Artificial Intelligence and the Student Experience: An Institutional Perspective

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Abstract

The paper outlines the potential for Artificial Intelligence (AI) to positively impact student success. This will be approached from a student life-cycle perspective, taking an integrated view of the student experience and identifying where AI can be most beneficial. Current usages of AI in education will be considered, in addition to those being experimented with and those still being considered. The paper will view the adoption of AI in education from a comprehensive perspective, considering technological, social, political, economic, cultural and ethical factors, providing a frame for understanding of the benefits and constraints of the most intelligent of information technology in the educational realm.

AI has started to emerge in educational institutions in the form of chat bots that are being used to provide student services as well as providing learning supports. Automated paper grading has started to be used, while academic advising and assessment are being trialed.

Keywords: higher education, artificial intelligence, Student Experience Practitioner Transitions frameworks

Artificial Intelligence (AI) has been increasing in its use in our everyday lives spanning a broad swath of uses ranging from personal assistants, purchase reference and prediction, smart homes and cars, fraud detection, online customer support, and even assisting personal relationships. This increasing use is fueled by the use of machine learning, computer modelling, and algorithmic creation enabled by ever bigger data sets combined with ever more capable technological capabilities driven by Moore's Law (Schaller, 1995) and Metcalfe's Law (Hendler & Golbeck, 2008).

The upward and accelerating trajectory of AI, encapsulated in the concept of the singularity, has drawn both excitement and concern from scientists, economists, and political and business leaders. The largest fear is that AI will outsmart its creators allowing the machines to turn the tables and become the masters, using our psychology to program our behavior. Further disquiet exists with respect to ethical considerations (Moore, 2006), governance of appropriate usage (Khatri & Brown, 2010) and to instances where programming bias have been shown to exist in early deployments of the technology (Devlin, 2017). These concerns are valid and remain to be addressed, however it is not our intention to pursue these here. We are viewing real applications of AI to education that are practical and achievable in the near term. More broad-based sociopolitical and economic issues are not discussed in this paper. Nor are implications for the curriculum and the almost certain requirement for the incorporation of AI literacy and information accuracy into all disciplines, lest intellectual laziness yield an unverified trust to systems that were based on their creators' assumptions.

The student higher education experience can be considered as a series of interdependent, overlapping, but not necessarily sequential, phases. This life-cycle approach is often used by administrators to manage student life as it distinguishes the critical elements of experience allowing the design and delivery of focused administrative services. The student lifecycle in higher education is defined as the journey of the student from first contact with an institution through to becoming an alumnus. The ultimate goal of a student is academic achievement accompanied by self-development through the academic experience. The academic success of students, however, relies on a composite of all aspects of the student's life. These other aspects include mental welfare and support, social interactions, sports and physical health, effective life balance, all of which contribute to the experience the student has in their higher education career (Morgan, 2013).

Applying a technology into a complex environment, particularly one as traditional as higher education, is a very challenging endeavour. As with many technologies, the key question is where to start, what use case would provide a fair test of the technologies capabilities? The purpose of this paper is to address this by providing an approach for the coherent adoption of AI into higher education institutions to lessen both the cost and time for its benefits to be available. The use of the student lifecycle and the grouping of activity sets creates target groups for experimentation and piloting within definable and accepted domains, allowing for effective hypothesis testing, collaboration and comparison with other institutions. While not wishing to underestimate the degree of difficulty such a shift may incur, it is reasonable to suggest that such an approach will improve the rates of early adoption and the speed to production.

One model developed to use this framework to understand the student journey, outlining the different stages that a student transitions through during their academic career, is the Student Experience Practitioner Transitions (SEPT). The model was developed to educate and guide practitioners about the various kinds of supports students need at each stage (Morgan, 2013).

In this article, using the Student Experience Practitioner Transitions (SEPT) model developed by Morgan (2013) as a basis, five potential areas in the process where artificially intelligent systems can be incorporated are analyzed (Figure 1). The functionality that these systems will perform, the tasks they would take over from the professors, teaching assistants and support staff, as well as related research, are discussed.

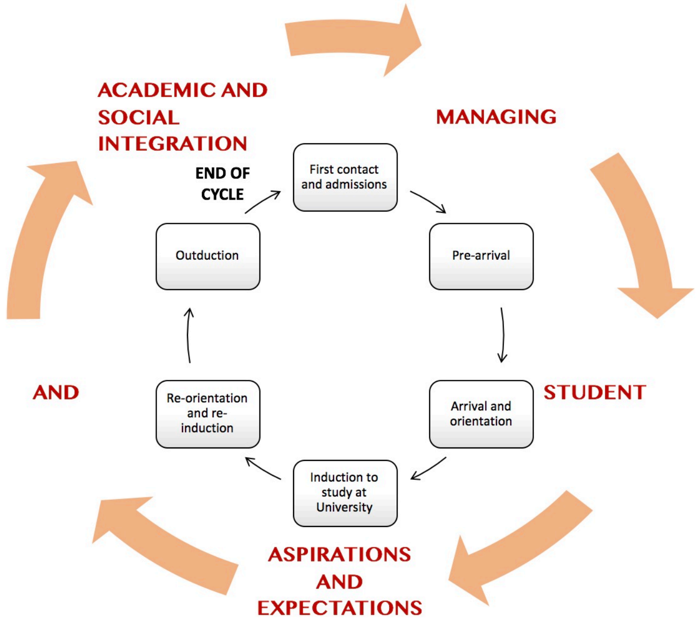

Figure 1. The Student Experience Practitioner Transitions (SEPT) framework (Source: Morgan, 2018)

The Student Experience Practitioner Transitions model has six stages of student life, each stage examining the unique position of a student at a certain point of time in his or her higher education (Morgan, 2013). The stages can be summarized as follows:

1. First Contact and Admissions – At this stage, the student makes an application to an institution based on his/her interests.
2. Pre-arrival – The student has been accepted to a program and any other requirements must be completed before the student arrives to embark on the course of study, such as receipt of final transcripts.
3. Arrival and orientation – Introduction to how the degree will be completed and getting used to campus life.
4. Induction to study – The first year of education when the student is introduced to coursework.
5. Reorientation and induction – gaining new skills as one progresses through their degree by taking advanced courses.
6. Outduction – entering the job market.

By viewing the student experience as a journey consisting of integrated steps one can use AI to analyse the steps and determine interdependencies between them to develop an integrated model of student behaviour. This model can greatly assist the understanding of behavioural determinants that impact students throughout their lifecycle. It further provides a classification for data sets that are available for model and algorithmic development.

The Artificial Intelligence Process

AI is a broad field that is comprised of many disciplines including computer science, statistics, linguistics, psychology, and decision science. It is essentially concerned with getting a computer to replace human intelligence in assigned tasks. Given the breadth of the field it is not surprising that there are quite a few definitions of AI. In addition these are non-constant as the capabilities develop. What was once considered AI begins to be seen as algorithmic development or big data analytics. A commonly accepted breakdown is to view AI as the overarching rubric which encompasses Machine Learning, which further encompasses Deep Learning. Rich and Knight (1991) state that "Artificial Intelligence (AI) is the study of how to make computers do things which, at the moment, people do better" (p. 3).

The definition of Artificial Intelligence, as stated in the first Volume of the Handbook of Artificial Intelligence is that "Artificial Intelligence (AI) is the part of computer science concerned with designing intelligent computer systems, that is, systems that exhibit the characteristics we associate with intelligence in human behavior - understanding language, learning, reasoning, solving problems, and so on" (Barr & Feigenbaum, 1981, p. 3). This definition is appealing, as in this paper we are imagining a system that can correlate data from different sources and present options and pathways to students based on their interests and eligibility, similar to a human counsellor. For the propose of this paper we take AI's meaning in the broadest sense, any use of a computer to replicate or substitute human intelligence to provide insights through the application of various machine enabled analytical processes to large data sets. Insights from Artificial Intelligence are only possible when data is available related to the sought for insight. This data may be collected by surveying people, gathered from people completing tasks, automatically generated and stored by a system in log files, entered in by an analyst, etc. Data may be structured, always in a particular format e.g. form entered data; semi structured, complying to a structure e.g. emails; or unstructured, where it does not comply to a given structure e.g. photographs. The latter two require reprocessing to be usable. After looking through all the data that is available and identifying the sources that would be helpful, this data has to be transferred and stored in a database or on a server, making it available in a format that the AI algorithm can process. Once the algorithm processes the data, insights can be obtained. Figure 2 describes a very simple and generic model: Data Generation – Data Storage – Data Processing – Actionable Insights.

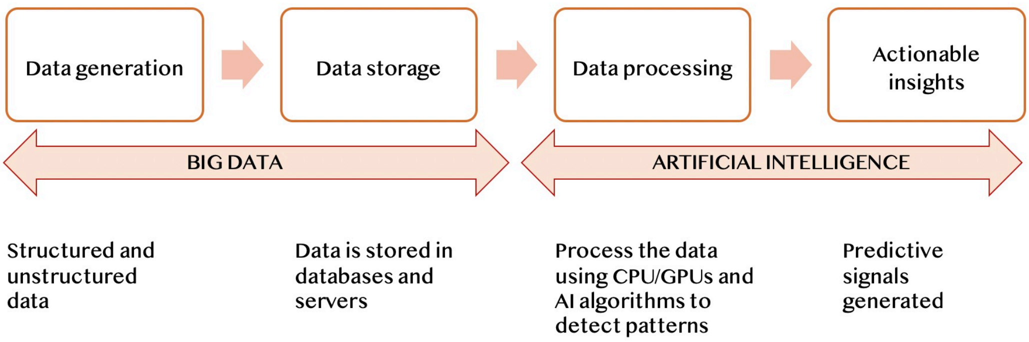

Figure 2. A simple AI process

Based on this Input-Process-Output model, data has to be collected and made available in a form for each stage in the Student Lifecycle, that the AI program can process and then yield insights that the student and organization can act upon. In the next sections, possible places where AI insights would be helpful are reviewed and a reference grid shows a high-level data to lifecycle stage mapping, articulating the data needed and the potential constraints and benefits of applying AI at each stage.

Incorporation of Artificial Intelligence at the Classroom Level

The mechanics have to be explained here and then the experience. The student would first interact with the system and input their interests, performance in studies to date, work experience, amongst other information. The intelligent system would then be able to provide a listing of the programs that the student is eligible for at the institute. If this system is utilized by more than one institution, programs across institutions might be suggested to the student as well. Possible pieces of information that could be utilized to train such a system could be the information from current students who are pursuing a program at the institution, their interests, the programs that they might have considered before pursuing the one they are in as well as career prospects. Similar data may be collected from alumni, noting the career that they are pursuing.

Once the student decides on a program of study and is accepted, the system would be able to show the student possible scholarships, volunteer opportunities, as well as present program specific information about preparing for the first day, book a tour of the campus, residence services, library services, potential student clubs (based on the interests that the system is already aware of), time scheduling, and so on. This would potentially cover the second and third stages of SEPT.

After classes have been selected and a term has been successfully completed, the system would be able to offer more refined job and volunteer opportunities based on the skills that the student has learned as a result of this education. Sweeney, Lester and Rangwala (2015) and Sweeney, Rangwala, Lester and Johri (2016) cited in Khare, Lam and Khare (2018) "predict whether the combination of courses that a student is taking in the current term would overwhelm the student. Thus, their research gives insight to students about courses they are taking, to counselors who advise the students about the course load and to instructors on considering differing course combinations" (p.43).

This would be an intelligent system that knows what the student is studying in all courses, the deadlines coming up as well the next set of courses that would become open to the student if s/he does well in his/her current set. This would integrate data from the various courses and the database of course dependencies to show the student possible what-if schedules for next term and year, one that can be changed according to interests and constraints facing the student. The system would also be able to analyze integrated data from the numerous sources to present the student his/her best options (Woolf, Lane, Chaudhri, & Kolodner, 2013). This also relates to the field of learning analytics and student competences and skills. Zhang and King (2016) analyse the order in which questions should be presented based on the knowledge level of the students. This can be further applied to the skills that courses teach and other courses require.

By keeping track of the time commitments of the student based on selected courses, volunteer work and part-time job, the student would have a more comprehensive idea of how their time is being spent and if they can take on more work. Woolf et al (2013) elaborate on the 21st century skills that artificial intelligence should work to address. These include self-direction and self-assessment. With information organized in a coherent way and presented such that only eligible options are shown, a student would be in better control of making choices that lead to the success he desires.

Intelligent systems make it possible for students to build a schedule for the term, while at the same time presenting financial aid and volunteer opportunities tailored to them for which they are eligible. This would reduce the number of human hours spent in counselling students regarding the courses they are eligible for as well as reviewing scholarship applications because the students would only be able to apply for the ones they are eligible for.

The Outduction of a student at the end of their course of study requires students to make a choice. Some students will seek to continue studying by taking another degree or pursuing an advanced degree. AI systems can provide guidance from their academic record as to a preferred course of study. Most students will want to move on to the workforce to start their careers. AI can assist students by providing career tools to align their aspirations with the pathways to get there. Further AI career coaches can provide personalized advice based on the student's history, experience, locational choice, skills combined with career requirements to supply students needed further study tracks and possible staging and development paths. IBM's AI powered Blue Matching system is an example of a job matching service that demonstrates the real potential here (Clegg, 2017).

All of the above are dependent on available and useable data. This is not a trivial requirement as most of the data will not be in a directly useable form and will need either significant reworking or will require to be newly gathered in the desired format. Machines, like humans, need information to learn from, they also need, at least with the present state of technology, humans to shape that data for them. While quicker when they have the appropriate data, available AI systems have yet to be able to effectively forage on their own behalf.

Forum Monitoring by Intelligence Systems

Forum monitoring offers another opportunity for AITAs to improve the efficacy of collaborative forums. Currently human Teaching Assistants (TAs) are asked to check the forum at least once a day such that all questions could be answered within 24 hours. The same rules are applied to emails and TAs are encouraged to ask the students to post a question on the forum if its answer would be helpful to other students.

Questions are often related to the concepts being studied in the class and the assignment. Thus, the scope of the questions is often defined. Using data from forum posts from previous iterations of the course, machine learning can be applied and trained to associate questions with answers. This reduces both response time (or eliminates it) and the effort of TA's to research and create an answer. If a set of resources are associated with each topic, it is possible to point out these resources to students, just like the TA would have done (Khare, Lam, & Khare, 2018). Algorithms can be used to time themselves for answering the student and if no answer is found or it is taking too long, a mechanism can be put in to notify a teaching assistant. Once the TA resolves the question, the algorithm may be trained further to answer it next time or to flag certain questions that must go to TA directly. Going beyond answering questions, reviewing the forum posts for the understanding of the students, using content analysis and text mining techniques can determine if the discussion coverage is as expected (Khare, Lam, & Khare, 2018).

Tutoring and Advising

The use of intelligent agents and chatbots are growing rapidly in use in consumer electronics and customer service. Commonly referred to as chatbots these devices use AI to provide context aware information to the user, usually in a relatively narrow range. The application of this technology to support students enables the potential for expanded one-on-one tutor engagement, not economically achievable in existing teaching models. These are being trialled in education, varying from providing administrative and service information to supporting academic study. A number of studies suggest that chatbots, also known as intelligent tutors or intelligent teaching assistants, are significantly beneficial to students and positively add to the student experience and probability of success. IBM Watson supported chatbots are being used in Deakin University (Deakin University, 2015) in Australia to provide student guidance to life on the campus and in the cloud, and at GeorgiaTech's online master's in computer science to provide teaching assistance. Both have proven very successful after initial training, due in large part to the question set remaining relatively consistent allowing AI to prove effective (Maderer, 2016). Georgia State University noticed that not all students who accept admission offers enroll in Fall. They called this phenomenon "summer melt" (Ravipati, 2017). They employed an AI chatbot called AdmitHub to significantly increase the number of students that enroll after admission by improving communication with students using text messages (Ravipati, 2017). Studies by Steenbergen-Hu and Cooper (2013; 2014) and VanLehn, (2011) have indicated that AI tutors are as good or better than human tutors, however the evidence is unclear, and the experimental designs used to date do not provide an unambiguous answer. Moreover, human to human interaction for teaching is unlikely to be replaced in the near term. As humans, we still need personal connections for inspiration, compassion, self-reflection, imagination and life context. Learning is every bit as much emotional and social as it is teaching technique and technology. The replication of intelligence by machines may not be matched by their abilities to emote or socialize, indeed the concept of artificial emotion seems to be a contradiction in terms. Thus, the ability of humans to express empathy and to provide emotional as well as intellectual understanding to form connections and form social bonds will ensure, at least for the near future, human advising and tutoring are superior supports for human learning.

Grading and Assessments

Many aspects of grading automation are currently in practice and are well accepted within the higher education community. In many instances logical rules and rubrics are used for grading and these can be taught to a program, such would result in a reduction in the number of human hours spent on grading. These are, in the main, straightforward tabulations of choice type questions, where there is a predetermined correct answer. Assessments and grading of less discrete answer sets, in particular long essay questions, are not likely to receive as warm a welcome by academics. Nonetheless AI is being applied to the grading of short and long essay types and is showing considerable success. The work done in this field includes automatic feedback. Zhang, Shah and Chi (2016) have worked on automatically grading short answer questions. Automatic Essay Grading is a growing field of research that aims to grade long essay questions (Page, 1994; Rudner & Liang, 2002; Chen, Liu, Lee, & Chang, 2010; Dong & Zhang, 2016). Recent work by Dong and Zhang (2016) elaborates the potential of deep learning algorithms to grade essays.

Christian (2018) formulated a rule-based system to evaluate C++ programs in the early stages when a student is learning a new concept by grading and informing the student on where he is with respect to the solution and learning objective.

It is quite likely to see AI aided formative assessment technology being employed as this aids academic productivity and assists students in their development of understanding and mastery of the material. Chen, Breslow and DeBoer (2018) analyzed a blended learning environment and the effects of immediate corrective feedback on student behavior. They found that the feedback led to reflective studying, and higher performance was predicted for students who used the corrective feedback feature.

Delivering content based on the performance or understanding of the student

Adaptive learning has been much trumpeted over the years and was seen as one of the early benefits of online or computerised enabled learning. The use of games in education follows a similar pedagogical approach of uncovering within a dependent interrelated environment of knowledge objects or situations. Squire and Jenkins (2003) discuss the pedagogical potential of games. Polin (2018) elaborates upon the features of games that make them spaces that support learning. Lamb, Annetta, Firestone and Etopio (2018) provide insights into the kind of games – Serious Games, Educational Serious Games and Educational Simulations that have the most impact on students' cognition and behavior. However, the recent troubles of Knewton, one of the flagship companies in this area (Young, 2017), indicates that this is still an area that has yet to fulfil its potential.

Self-paced learning is where the program can judge when a new topic has to be introduced or an older topic has to be reviewed by the student. The models used by Intelligent tutoring systems would be helpful here to determine when a student has learned a concept and is ready to move on to the next one (Lin & Chi, 2016; David, Segal, & Gal, 2016). The data from assignments and practice questions as well as response time is often used to find the state of 'learned' and build a student model which represents the knowledge of students (Lin, Shen, & Chi, 2016). These systems provide feedback, timely guidance and explanations when students make mistakes (Shute, 2008). They keep track of the learning outcomes and are able to determine the content appropriate to the student's difficulty level (VanLehn, 2006). In this way, students' learning experience has a bigger focus than the lessons themselves.

Intelligent Tutoring Systems such as Carnegie Learning and Front Row have been tailored to school students. To the best of our knowledge, there are no cognitive tutors at university level. These could be used to supplement the understanding of students.

Augmenting this information about the student with 'smart content', Cram101, built by Content Technologies Inc., uses artificial intelligence to breakdown the textbook into smaller sections, including chapter summaries, practice questions and flashcards to form a 'digestible "smart" study guide' (Faggella, 2017).

AI applied to the classroom level can provide significant benefits which are even more telling in the online environment where the delivery of courses can be enhanced economically through AI enabled automation. The ability to provide responsive support to students on a consistent basis, although inferior to human interaction, is nonetheless superior to current online delivery models that normally have time limited support due to the cost of human TAs. Even moderate quality support that is consistently available is preferable to high quality support that is rarely available. Moreover, a human TA or professor can review and provide additional support to the AITA whether due to AI restrictions or by providing additional learning moments. The potential impacts on the online business model are substantial, by reducing the total cost of providing online courses, a significant lowering of tuition to students is possible. Such would allow greater access to secondary and tertiary education particularly in less economically advanced countries. Slightly ironic that artificial intelligence may be the key to growing global human intelligence.

Combining Artificial Intelligence with the SEPT Model

There is an iterative loop here as data generates insight creating the need for additional data that generates enhanced insight. It also can demonstrate the gaps in data for a given desired insight as well as potential insights from given data sources. By doing this we can show the potential for AI to provide benefit to learning and student success. Morgan (2013) identified five themes in the SEPT model – curriculum and assessment, pedagogy, support, finance, and employment. Table 1 is based on the data available from these themes and presents a further analysis of the data sources, possible insights, and barriers to using the data.

Table 1. Artificial Intelligence (AI) Lifecycle Matrix using SEPT framework

Question \Stage	First Contact and Admissions	Pre-arrival	Arrival and orientation	Induction to study	Reorientation and induction	Outduction
What data is available for each stage	Student interests Subjects taken by student Grades in subjects Degree applied for Courses to be taken in the degree Fee estimates Possible scholarships and financial aid Part-time work opportunities	Subjects selected by student to study – coursework Money management advice Financial support available Placement options Internships Volunteering opportunities	Subjects that make up the degree Assessments Money management advice Financial support available Placement options Internships Volunteering opportunities	Subjects being studied Assessments Money management advice Financial support available Placement options Internships Volunteering opportunities	Skills gained after a term/year of study Subject choices available Money management advice Financial support available Placement options Internships Volunteering opportunities Future job opportunities Professional development opportunities	Job opportunities Further study prospects Debt control Professional development opportunities Transitioning into a workspace
What are the sources of this data	Student application Reference letters for the student Previous examination results Career development system at the institution	Student profile Financial profile of student Scholarships applied for and rewards Career development system at the institution	Student profile Financial profile of student Scholarships applied for and rewards Career development system at the institution	Student profile Financial profile of student Scholarships applied for and rewards Career development system at the institution	Learning outcomes and competencies of previous courses Job profiles of graduates from selected degree Career development system at the institution	Requirements of graduate degrees student is eligible for Job profiles of graduates from selected degree Career plans
What systems does the information reside in		Student Information System Customer Relationship	Student Information System Customer Relationship	Student Information System	Student Information System Faculty databases	Student Information System

Question \Stage	**First Contact and Admissions**	**Pre-arrival**	**Arrival and orientation**	**Induction to study**	**Reorientation and induction**	**Outduction**
		Management System Faculty databases	Management System Faculty systems Residential database Student union systems	Faculty databases Residential systems Learning management system Student union databases Library systems Volunteer systems	Residential database Learning management system Student union databases Library systems Physical activity systems Volunteer systems	Faculty databases Residential database Learning management system Student union databases Career development system
What Insights can we develop for each stage	Degrees and Courses that match and best fit student's interest and likely success What-if Financial scenarios Optimal path to complete degree	Volunteering choice Optimal schedule to manage coursework, work and volunteering Steps to take to be successful in classes Career opportunities Residential choice	Time management Subjects to take Campus Orientation	Optimal study plan Resource suggestions and provision Study aides and course strategies Practice assignments Daily schedule management Time management	Optimal study plan Resource provision Study aides and course strategies Practice assignments Schedule to manage coursework, work and volunteering Time management Career opportunities Job shadowing opportunities Projects/Workshop suggestions that would strengthen job prospects later Skills that are underdeveloped or need improvement Learning progress and success supports	Best fit Jobs to apply for Further job specific training opportunities Application deadlines for graduate programs Best fit International study opportunities
What barriers to usage and value exist	Privacy of student information Maturity of IT systems Data accuracy, availability and access Institutional culture and policies Lack of systems integration Lack of data sharing agreements with external organisations Lack of appropriate data Lack of understanding of AI					
What enablers to usage and value exist	Data governance to develop and ensure consistent data architecture in combination with standardized data definitions Identification of additional key data sources that bear on student experience Policy review of data sharing to facilitate and frictionless access Integration of data and applications to provide real time data across the enterprise					

Question \Stage	First Contact and Admissions	Pre-arrival	Arrival and orientation	Induction to study	Reorientation and induction	Outduction
Where can it go next	Enhanced engagement of potential students through intelligent selection and information provision to select institutions, programmes and career paths	Augmented reality campus guide Campus life planner Residential planner Social life assistants	Data sharing across the institution to provide insights into success patterns Learning materials agent to reduce costs	Real time data availability for improved decision making on programmes and course selection	Study buddy agents Virtual and augment reality learning resources	Integration with work placement dbases to provide best-fit opportunities for job placement and career advisement

Conclusion

The two main bodies of systems analyzed in this paper were those of the student lifecycle and the learning management system. While the lifecycle management systems keep track of overall student progress, the courses they have taken, venues of financial support, volunteer opportunities and schedule management, the learning management systems are focused on the academic progress of the student. From this it is seen that student lifecycle management relies more on the administrative staff while learning management systems are supervised by the academic staff at a higher education institute.

As with all innovations their adoption is not an either-or, but a blending and integration of the strengths of both the existing and the new to provide a superior capability. If we, therefore, assume that we can combine activities currently managed by these systems with an intelligent system, we can begin to redesign a new system of education, one breaking out of the traditional roles of professors, teaching assistants and support staff, making them facilitators of knowledge and managers of the new systems. At the classroom level, in many cases, it will free up time to use the in-class time in a different way. The concept of flipped classrooms is where students study the assigned material at home and come to the class to discuss it. This might be supplemented with learning activities in class such as discussing complex concepts or examining real-world examples. On the other hand, at an administrative level, work of support staff may be reduced with regards to providing counselling to the student about potential next steps as the student would already have access to the courses they are eligible for, credits they can take from other universities, the career venues and graduate programs open to them based on his/her current performance and volunteer opportunities to augment his/her resume, to name a few areas. The advantages of such an integration of the student lifecycle and learning management systems is to give students the choices and options, right for them, at the right time in their higher education journey.

Another system using artificial intelligence which we did not explore here is at the academic department and faculty level for curriculum design. Such a system would analyze the needs of the discipline, trends in the current job market and research as well as the new knowledge skills that graduates require for being successful. This information would feed into design and development of new courses and programs, enhancing student experience by increasing their employability.

This paper has attempted to show that AI is and can be a significant aid to all aspects of the student experience and to the organisations, structures, processes and people that make up educational systems. It further provides an architectural approach that is a coherent representation of real experience, which provides a context for experimentation and the development of a referenceable literature. It does not try to make the case that AI is superior or equal to human equivalents, rather it attempts to demonstrate the benefit of synergistic integration of both forms of support for student success, allowing each to support the other to provide what they are best at. By so doing all stakeholders benefit and the student experience is improved with the expectation that student success increases *pari passu*.

Finally, we need to be aware of techno-solutionism to address wickedly complex problems, but we should also explore its capabilities to find the best-fit for its application and benefit to an increasingly expensive and technology resistant system. The pace and depth of adoption will depend not only on the continued growth of AI capabilities, but also on the opening and sharing of data and the acceptance of a highly conservative system unused to collectively integrating technology into its corpus. By providing an adoption framework this paper desires to enable a more structured and efficient introduction of AI technology into Higher Education. One that can benefit students, faculty and administrators through an enhanced user experience that improves the ability of educational institutions to deliver on their core mission of teaching, learning and research.

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