a higher level of analytics maturity than the academic units in other academic fields due to the expertise in data analytics residing in engineering faculty and student communities. Some approaches and methodologies already used in the engineering fields may be transferrable to engineering education research on data analytics.

Exploring the Potential of Data Analytics

The recent development in data analytics in postsecondary education has brought forth both opportunities and challenges to engineering education research.

Opportunities

How can data analytics strategies enhance the current engineering education research (EER) related to student experiences and outcomes? Three main areas of research have been identified in EER: instructional or curriculum development, student learning and its assessment, retention and diversity of engineering students [4, 5]. Research on instructional or curriculum development focuses on educational interventions introduced to courses, programs or curricula, often from the perspective of instructors and educators. Research on student learning and assessment typically examines engineering students' learning experiences and perceptions, and contributing factors to their learning outcomes such as academic achievement and competency development. Research on retention and diversity of engineering students addresses how to retain engineering students in their engineering studies, particularly female and other minority students. Other possible research areas include paradigms, methodologies and communities of engineering education research itself; academic and career pathways of engineering students; admission process of engineering students; engineering workplace practice; and validation of new instruments [5]. Most of these areas involve use of student data to probe learning experiences and outcomes. Based on the taxonomy presented in the previous section, the first two main areas of EER (i.e., instructional or curriculum development; and student learning and assessment) fall under the domain of learning analytics whereas the last one (i.e., retention and diversity of engineering students) can form part of institutional analytics. Among other areas of EER, admission, and academic and career pathways of engineering students can also fall under the domain of institutional analytics.

To understand the current status of how data analytics has been used in EER, we conducted a literature search using keywords of "engineering education" and "data analytics" or "machine learning" in Google Scholar and in the proceedings of the American Society of Engineering Education (ASEE) annual conferences. The ASEE proceedings search showed that there has been a steady increase, in the past decade and particularly during the last five years, in the number of papers that addressed different topics related to machine learning, a technique for predictive data analytics. These papers discussed cases of course or program development that integrated data science and machine learning into the engineering curriculum, and applications of machine learning techniques to understand engineering education related issues. Many of these papers were situated in classroom teaching and learning, and addressed issues in the domain of learning analytics. The considerable increased interest in machine learning among engineering educators and researchers reveals that machine learning incorporating learning analytics may become a new area for growth in EER.

The articles we reviewed provided a few interrelated patterns that may shed light on the foreseeable future of the evolving field of applying data analytics to EER. First, more researchers are using or building new data systems to capture a broader range of student data than ever before. These new data systems can be created by integrating existing data sources. For example, a study on the use of the flipped classroom approach [33] integrated data from traditional assessment methods, such as assignments and exams, with student demographic data and the "hidden" data collected from educational technology tools, for a new data system. A combined analysis of data mining and classical statistical techniques was then applied to the integrated data set. In addition, data from learning management systems have been used to examine the predictors for engineering students' academic performance in an entirely online learning environment [34]. New data systems can also be built using new data sources. For example, in a study on introductory programming classes [35], researchers developed an online coding environment capturing time-stamped keystroke-by-keystroke data and embedded it in the learning management system so that students could receive instant feedback to allow for early interventions. Similarly, clickstream data have been used to capture students' design behaviour and associated metadata (e.g., the system time when a click was made) in aerospace engineering capstone courses [36]. Efforts to integrate various data sources for analytics and visualization purposes have also been documented in ASEE conference papers (for example, [37]).

Second, researchers have extended data analysis to examining student experiences that were not observable using traditional analytical methods. A new area is affective assessment. For example, a study [38] captured students' facial keypoint data when they were reading the instructions of a task to assess their affective state, and used the assessment results to predict student performance. In another study [39], researchers used data mining techniques to capture the curiosity levels among students. In addition, fine learning behaviours, such as students' learning engagement [26] and design behaviors [36]. can be examined using data analytics. In a pedagogical module framework, manufacturing engineering educators have suggested that collecting real-time operational data from the target machine tools allows process-based information to be condensed and block-by-block simulations to be demonstrated in real time, to achieve the educational goals in manufacturing courses [40].

Third, as all these applications entail new analytical techniques,. machine learning techniques, such as classification, ensembling, and K-Nearest Neighbours [22, 41], offer new methodological approaches to analyzing student data. An illustration of a new approach is a web-based technique known as Social Networks Adapting Pedagogical Practice, or SNAPP, which built an extension for multiple learning management systems and performed social network analysis of data collected from online student discussion forums. The generated network diagram can help instructors identify high-performing and low-performing, disconnected (at risk) students so that they can better plan learning interventions. Potentially, these learning analytics could allow a learning design to be evaluated in light of its pedagogical intent, by using a set of real-time, behavior-based data on learner interaction within the learning environment [26, 42-44]. Another set of techniques being introduced is related to text analysis. For instance, researchers went beyond traditional coding approaches to analyzing texts and used unsupervised learning clustering algorithms and information retrieval techniques for text analysis [45]. Researchers also used text mining and web log mining techniques to gain deeper insights on major discussion topics in design capstone engineering courses [36]. As such, new data sources, integrated data systems and emerging analytical techniques demand technology-enhanced learning analytics system design emerge [46] and, once the system is in place, will enable what is called "multimodal learning analytics" [47]. These developments have already begun in EER.

On the side of institutional analytics, a possible way of enhancing research on academic and career trajectories of engineering students is to create data-driven student personas. The use of personas, sometimes called "user profiles," is a user-focused design methodology [48] and has been used in education research to understand experiences and perceptions of faculty [49], library users [50] and students [51]. Personas are user archetypes that characterize the needs, goals, technical experience, accessibility requirements and other personal characteristics of larger groups of people [48]. In the context of EER, personas are fictional descriptions of groups of engineering students, who have experienced engineering education in certain ways and followed particular academic and career pathways; these experiences and pathways may be specific to students with certain demographic characteristics. The first step toward the creation of student personas is to build an integrated data set that is able to capture curricular, co-curricular and extra-curricular activities among engineering students. Data integration is important because student learn lifewide, and multiple contextual factors, including different kinds of student experiences, influence engineering students' career pathways [52] and presumably academic pathways as well. A recent US national report [7] also pointed out that national survey-based datasets provide only periodic snapshots of employment status of engineering students and recommended linking administrative and survey data to obtain a more fine-grained understanding of engineering educational and career pathways. Potential methods for data analytics to create student personas include k-means cluster analysis, latent class analysis and random forest approach. The creation of student personas can not only help better understand the student population, but also improve data efficacy in terms of predictive power. The identified student personas may also shed light on how engineering students integrate their learning from different experiences to build various academic and career pathways, thus complementing the existing research related to integrative learning among engineering students [20, 21].

Examining the role of experiential learning in engineering education and investigating the structure and integration of professional and transdisciplinary skills among engineering students have been identified as two areas underrepresented in EER literature [53]. Experiential learning for engineering students is often exemplified in co-op programs and internships. Better understanding of students' co-op or internship experiences require synthesizing perspectives from students, the postsecondary institutions that support students' work-integrated learning, and the workplaces that offer co-ops or internships [54]. Therefore, data analytics built upon integrated data points could help inform contextual factors that contribute to, or impede, achievement of positive student outcomes. Similarly, while engineering students' skill development takes place in both formal in-class and experiential off-class settings, how integrative learning happens has been rarely studied. Additional data sources, new data system building and analytical techniques will be needed to explore transdisciplinary skill development in greater depth.

Challenges

Implementing data analytics in EER is not without challenges. As suggested earlier in the discussion, identifying opportunities for data collection and integration will be an enabling factor for enhancing research in both institutional and learning analytics domains. However, landscape analysis of analytics in postsecondary education reveals that some of the student-related data sets are either not systematically collected or not connected with one another. For example, a US study [23] showed that over 50% of the surveyed institutions systematically collected learning management data but did not link them with other data sources; and a similar failure to link admission data to other sources occurred at nearly 25% of the surveyed institutions. Similarly, an Australian report [55] shows that while course/program enrolment and student assessment data were systematically collected at all institutions, they were not used for the purpose of learning analytics; and only less than half of the institutions systematically collected data that could inform lecture attendance and interpersonal interactions. While little research is available regarding data use within engineering schools, the patterns may be quite similar to the overall picture in postsecondary education. On the other hand, as technology-enhanced learning environments are increasingly deployed in engineering classrooms, so it can be anticipated that even more data sources on student learning engagement will become available for use. Therefore, the question is how these new data sources are purposefully connected to existing data sources for analytics. A necessary step for making data integration possible is establishing a data governance policy. Most engineering schools will be able to draw upon an existing institution-based data governance policy. If the existing policy does not include data integration as part of the framework, researchers may need to seek agreement with relevant stakeholders to formalize a data integration process.

As the number of data sources to be included into analytics-oriented research expands, the need to capture quality data that truly measure what the researcher wants to assess becomes another challenge. Existing research [35, 38, 43] has demonstrated that new tools and platforms need to be created to capture new data sources that measure student learning. The design of these new tools often requires both technical skills and disciplinary knowledge. For example, in affective assessment, researchers need to validate the results from the new tool with the properties of a socio-cognitive construct, such as curiosity [39]. Along a similar line, a potential area of future research will be to draw upon the tools and techniques from cognitive psychology for learning analytics. For example, a neuroscience research tool called portable electroencephalogram, or EEG, has been used in cognition-based education research, for example, on the relationship between brain-to-brain synchrony and learning outcomes [56]. This tool could be used in engineering education research to capture brain activities; the obtained new data source could then be integrated with other student data to predict learning outcomes among engineering students.

Another area of challenge that needs to be addressed is creating ethical policies for using data analytics methods in research. The limited availability of policies tailored for analytics-specific practice to address issues of privacy and ethics has been identified as a major challenge in the adoption of learning analytics in the United States [23], Australia [55, 57] and Europe [58]. A comprehensive review of the ethical and legal issues in learning analytics [59] has suggested that postsecondary institutions follow a code of practice when undertaking learning analytics so that their practices are legal, ethical and truly beneficial to students. Some of the guiding principles are:

- Clarity and transparency on practices: letting students know what data are being collected from them, how and when data are collected, and how data are stored in real time.
- Privacy by design: incorporating privacy protections in every procedure
- Accountability: ensuring that every aspect of learning analytics has a person or unit designated as responsible for its proper functioning

Concluding Thoughts

In this paper, we have drawn upon different sources of literature to discuss theoretical underpinnings and the development of data analytics in postsecondary education. Based on the integrated knowledge on these areas, we argue that expanding EER using data analytics techniques should be grounded in well-studied notions in student development literature and can be a direction to take in EER.

Without doubt, a promising analytics-oriented area of EER will emerge and potential opportunities and challenges are in store. We would like to make the following recommendations.

- For engineering schools (and affiliated postsecondary institutions). It is essential for institutions to enhance data infrastructure, along with data governance policies that include protocols for data security, as data governance is the precursor for data integration and data system building. Fostering a culture of collaboration among units and divisions within an engineering school and with IT and business intelligence offices of the institution will facilitate the process. Greater efforts need to be made to cross-link existing data sources within engineering schools to better use those data and enhance data efficacy. Engineering schools could then demonstrate a stronger capability in implementing student data analytics.
- For engineering education researchers. Researchers should equip themselves with two types of knowledge: (a) knowledge on data science and machine learning, which is a driver of the fourth Industrial Revolution; and (b) knowledge specific to the types of student experiences (i.e., curricular and co-curricular) of their research interest. These two bodies of knowledge appear to be increasingly important to the

interdisciplinary field of engineering education. Researchers also need to keep an open mind and explore a wider range of data sources for EER.

In conclusion, we envision a landscape for engineering education research and practice where different administrative units of an engineering school collaborate with each other to create integrated data platforms that are enabled by a set of data governance procedures; and researchers draw upon their interdisciplinary knowledge and skills to use the linked data sources in analytics to generate explanatory and predictive information about engineering students' experiences and associated outcomes. We encourage engineering communities—researchers, educators and students—to take lead in building this new landscape so that the power of data analytics can exert a transformative impact on engineering education research and, more broadly, postsecondary education research in general.

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