UNIVERSITIES MOVING CLOSER TO INTELLIGENT LEARNING SYSTEMS

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Abstract - This discussion paper explores how universities are using artificial intelligent to meet complex contemporary educational challenges. Following a characterization of the field, recent contextual developments in artificial intelligence is examined, specific to innovations that include automated essay grading, adaptive and personalized learning, digital courseware, virtual tutoring, and learning analytics. Evidence-based examples are identified to demonstrate real-world applications and highlight implications for future development. It is concluded that the development trajectories across both fields could be better served with improved convergence in the developmental cycle.

Keywords - Artificial Intelligence, Artificial intelligence in education, Learning analytics, Intelligent systems

I. INTRODUCTION

Ubiquitous connective hand held devices with converged visual perception, speech recognition, decision-making, and language translation tools are uniquely distinctive of 21st century technological advancement. The evidence of this inflection is seen in personal virtual assistants with capabilities to interpret verbal cues and respond conversationally mirroring human interaction. Apple's *Siri*, Amazon's *Alexa*, Google's *Google Home* and *Google Car* are just a few examples. The transformative effects of 'invisible' intelligent softwareare rapidly becoming mainstreamed. Predictive text in Google's search engine, system generated viewing recommendations from Netflix, merchandise recommendations from Amazon, and intelligent sensors that help us take perfect photos, enable autonomous parking, and provide real-time updates on traffic conditions and route planning are other examples. There is no doubt that the Artificial Intelligence (AI) is rapidly entering most areas of human activity.

Resurgence in AI in the last decade is driven by continuing rapid growth in computer speed and the declining price of processing power, consequently doubling and redoubling the capabilities of machines and machine learning. Exponentially increasing processing power, ubiquitous connectivity, together with developments in other technologies (e.g., sensors, GPS systems, gyroscopes) means that some smart machines are imbued with not only AI but may also include artificial eyes, ears, hands, and feet! The transformative potential of recombining AI, robotics, virtual reality, synthetic biology and computation is advancing vigorously in all sectors. In fields as diverse as education, health, transport, social services, commerce, and agriculture human-data collaboration tools are rapidly advancing. In this paper, the author provides a non-technical exploration of some of the current applications of intelligent computing systems in higher education, identifying current and future challenges that are likely to drive advancements in both areas. The discussion is to potentially relevant to both educational and engineering professionals, and is designed to stimulate improved cross-discipline collaboration.

II. DEFINITION AND CHARACTERISTICS

Despite it's long history and rapid proliferation in the last decade, AI remains a difficult concept to define for two reasons. One, the field is constantly shifting, and as cutting edge developments filter into general use they are no longer referred to as AI. Two, being interdisciplinary in nature, each discipline brings to the field unique perspectives. Emergent developments are attracting greater convergence amongst the sub-disciplines of philosophy, psychology, linguistics, neuroscience and computer engineering (programming, architectures, methods and techniques) to instill attributes of human cognition in computers [1], [2]. Essentially AI is the study of "agents that receive percepts from the environment and perform actions" [3]. It engages "a constellation of technologies that allow smart machines to extend human capabilities by sensing, comprehending, acting and learning" [4], representing the transformative inflection point of intelligent machines. Capacity for human cognition and behavior are critical features of intelligent machines (Table I) [3].

Thinking Humanly Automation of activities associated with human thinking (e.g., problem solving, decision-making, learning)	*Thinking Rationally* Studying computations that make it possible to perceive, reason, and act.
Acting Humanly Creating machines that can perform functions that require intelligence when performed by people.	*Acting Rationally* The study of the design of intelligent agents.

Table I: Differentiated Definitions of Artificial Intelligence

The field is philosophically divided between weak AI (i.e., at best computers will only seem to be intelligent) versus strong AI (i.e., computers someday can be as intelligent as humans) proponents. The related separation of classicalism (i.e., the view that human minds are computational by nature through a built in circuitry) and connectionism (i.e., the view that the human mind can learn, expand, and change, but many of the expert systems are too rigid and do not learn), as represented respectively in weak AI and strong AI debates provides the conceptual basis for how intelligent machine systemsare designed.

Several interrelated AI sub-disciplines are driving initiatives to solve practical problems. These include planning and searching for solutions (i.e., solving problems with multiple constraints), machine learning (e.g., building game playing programs), neural networks (i.e., solving difficult problems by allowing computers to discover patterns in large data sets), robotics (i.e., hardware and systems), and multi-agent systems (i.e., improving the ability of robotic agents to plan courses of action or strategize about how to interact with other robots or people).

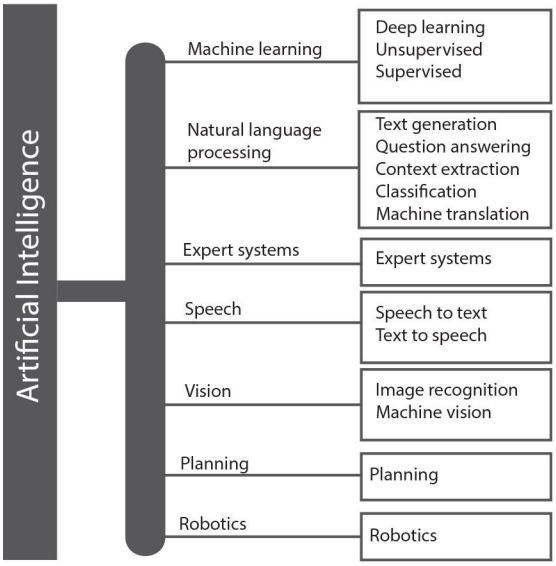


Fig. 1. Sub-disciplines of AI driving solutions to complex problems in diverse fields

Ubiquitous computing, low-cost cloud services, new algorithms, and data analytics are influencing current developments in AI[3]. Rapid expansion of machine learning systems (data mining and pattern recognition)in the last decade has brought solutions to a range of practical problems across various fields representing Stage 1 developments. Intelligent machines that integrate combinations of robotics, speech recognition, autonomous planning and scheduling, game playing, spam fighting, logistics planning, and machine translation are driving Stage 2 developments. The evolution of thinking machines or machine consciousness is the goal of Stage 3 development (see Fig. 2).

Stage 1 and Stage 2 developments are already appearing in the university sector to solve challenges to transform the relationship between humans and machines, re-configure business models and processes, and unlock the value of data held in their systems. Universities are embedding AI to reduce costs, improve efficiencies, innovate their services and solutions, and most importantly, augment the work of highly skilled teaching professionals to improve the student learning experience. In exploring such initiatives the main thrust of this paper is that intelligent machines can expand opportunities to better understand what is happening for students and to apply this knowledge to activate effective support systems to strengthen the student experience.

To wrestle with what is fundamentally useful about the applications of AI in higher education, it is necessary to think beyond the technology itself. This requires consideration of how AI can offer improvements and solutions to some of the important challenges facing higher education globally, namely increasing learner diversity and mobility; escalating costs and diminishing resources, growing teacher and expertise shortages, gaining and retaining competitive advantage in a global education market; improving student retention and success, and preparing graduates for the changing workplace. AI can have a role in unpacking the 'black box' of learning in these emergent conditions. Before considering examples of how this is occurring, an overview of recent developments in AI technology deserves mention.

III. RECENT AND CONTINUING DEVELOPMENTS

Resurgence in AI research and developments in the last two decades have been driven by three factors, according to experts [5], [3]. Machine intelligence experts attribute recent developments to enormously increased data, significantly improved algorithms, and substantially more-powerful computer hardware. MIT researchers Brynjolfsson and McAfee [6] explain, "data availability has increased as much as 1,000-fold, key algorithms have improved 10-fold to 100-fold, and hardware speed has improved by at least 100-fold [known as Moore's Law]."They propose these affordances "can combine to generate improvements of up to a million-fold in applications such as the pedestrian-detection vision systems used in self-driving cars." The synergistic effect of each factor together with global networking and cloud computing has further amplified the current capabilities of AI, the potential of which is being recognized in the university sector.

Experts differ in their views on how widespread AI is currently. For instance, Milford a robotics researcher at University of Queensland explains that whilst basic machine learning algorithms underpin many technologies that we interact with daily (e.g., voice recognition, search engines), these are

application-specific and can only do one very specific defined task (also described Artificial Narrow Intelligence or ANI); moreover some applications have not mastered accuracy consistently [7]. Universities are looking towards system integration to maximize intelligent machine learning.

More capable (or 'smart') AI is currently unevenly distributed, with most reliable success in areas such as online retail and marketing, smartphones, assistive car systems, and service robots, but is still developing in health care and education, for example. Russell [8], a professor of computer science at University of California, Berkeley and a member of the World's Economic Forum Council surmises that it is very difficult to predict how far along the path of development AI science is, explaining that although the rapid advancements of the past five years have opened up many new markets for real world AI applications, and attracted more research funding, he contends current AI methods are still not sufficiently advanced to reach a state of Artificial General Intelligence (AGI) by 2040 because they do not scale and do not have the characteristics to integrate cross domain optimization. Universities are already considering learning futures that AGI (also referred to as Strong AI and Full AI) could unleash [9]. Speculative predictions suggest AGI will come to fruition within the next 10 years in the form of general-purpose driverless cars, multi-functional virtual personal assistants (e.g., accountants, financial advisors, doctors, shop-bots, museum guides, cleaners), and robotic tools (e.g., vacuum cleaners) [7], raising consternation in some areas that virtual personal assistants could replace teachers.

In the foreseeable future advancements in AI will be shaped by continuing development of large, complex neural networks and algorithms, and brain-based networks (i.e., deep artificial neural networks). Forecasts consistently indicate that many jobs will increasingly become transformed by innovations that deploy human-like emotional capabilities in machines. By 2050, Artificial Super Intelligence (ASI)is imagined to have capacity to solve problems that are unsolvable today[10](Fig. 2).

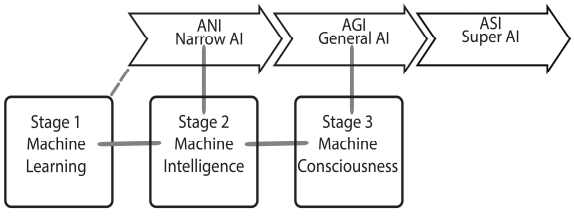


Fig. 2. Varied representations of the intelligence scaledescribed as developmental phases.

A substantial body of work supports the resurgence of interest in AI in education. For several decades AI researchers have been investigating how the two fields intersect, covering areas such as tutoring systems, automated grading and feedback, peer collaboration systems, remote laboratories, and learner modeling.

Currently, many higher education institutions are adopting AI software to improve the student experience throughout the student lifecycle from recruitment; to teaching, learning, and assessment; to student support, career development and engagement with alumni (i.e. improving academic, social, welfare and support services whilst keeping the academic imperative central). Such systems supported by intelligent automation, machine learning, natural language processing, and smart data gathering are geared to achieve predictive capabilities that can usefully inform actions.

Globally, higher education providers are exploring ways in which AI based systems could be integrated to augment services and improve efficiencies. The uptake has been relatively slow and uneven due to skepticism firmly rooted in the concern that AI technologies no matter how human-like cannot and should not replace educators, which the author concurs with. Emergent strategies reveal that a more balanced future where AI can make significant contributions deserves closer attention and continuous development. In the next section, the author discusses the most common AI technologies currently in use in higher education settings and considers possible implications for the future.

IV. CURRENT AI APPLICATIONS IN EDUCATION

Globally there are many projects applying emergent AI systems to help students, teachers, and institutions improve the student experience, and enhance retention and success. The five categories of AI systems together with evidence-based examples that follow provide insights into the transformative capacity of AI in higher education.

A. Automated essay grading

At university, grading assessments in large classes can be tedious, time consuming and costly. For many years it has been possible to automate a wide variety of tests (e.g. multiple choice, fill in the blank), with the range of test types continuously widening. Essay-grading software though still in its infancy is set to improve phenomenally in the next few years, promising transformative potential in university settings.

Automated essay grading systems had limited progress between1966 [11] and the 1990s, when the advent of the Internet increased the ability to store data electronically. AI capabilities have since evolved from simple rule-based coding to highly sophisticated software systems. Statistical techniques from computational linguists, natural language processing, and machine learning have helped develop better ways of identifying certain patterns in writing, but challenges remain in coming up with a universal definition of good writing, and in training a computer

to understand nuances such as 'voice.' Alongside these historical challenges, universal consensus that automated grading would be better than humans is elusive. For instance, Perelman, director of the student writing program at MIT, remains a skeptic. Using eRater, the automated essay grading program produced by Educational Testing Service, purported to grade 16 000 middle and high school essays in 20 seconds, Perelman found, "of the 12 errors noted in one essay, 11 were incorrect," and when comma errors were intentionally included it went undetected, suggesting the program was not 100% accurate [12], [13]. Contrastingly, Shermis, dean of the College of Education at the University of Akron, used automated systems developed by nine companies to score 16 000 middle and high school standardized test essays that had been previously graded by humans. He found that automated grading produced "virtually identical levels of accuracy, with the software in some cases proving to be more reliable" [14].

Currently, essay-grading software such as *Pearson WritetoLearn* uses machine reading intelligence, and although still very far from the capabilities of human grading, appears to have a promising future. Improvements in the technology's ability to evaluate language, grammar, mechanics and style; detect plagiarism; and provide quantitative and qualitative feedback is potentially of interest to the university sector, particularly MOOC-providers.

EdX, a MOOC provider working in combination with Harvard University and MIT to improve online education, are researching automated grading. To initiate the machine learning in the software, teachers' input graded essays into the system to provide a few examples of what is good and what is bad. The software becomes increasingly better at its job as more and more essays are entered, eventually gaining the capacity to provide specific feedback almost instantly. EdX president, Agarwal, acknowledges substantial progress is needed claiming that the quality in grading is fast approaching that of a human teacher [15]. Currently 11 major universities are contributing to the ongoing advancement of this grading software. Interestingly, Agarwal further claims AI-grading has more advantages than just freeing up valuable time. He explains that the instant feedback made possible with the new technology has a positive impact on learning [15]. Traditionally, grading essays can take days or even weeks to complete, but automated grading makes it possible for students to receive instant feedback, whilst the work is fresh in their memory making it potentially more effective in facilitating improvements in learning.

In 2016 Nguyen and Dery [16], Stanford University researchers reported they had applied different neural network architectures to build an accurate automated essay grading system, compared to previous machine learning models that have been built using predefined features without deep learning features. Nguyen and Dery's [16] models included three steps: data processing, training the models with their loss functions and tuning of hyper-parameters, producing an accuracy score of 94.5% using the data set supplied for the 2012 Hewlett Foundation Automated Essay Scoring challenge. Software improvements such as that reported by Nguyen and Dery suggest that it is likely a matter of time before automated grading software would be sufficiently robust to recognize small but significant nuances to finely differentiate grades and capture the essentials of written communication, such as reasoning, ethical stance, argumentation, and clarity of thought, making them sufficiently robust for use with university-level essays.

B. Adaptive and personalized learning

The idea that no two students are exactly alike has been a long held view and a challenge in traditional education systems modeled on teaching most students the same self-material in the same way. Intelligent adaptive learning systems seek to enable differentiated instruction at a personalized level of learning. Designed to intelligently and dynamically adjust to the level or type of course content based on an individual student's abilities or skill attainment, automated processes together with teacher interventions are designed to accelerate a learner's performance. They are potentially useful for addressing challenges associated with increasing student diversity, resource limitations and scalability.

Digital courseware with adaptive learning capabilities is driven by predictive modeling, learning analytics, and current research in brain science, cognition, and pedagogy. These systems can autonomously recognize what individual students know and accurately and logically move them through a sequential learning path to achieve mastery as per prescribed learning outcomes. Fundamentally they require an architecture that integrates key functions of modular content, assessment, and competency mapping that work together to support a personalized learning ecosystem.

Proponents of adaptive learning systems have argued the technical aspects of automation and personalization strengthen a student-centric focus. The benefits include improved teaching related efficiencies linked to automation and predictive analysis of activity driven learning; the impact of varying levels of prior knowledge on course progression, cost efficiencies linked to automated feedback; learning enhancements derived from immediacy of feedback on some forms of assessment; remediation without formal instructor intervention; greater student self-regulation in the learning journey; improved flexibility in the pace and nature of learning; and rich data analysis that can guide teaching strategies and learning interventions [17]. However, adaptive learning systems currently lack specific guidelines, taxonomies, and a common vocabulary, making evaluation of their instructional design techniques difficult. First generation adaptive learning systems utilize principles of automation,

sequencing, assessment, real-time data collection, and self-organization (Table II).

Principle	Explanation
Automation	Manual processes in assessment, evaluation, remediation, and competency attainment are reduced.
Sequencing	A sequenced progression of skills in a finite learning path is created in a specified or non-specified time period.
Assessment	Combinations of benchmark, diagnostic, and formative assessments are activated with immediacy in feedback, to support continuous evaluation of achievement.
Real-time data collection	Data collection, calculation, and analyses from multiple sources are processed, with methods of inference in real or near-real time.
Information organization	Information self-organization supports ongoing and persistent feedback throughout the teaching and learning cycle.

Table II: Core Principles of First Generation Adaptive Learning Systems

The above-mentioned principles are used to support different types of adaptive learning systems (Table III). Adaptive learning systems offer several potential benefits. Rather than replace the teacher, adaptive learning systems can potentially strengthen instruction by allowing the teacher to take on a supporting, coaching role, with less time focused on delivery of content that students may or may not already have mastered through self-paced learning, and more time focused on one-to-one student engagement. Essentially, these systems can help teachers automate learning designs to suit the needs of individual learners, and track how individual students are performing by accessing data aggregating reports. Several studies have pointed to the benefits of using adaptive technologies in online learning [18], [19], [20], [21], with findings suggesting learning improvements linked to receiving real-time response for work; teachers using data to gain insights into students' learning; reductions in students falling behind; improved productivity in teacher-student interactions in online courses; and intuitive application of theories of learning in the automated processes.

Type of adaptive learning system	Description
Machine-learning	Learning algorithms are used to generate other algorithms, which then create adaptive sequences. Predictive analytics generated by real time data is used to move a student through a guided personalized learning path (i.e., instructional techniques, content, remediation, and feedback) based on achievement of mastery.
Advanced Algorithm	Learner profiles linked to prior proven mastery of knowledge are used to generate large real-time data sets (e.g., clickstreams, time intervals, assessment attempts, and other transactional behavioral data), establishing personalized learning paths by comparing individual learner profiles with data from other students exposed to the same or similar content.
Rules-Based	An established set of rules and machine learning techniques that do not adapt to individual learners are used. A predetermined sequential learning path rather than an algorithmic approach is supported with limited personalization based on assessment of prior knowledge, enabling self-paced learning. Persistent diagnostic assessments control individual progression and or regression.
Decision Tree	An established rules set linked to prescribed repositories of content, assessments, and answer banks are used. Instead of using specific learner profiles, 'if this, then that' (IFTT) branching sequences are deployed to infer case-based reasoning to support individualized workflows.

Table III: Description of Four Types of Adaptive Learning Systems

Proprietary adaptive learning courseware such as Smart Sparrow (https://www.smartsparrow.com/) and Creatrix Campus (https://www.creatrixcampus.com)provide customized suites of tools. These and similar products include tools to teach subjects as diverse as collecting genetic information from a patient in a virtual laboratory, to engineering drawing, and testing and using a defibrillator in a virtual emergency department, thus generating substantial interest from universities.

A useful example is the Hewlett Foundation funded, Open Learning Initiative (OLI) at Carnegie Mellon.

This program builds online courses based on best practices in science and technology learning with the aim of linking learning experiences to course performance and outcomes in more quantifiable ways. Lovett, Meyer, and Thill [18] found no significant difference in exam scores for students enrolled in the adaptive OLI introductory statistics course compared to the traditional course. Furthermore, this study also found that the students in the adaptive OLI course took 50% less time to learn all the content and perform the same or better relative to the students in the traditional course. Noting that this course was conducted at a highly acclaimed research university and under circumstances that may not resemble those of mainstream adopters, emergent data shows comparable 'successes' at other institutions, making a compelling case for the linkage between adaptive learning and student success.

Proponents of adaptive learning are quick to claim that adaptive learning can break the 'iron triangle' of cost, access, and quality, by substituting technology for labor and conversely allowing best practice pedagogy (including Teacher Pedagogical and Content Knowledge) to be driven by algorithms to meet learner needs in a increasingly diverse, mobile populations. It is likely that some of this may be overstated considering the up-front investment for adaptive technology is still relatively high and the long term payoff remains largely unproven. Notwithstanding, adaptive learning holds promise for teaching and learning innovation that is needed as a next generation solution.

C. Digital courseware

AI software is also impacting a move from traditional to digital courseware. Rather than just replacing textbooks, AI is bringing added capacity for the teacher to know in real time what each student is doing when they access their digital textbook. Assessment and Learning in Knowledge Spaces (ALEKS) (https://www.aleks.com/), an adaptive AI courseware system provides students with a personalized learning experience.

Based on Knowledge Space Theory developed by Falmagne and Doignon [22], ALEKS has capability to teach and efficiently and accurately assess learning. It is being used globally to teach more than 100 different academic subjects. In contrast to standardized tests, which typically result in numerical measures of achievement, the outcome of an ALEKS assessment consists of: (i) the precise and comprehensive delineation of an individual's competence in a subject in the form of a *knowledge state* describing all the types of problems mastered by the student, and (ii) a comprehensive list of the topics the student is ready to learn (referred to in Knowledge Space Theory as the *outer fringe* of that individual's knowledge state).

ALEKS starts a cohort of students at the same point, but as students begin to answer the practice questions that are automatically generated for them, ALEKS' machine-learning algorithms analyzes their responses to figure out the concepts the student understands and which they need to work on further. When a student produces a few wrong answers to a given type of question, the program may prompt them to read some background materials, watch a short video lecture, or view some hints on what they might be doing wrong. Contrastingly, if a student is progressing accurately through a set of questions on a given topic, they may be appropriately redirected to a topic that matches the level of conceptual understanding that they have demonstrated in answering earlier questions. As a student shows mastery at progressive levels, they will be prompted by ALEKS as to whether they are ready to take a test. If the test is passed, the student is directed to the next topic, unless they would prefer to take a detour into a different topic. As long as the student has mastered the prerequisites, which topic comes next is up to them.

As students work independently using the software, the teacher can access a series of spreadsheets and data visualizations to track each student's progress in real time. This system frees up the teacher to work with students, as they need help. The teacher's online dashboard will indicate when several students are struggling with the same concept, thus enabling the teacher to provide remediation with small groups, in a form of 'triage'. Rather than seen as replacing the teacher, intelligent digital courseware such as ALEKS frees the teacher to focus on high-level, conceptual instruction that only a human can provide.

Another example, Third Space Learning, is an online Math tutoring platform that uses machine learning algorithms to assemble patterns from data and provide insights and suggestions to help teachers find gaps in their teaching and to point to where students are struggling with subject matter. Hooper, the founder of Third Space Learning says, "If we can aim to shape the performance of the teacher . . . then you're creating something truly powerful," [23].

Other variants of digital courseware include smart content creation, which varies from digitized guides of textbooks to customizable learning digital interfaces that integrate gamification, simulations, and rich media in app-based learning systems with self- or online-instructor assessment.

D. Virtual tutoring

AI-based tutoring systems also use data analytics and machine learning to provide personalized, supplemental guidance to students. Typically, an AI tutoring system will present learning content and monitor student responses to evaluation questions. The system feedback determines the best path for the learner to follow to gain mastery of the subject. Such tutoring systems are designed to help students adopt productive learning behaviors (e.g., self-regulation and self-learning). *Mika*^{TM}, an AI cognitive science based remedial math tutoring systemfor incoming university students, developed by Carnegie Learning [24],

delivers hints and just-in-time feedback to each student based not only on what a student knows, but also on the specific strategy a student uses to solve a problem. A randomized trial of more than 18,000 students at 147 middle and high schools proved thatgrowth in performance on standardized tests nearly doubled relative to students using traditional learning methods[24]. *Mika*^{TM}continuously analyses every keystroke to determine how each student masters each discrete skill (or fails to), and customizes a remedial tutoring program for each student.

There is some evidence to suggest that intelligent tutoring systems perform as well, if not better, than individual human tutors for many students [25]. For example Carnegie Learning's *Mika*^{TM}software uses cognitive science and AI technologies to provide personalized tutoring and real-time feedback to first year university students, who would otherwise need remedial courses. This product is being promoted for its cost-cutting advantages (i.e., time vs success rate for maths courses), as it offers a flexible and more personalized mode of learning.

E. Learning analytics

Analytics has been discussed in the literatures under different labelsincluding business intelligence, big data, and data mining. The long and diverse history and practice of analytics suggests a developmental path with varied categorisationand a range of tools [26]. The matrix presented in Fig. 3 identifies the developmental stages and levels of sophistication.

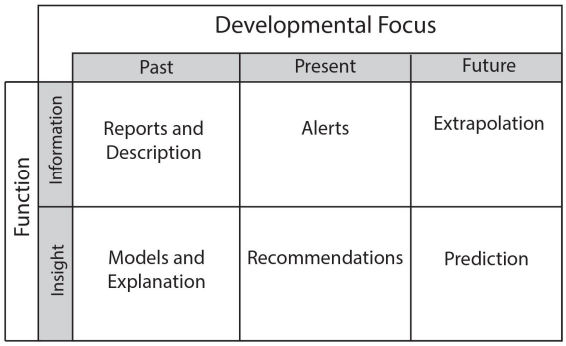


Fig. 3. Categorisation of analytics tools based on developmental stage and level of advancement.

Despite different approaches, analytics share a recognizably similar set of criteria as shown in Table IV.

Analytics Tool Workflow	Categorization of Different Analytics Approaches			
Functions	**Data**	**Information**	**Knowledge**	**Wisdom**
Steps	Capture	Report	Predict	Act & Refine
Objectives (web applications)	Define goals	Measure		Use & Share
Objectives (collective applications)	Select & Capture	Aggregate	Process	Display
Processes	Select & Capture	Aggregate & Report	Predict	Use, Refine & Share
Tool workflow	Collection, Acquisition & Storage	Cleaning	Integration, Analysis, Representation and Visualisation	Alerting

Table IV: Categorization of different analytics approaches mapped to an analytics tool workflow

Designed to be general-purposein use, some customization of tools isusually necessaryto allowfor integration of a wide variety of data sources. However, greater tool customization also increases the technical demands on the user, and influences sustainability and long-term impact. A recent study determined the flow of system resources in universities, noting the mutually influencing and reinforcing feedback effects [27] (Fig. 4). Strategic capability appears to propel the desire for LA implementations, which can thrive when positively supported by both implementation capability, and tool/data quality to yield useful research and learning outputs.

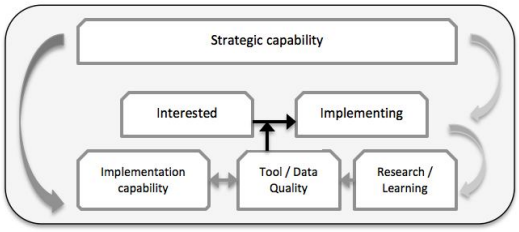


Fig. 4. A model of university system conditions that make uptake of LA feasible.

Seven categories and examples of tools used in the university sector follows. These include: (1) Business Intelligence (e.g., Microsoft BI, Pentaho); (2) Web Analytics (e.g., AWStats, Google Analytics, Bluefin Signals); (3) Information Visualization (e.g., Many Eyes, Tableau, Processing); (4) Operational Research (e.g., IBM ILOG); (5) Data Mining (e.g., Oracle Data Miner, R); (6) Social Network Analysis (e.g., Gelphi, Network Bench); and (7) Learning Analytics (e.g., Blackboard Analytics for Learn, Austin Peay Degree Compass) [26], [27]. Tool choices open to universities can be easy to install, flexible and comprehensive, but

occasionally limited in scope, inflexible, expensive and time consuming. Given theseresource constraints, it would be more prudent for universities as an initial move to experiment with low cost components before moving to bespoke LA tools.

Various reported case studies provide insights into how LA is informing institutional policies, planning and practice. For example, at the University of Derby [28], a service design approach integrating technology and data analytics was used to find out how, where and when students were (or were not) interacting with the institution. Multi-system data collection representing student engagement touch points, allowed the university to look 'beyond the classroom' (see multi-system example in Fig. 5). This enabled identification of academic and non-academic patterns of student behavior that might lead to student withdrawal. This LA project resulted in improved processes to better support 'at risk' students, as well as providing a basis for scoping student and staff facing 'traffic light' dashboard systems.

Although there is broad consensus across the university sector on the importance of LA, there are challenges in how such endeavours are to be implemented at the organizational level. A 2016 study of 16 Australian universities revealed two distinct implementation profiles, noting the complexity and multidimensionality of individual LA projects [26]. These LA implementation trajectories are: (1) implementation of a predictive or measurement tool for identifying students at risk; and (2) developing understanding of, and improvements in teaching and learning.

The above mentioned study involving a panel of international experts concluded that further investigation in the following areas is needed if LA is to provide a sustainable long term impact in higher education: (1) broader discussions to inform how LA can address sectoral level challenges; (2) building capacity for LA use; and (3) improved understanding and resources for supporting LA ethics and privacy issues [26].

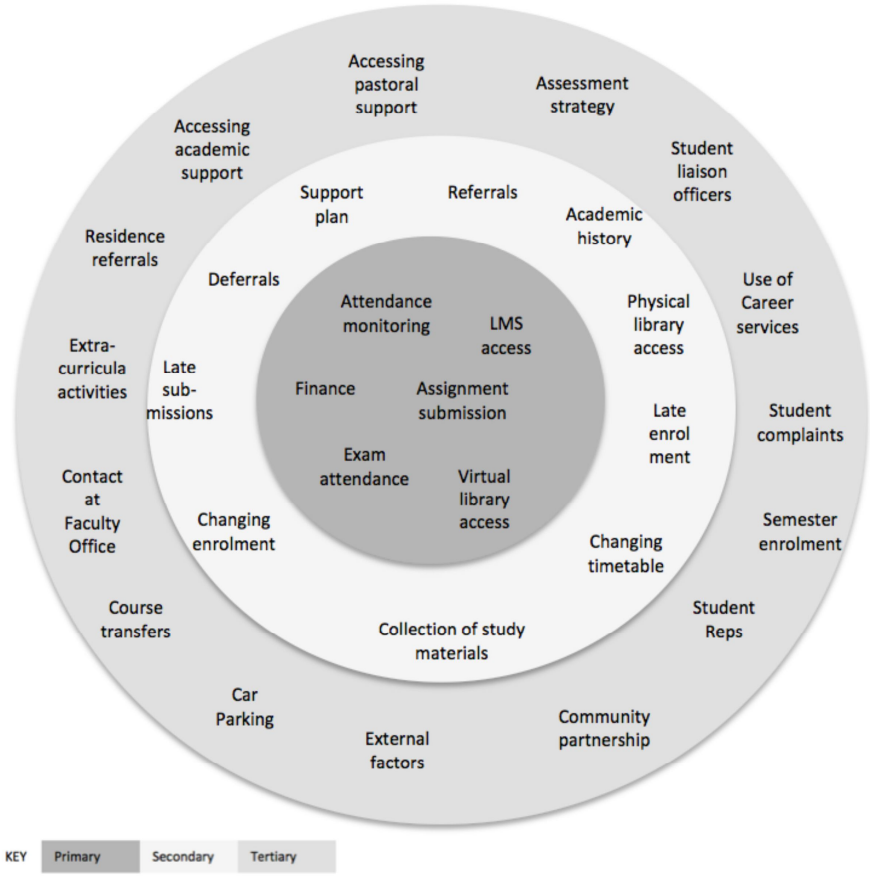


Fig. 5. Example of an integrated data system showing Primary, Secondary and Tertiary indicators of student engagement.

CONCLUSION

This paper has presented a review and discussion of current AI developments occurring in the higher education sector globally. Notably, AI is a field advancing faster than our understanding of it, making it as complex as it is opaque. In an attempt to appeal to the interests of a dual audience (educational and engineering researchers and practitioners), the author has framed current and future challenges in education against emergent developments in AI. The author argues that the development trajectories across both

fields could be better served with improved convergence. Technical advancements in AI can both inform and be informed by the kinds of practical solutions that the university sector is seeking. An implication that cannot be overlooked by AI researchers is that technological advancements must be tempered to meet the complex challenges universities are grappling with. Collaboration among multiple stakeholders throughout the developmental cycle of intelligent systems is essential to integrate the unique perspectives of educational executives, researchers, and practitioners with the design ideas of engineers, alongside the marketing imperatives driven byvendors, if we are to genuinely advance AI to continually improve the student experience.

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