2 Artificial intelligence in education: Bringing it all together

Ryan S. Baker
University of Pennsylvania, United States

Artificial intelligence has led to a generation of technologies in education – for use in classrooms and by school systems more broadly – with considerable potential to bring education forward. This chapter provides a broad overview of the technologies currently being used, their core applications, and their potential going forward. The chapter also provides definitions of some of the key terms that will be used throughout this book. It concludes with a discussion of the potentials that may be achieved if these technologies are integrated, the shifts in thinking about supporting learners through one-on-one learning experiences to influencing systems more broadly, and other key directions for R&D and policy in the future.

Introduction

For decades, educators and researchers have looked to computers as having the potential to revolutionise education. Today, much of the use of computers in education still falls short of revolutionary – a lot of learning still involves one instructor teaching many students simultaneously, and considerable computer-based learning takes place using curricula and technologies that replicate traditional practices such as drill and practice. However, the best practices of computers in education appear to go considerably beyond that. Millions of learners now use intelligent tutoring systems as part of their mathematics classes – systems that recognise student knowledge, implement mastery learning where students do not advance until they can demonstrate understanding of a topic, and have hints available on demand (VanLehn, 2011[1]). Millions of learners around the world watch lectures and complete exercises within massive online open courses, offering the potential to study thousands of topics that would not be available in colleges locally (Milligan and Littlejohn, 2017[2]). An increasing number of children and adults learn from (and are even assessed within) advanced online interactions such as simulations, games, virtual reality, and augmented reality (De Jong and Van Joolingen, 1998[3]; Rodrigo et al., 2015[4]; Shin, 2017[5]; De Freitas, 2018[6]). Perhaps none of these systems fully captures the sophistication dreamed of in early accounts of the potential of these systems (Carbonell, 1970[7]) (Stephenson, 1998[8]). On the other hand, their scale and degree integration into formal educational systems have gone beyond what seemed plausible even as recently as the turn of the century.

Increasingly, computer-based education has been artificially intelligent education. Advances in artificial intelligence (AI) in the 1980s, 1990s, and first decade of the new millennium have translated to new potentials for learning technologies in several areas. The core advances in AI in those decades led to advances in more specialised use of AI in education – the research and practice communities of learning analytics and educational data mining – from around 2004 to today. As the research field advanced, new methods filtered into systems used by learners at scale. AI is today used to recognise what students know (and their engagement and learning strategies) to predict their future trajectories, better assess learners along multiple dimensions, and – ultimately – help both humans and computers decide how to better support students.

As these technologies develop, as they mature, as they scale, it becomes worth asking the question: where are we going? And where could we be going? If we can understand the frontiers and potentials of artificial intelligence in education, we may be able to shape research and development through careful design of policy over the next decade to get there.

In the chapters of the book, the authors use their expertise in specific areas and challenges in artificial intelligence in education to explore the frontiers and potential of this area. What technology and teaching approaches are just becoming available in research classrooms that could soon be available to a much broader range of students? How can artificial intelligence shape educational systems more broadly, from academic advising to credentialing, to make them more adaptive to learner needs? Where could we be in 10 years with the right guidance and support for research and development? Where are the opportunities for incremental but positive impacts on learners? And where are the opportunities for radically transforming education and learner experiences?

In the remainder of this overview, I will clarify some terms and domains relevant to this book. Next, I will situate the chapters of this book in the context of broader trends and opportunities in the field (including some trends and opportunities that were not explicitly covered by the authors). The final section will discuss upcoming opportunities of a broader nature, cutting across types of artificially intelligent learning technologies that can be supported through shifts in policy.

Smart education technologies: Definitions and context

In this section, some definitions and context that are key to understanding smart technologies in education are presented.

Educational technology

Educational technology at its most obvious level refers simply to the use of any technology – any applied machinery or equipment – in education. Throughout the last hundred years, practitioners and researchers have sometimes become overly enthusiastic about finding applications for new technologies in education. See, for instance, reports by Cuban (1986[9]) of instructors teaching students with traditional lecture pedagogies but inside an early-generation airplane.

Today, most discussion of technology in education is focused on computers and digitalisation, though older technologies such as radio and television still play an important role – especially in many middle-income countries during the recent COVID-19 pandemic (OECD, n.d.[10]). Educational technologies can refer to a range of technologies. I provide a few examples here (others are given in the context of the chapters in this book).

- *Computer tutors or intelligent tutoring systems* provide students with a learning experience where the learning system adapts presentation based on some model or ongoing assessment of the student, a model of the subject area being learned, and a model of how to teach (Wenger, 1987[11]). Each of these models can be more sophisticated or more basic. Baker (2016[12]) notes that contemporary intelligent tutoring systems tend to be sophisticated in only one area (which differs between systems) and very simple in other areas.
- *Digital learning games* embed learning into a fun activity that resembles a game. The degree of gamification can vary from activities that embed learning into core gameplay and which may not even seem to be a learning activity (see, for instance, SimCity and Civilisation) to more obvious learning activities where the student gets rewards for successful performance (for instance, getting to throw a banana at a monkey after answering a math problem correctly in MathBlaster).
- *Simulations* are computerised imitations of a process or activity that would be difficult or costly to do in the real world as an educational activity. Increasing numbers of students today use virtual laboratories to conduct experiments that could be dangerous, expensive, or difficult, and also to receive feedback and learning support while completing these activities.

- *Virtual reality systems* embed learners in 3D depictions of real-world activities. Like simulations, they make it feasible to engage in activities from a home or computer lab that would be expensive, dangerous, or simply impossible to engage in otherwise. Augmented reality systems embed additional information and experiences into real-world activities, ranging from pop-up details that appear and ambient displays (information that is available in the environment without having to focus on it) to overlaying a different world on top of the current one. Both augmented reality and virtual reality often rely upon headsets to present visual information to learners.
- *Educational robots* have a physical presence and interact with students in real-world activities to support their learning. While robots as educational DIY kits have been available since the 1980s, a recent development sees robots take up the role of tutor.
- *Massive online open courses (MOOCs)* provide students with a basic learning experience, typically consisting of videos and quizzes. The innovation around MOOCs is not in the learning experience – it is typically a simplified version of a large lecture class – but, rather, in making materials developed by faculty at world-famous universities, often on highly specialised topics, accessible to learners around the world.

Educational data

Data are, quite simply, facts gathered together. Whereas a few facts gathered together do not enable us to reason about the relationships represented in that information, the accumulation of large quantities of information does and that is the modern power of big data. Educational data used to be dispersed, hard to collect, and small-scale. Individual teachers might keep a gradebook on paper; the school might keep disciplinary records in the basement; and curriculum developers would have a very limited idea of how their materials were being used and what students were struggling with. Today, educational data is gathered at a much larger scale. Gradebooks, disciplinary data, assessment data, absence data and more is stored centrally by local education agencies (or often by national or even trans-national vendors). Curriculum developers often gather extensive data on usage and learning. As of this writing, the regulations around handling, storage, and use of educational data vary considerably between countries, with some countries having very strict practices (particularly on the European continent), and other countries having less restrictive regulations. Each of these sources of data can be used to improve educational quality and support learning, supporting both artificial intelligence/machine learning (next definition) and human refinement of learning content and experiences.

Artificial intelligence and machine learning

Artificial intelligence is the capacity for computers to perform tasks traditionally thought to involve human intelligence or, more recently, tasks beyond the ability of human intelligence. Stemming from relatively simple, general-purpose systems in the 1960s, artificial intelligence today generally involves more specific-purpose systems that complete a specific task involving reasoning about data or the world, and then interaction with the world (more commonly through a phone or a computer interface than actual physical interaction). Machine learning (increasingly called data science, and also called both data mining and analytics) is a sub-area of artificial intelligence, present at a low level since the beginning of the field but becoming a particular emphasis in the 1990s through to today. Machine learning is when a system discovers patterns from data – becoming more effective at doing so when more data is available (and even more so, when more comprehensive or representative data is available). There is a broad range of machine-learning methods, classified mostly into supervised learning (attempting to predict or infer a specific known variable) and unsupervised learning (trying to discover the structure or relationships in a set of variables). There have roughly been two generations of machine learning: a first generation of relatively simple, interpretable methods and a second generation of much more complex, sophisticated, hard-to-interpret methods.

Artificial Intelligence in Education (AIED)

Artificial Intelligence in Education (AIED) arose as an interdisciplinary subfield in the early 1980s with a bi-annual (now annual) conference and peer-reviewed journal, although examples of this research area were present even before that. Much of the early work in artificial intelligence in education involved intelligent tutoring systems but the field has broadened over the years to include all of the types of educational systems/interactions defined above, and has expanded to include several independent conferences and journals. The revolution in machine learning and data mining impacted artificial intelligence in education as well, with a significant shift around 2010 – influenced by the emergence of a separate scientific conference, Educational Data Mining – towards much more use of this type of method. Today, AIED systems incorporate a range of functionality for identifying aspects of the learner, and a range of ways they can interact with and respond to learners.

Learning analytics

Learning Analytics, also referred to as Educational Data Mining, has emerged as a field since 2008 with two major international conferences and peer-reviewed journals. The goal of learning analytics is to use the increasing amounts of data coming from education to better understand and make inferences on learners and the contexts which they learn from. Learning analytics and educational data mining apply the methods of machine learning/ data science to education, with methods and problems emerging specific to education. Challenges such as inferring student knowledge in real-time and predicting future school dropout have seen particular interest, but there have been a range of other applications for these methods, from inferring prerequisite relationships in a domain such as mathematics to understanding the factors that lead to student boredom. A taxonomy of methods and applications for learning analytics is given in (Baker and Siemens, 2014[13]; DeFalco et al., 2017[14]). Learning analytics models are most frequently deployed in two types of technology: intelligence augmentation systems and personalised learning systems (discussed in the next section).

Intelligence augmentation systems, also called decision support systems, communicate information to stakeholders such as teachers and stakeholders in a way that supports decision-making. While they can simply provide raw data, they often provide information distilled through machine-learning models, predictions, or recommendations. Intelligence augmentation systems often leverage predictive analytics systems, which make predictions about students' potential future outcomes, and – ideally – also provide understandable reasons for these predictions. Predictive analytics systems are now used at scale to try to understand which students are at risk of dropping out of high school or failing to complete college, with an eye towards providing interventions which get students back on track. Intelligence augmentation systems often communicate information to stakeholders through dashboards, which communicate data through graphs and tables that allow the user to drill down for information about specific learners. Today, personalised learning systems and predictive analytics systems often use dashboards to communicate information to teachers, occasionally make dashboards available for school counselors, academic advisors, and school leaders, and rarely make dashboards available for parents. The quality of the data presented in dashboards can vary considerably from learning system to learning system.

The uses of artificial intelligence in classrooms and educational systems

This book focuses on two key areas: 1) New Educational Technologies and Approaches for the Classroom, and 2) New Educational Technologies and Approaches for Educational Systems. These new technologies often but not always involve artificial intelligence. Within this section, I will summarise work in each of these areas, including both the work discussed in the chapters in this report, but going beyond as well.

New educational technologies and approaches for the classroom

As computerised educational technologies become more commonly accessible to teachers and students, there is increasing awareness that the technology does not simply increase convenience for teachers or provide a fun alternative activity for students – it can promote new methods for teaching and learning.

Personalised Learning. One major trend within learning, driven by these technologies, is the move towards personalising learning to a greater degree. Personalisation of learning did not start with computerised technology – in a sense, it has been available since the first use of one-on-one tutoring, thousands of years ago (if not earlier). However, with the increase in systematised, standardised schooling and teaching over a hundred years ago, awareness increased that many students' learning needs were being poorly met by one-size-fits-all curriculum. Classroom approaches such as mastery learning (each student works on material until mastery and only then moves on to the next topic) were developed, but proved difficult to scale due to the demands on the teacher. Educational technologies provided a ready solution to this problem – the computer could manage some of the demands of personalising learning, identifying each individual student's degree of mastery and providing them with learning activities relevant to their current position within the curriculum.

The first dimension that educational technologies became effective at personalising for was a student's knowledge or state of learning. Molenaar (2021[15]) details efforts to develop better personalisation of learning for learners, providing a framework for the degree of automation in personalised learning systems. Her chapter discusses the shift from teacher-driven systems to computer-based technologies that can take a larger role in immediate decision-making, remaining within guidelines and goals specified by the teacher.

Next, educational technologies became more effective at personalising for differences in students' self-regulated learning – their ability to make good choices during learning that enhance their learning outcomes and efficiency. This topic is also discussed in Inge Molenaar's chapter (Molenaar, 2021[15]). Modern educational technologies in many cases have the ability to recognise when students are using ineffective or inefficient strategies, and to provide them recommendations or nudges to get back onto a more effective trajectory.

A contemporary trend, which is still primarily in research classrooms rather than wide-scale deployment, is the move towards also recognising and adapting to student engagement, affect, and emotion. Discussed by Sidney D'Mello (2021[16]), these systems recognise these aspects of a student's experience either from their interaction and behaviour within the system or from physical and physiological sensors. There are now several examples of educational technologies – particularly intelligent tutoring systems and games – which have been able to identify a student who is bored, frustrated, or gaming the system (trying to find strategies to complete materials without needing to learn) and re-engage them productively (e.g. DeFalco et al., 2017[14]).

Increasing research also looks at trying to personalise to increase broader motivation or interest. This work differs from the work on engagement and affect in terms of time-scale. Whereas engagement and affect often manifests in brief time periods – as short as a few seconds – motivation and interest are more long-term stable aspects of student experience. Work by Kizilcec and colleagues (Kizilcec et al., 2017[17]), for instance, has tried to connect student learning experiences with their values, leading to greater degrees of completion of online courses. Work by Walkington and colleagues (Walkington, 2013[18]; Walkington and Bernacki, 2019[19]) has modified the contents of learning systems to match student personal interests, leading students to work faster, become disengaged less often, and learn more.

New Pedagogies. Although the most obvious impact of artificially-intelligent educational technologies is through personalising learning directly, new pedagogies and teacher practices have also emerged. These pedagogies and practices enable teachers to support their students or provide their students with experiences in ways that were generally not feasible prior to the technology being developed.

Perhaps the largest shift has been in the information available to teachers. Dashboards provide teachers with data on a range of aspects of their students' performance and learning. This has produced a major shift in how homework is used. In the past, homework would need to be brought to class by students. It could be graded by the teacher after that (meaning that feedback and learning support would be delayed), or students could grade it with the teacher in a large group, which is not a very time-efficient approach. In contrast, data from homework technologies today can become available to teachers in real-time. This means that teachers can identify which students are struggling and which materials students struggled on in general before class even starts. This enables strategies where, for instance, teachers identify which students displayed common errors and can identify students who can demonstrate both incorrect and correct problem-solving strategies for whole-class discussion. It also enables teachers to message students who are behind in completing materials (or even in starting to work through materials), helping get the student back on track (Arnold and Pistilli, 2012[20]).

Similar uses are available for formative assessment systems, which are being increasingly used in contexts where students have high-stakes end-of-year examinations. These systems often go beyond teacher-designed homework in terms of their breadth and comprehensiveness of coverage of key skills and concepts. They are increasingly used by teachers to determine what topics to review with their classes as well as what types of supplemental supports to provide to specific students.

Box 2.1 Formative assessment systems

Formative assessment systems are increasingly used in K-12 education worldwide. The most widely used formative assessment systems, such as NWEA MAP (Finnerty, 2018[21]), present students with traditional multiple-choice items and measure straightforward mathematics and language arts competencies – essentially providing another test to students to complete, but one where their teachers will get useful data linked to competencies that will be seen on future standardised examination. A small number of emerging formative assessment systems assess more complicated constructs and/or embed assessment into more complex activities, such as games (Shute and Kim, 2014[22]).

Data from formative assessment systems can be used with platforms designed to provide lists of supplemental resources for specific skills, concepts, and topics. Especially post-COVID, both local education agencies, and regional and national governments have worked to develop platforms with supplemental learning resources for students and parents. However, right now, these platforms are generally not connected directly to formative assessment systems so the teacher or parent needs to look up the resources for a student struggling with a specific competency.

One concern about formative assessment systems is that time spent using a formative assessment system is time not spent learning – a loss of instructional time. For this reason, there has been a trend towards embedding formative assessment into personalised learning. Several widely-used personalised learning systems, such as MATHia, Mindspark, Reasoning Mind, and ASSISTments, provide teachers with formative assessment data on which competencies the student is missing (Feng and Heffernan, 2006[23]; Khachatryan et al., 2014[24]). This information is distilled from students' regular learning activity, avoiding a loss of instructional time.

There is also better information available to teachers on what is going on in their classes in real-time, an area discussed in detail by Pierre Dillenbourg (Dillenbourg, 2021[25]). Classroom analytics can provide the teacher with information on a range of aspects of class performance, from individual students' difficulties with material in real-time to the relative effectiveness of collaboration by different student groups. A teacher cannot watch every student (or every student group) at all times – better data can help them understand where to focus their efforts, and which students would benefit from a conversation right now.

Beyond just providing better data, it is possible to use technology to give students a range of experiences that were not feasible a generation ago. In their chapter, Tony Belpaeme and Fumihide Tanaka (Belpaeme and Tanaka, 2021[26]) discuss the new potentials of having robots interact with students in classrooms.

Using simulations and games in class can enable teachers to demonstrate complex and hard to understand systems to students. They can also allow students to explore and interact with these systems on their own. There seems to be particular educational benefit to the combination of a rich simulation or game experience that enables a student to develop informal, practical understanding, and then a teacher lecture or explanation that helps a student bridge from that informal understanding to more formal, academic conceptual understanding (Asbell-Clarke et al., 2020[27]). Modern technologies also offer new potentials for the use of collaborative learning, with systems that can scaffold effective collaboration strategies (Strauß and Rummel, 2020[28]), and systems that can provide rich experiences to collaborate around, such as interactive tabletops (Martinez Maldonado et al., 2012[29]).

Equity. New educational technologies are typically designed with the goal of improving student and teacher experiences and outcomes. However, the designers of these systems do not always consider how the full spectrum of learners are impacted. Often, systems are designed by members of specific demographic groups (typically higher socio-economic status, not identified as having special needs, and members of racial/ethnic/national majority groups) with members of their own groups in mind (not always intentionally). This can lead to lower educational effectiveness for members of other groups.

For example, Judith Good (2021[30]) discusses how there has been little effort to create educational technologies specifically designed for students with disabilities or special needs. She discusses examples of technologies that could support learners with autism, dysgraphia and visual impairment. The lack of attention to individuals with special needs by the scientific community and by developers of artificially intelligent educational technologies is a major source of inequity and a missed opportunity. Designing policies that facilitate developing systems to support learners with special needs (for instance, by developing approaches that improve access to data on disabilities while protecting student privacy) and the creation of incentives to develop for special needs populations may help to address this inequity.

Another key area of inequity is in support of historically underserved and underrepresented populations, including ethnic/racial minorities and linguistic minorities. Most educational technologies are developed by members of historically well-supported populations. They are often first piloted with members of historically well-supported populations. Testing for effectiveness with historically underrepresented populations often occurs only in later stages of development (or in final large-scale evaluations of efficacy) when it is too late to make major design changes. There is increasing evidence that both educational research design findings and algorithms obtained on majority populations can fail to apply or function more poorly for other populations of learners (Ocumpaugh et al., 2014[31]; Karumbaiah, Ocumpaugh and Baker, 2019[32]).

New educational technologies and approaches for educational systems

The benefits of modern educational technology – artificial intelligence and machine learning – goes beyond just supporting teaching and learning. There are a range of other ways that modern educational technology (not always artificially intelligent) benefits students and the schools supporting them in their educational journey. In a sense, this entire area is a focus of Dirk Ifenthaler's chapter (Ifenthaler, 2021[33]), but specific areas are also emphasised in other chapters.

Early Warning Systems. One of the major uses of predictive analytics in education is the creation of early warning systems. These systems, discussed in detail in Alex Bowers's chapter (Bowers, 2021[34]), attempt to predict in advance which students are at risk of a negative outcome – most frequently dropout and failure to graduate, but sometimes other outcomes such as failing a course as well. These predictions are often augmented with information on why a student is thought to be likely to have this negative outcome, such as poor grades in a specific class or an overly high number of disciplinary incidents.

The same types of data are also used in school-wide reporting systems for tracking student learning or disciplinary incidents. These school- (or district-) level dashboards give school and district leaders a broad picture of school climate and success. In the United States, these systems are increasingly provided to districts by a small number of vendors who combine expertise in ingesting school information system data (often in a disconnected set of different databases) with expertise in creating meaningful dashboards. Through these vendors, this type of artificially intelligent technology is made available for millions of students.

Reports for Parents. Many schools, school districts, and other local education agencies provide reports to parents on their students' progress. Often expanded over time from classic report cards, which simply provided a grade for each subject, these reports now provide a variety of information about learners to parents.

Admissions and School Allocations. Admissions and school allocations come down to the same process – determining if a student will be invited to attend a specific school or university – but from different perspectives. Admissions typically involve a decision made by a single school in an environment where students can be admitted to multiple schools; allocations typically involve a single centralised decision-making facility. Either way, algorithms are used to allocate limited resources (school/university placements) in line with institutional values, be they equity or selectivity. This is done in an increasing number of places – from charter school networks in the United States and public high-school systems in France to universities in Hungary.

Proctoring Systems. With intermittent (or continual) school closures occurring almost worldwide due to the COVID-19 pandemic, concerns about the security of examinations have emerged – for instance, that students will cheat by having another individual take a test for them, or that students will access unauthorised resources while taking a test. This has led to an explosion in proctoring systems where students will (for example) show a picture ID at the beginning of the test and keep their webcam on while taking it, and a proctor will watch a group of students' webcam feeds. Some proctoring systems also monitor other activity on students' computers during the duration of the test and what is going on in the room where students take the test, in many cases using artificial intelligence to supplement human proctors.

Box 2.2 Reports for parents

Increasingly, parents are provided with reports on their children's learning and activity in school. These reports for parents vary considerably in what information is provided. There is considerable variation in what data are provided to parents. Reports can range from very macro-scale reports (a student is at risk of dropping out of school or failing a course) to meso-scale reports (a student has 7 absences or is getting a C in mathematics) to micro-scale reports (the student answered "D" on problem 6, and here's why it was wrong).

These reports are provided in a variety of fashions. Many schools, school districts, and local education agencies still provide information to parents via physical letters. Text messages and phone calls are also used, particularly for warnings or reminders of various sorts. Some learning platforms and learning management systems provide web-based portals that parents can log into and look through. These platforms tend to provide relatively more data. For example, the ASSISTments platform (Broderick et al., 2011[35]) provides parents with data on which items the student has recently worked on, what their performance was, and what the correct answers were. The Edgenuity platform provides parents with data on how many minutes their student worked on each subject, and how much the student is behind pace or ahead of pace for the semester.

Though there is general agreement that providing data to parents is beneficial, there is debate as to how much parents look at the reports and data they have access to (Broderick et al., 2011[35]), and there has been research into developing reports that parents are more likely to use. When effectively designed, data reports can have positive impacts on parental engagement and student outcomes (Bergman and Chan, 2017[36]; Kraft and Monti-Nussbaum, 2017[37]).

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Advances in Credentialing. Recent advances in computational technologies have led to advances in credentialing. Perhaps the most noteworthy advance in credentialing is the use in blockchain in education, discussed in Natalie Smolenski's chapter (Smolenski, 2021[38]). Blockchain offers a secure way to reduce credential fraud and streamline credential validation.

Recent major shifts in credentialing coming from the supply side (the availability of new credentials) make these new advances even more relevant. Increasing numbers of organisations offer certificates, such as the technical certificates available from Cisco, Microsoft, or CompTIA. In addition, massive online open course providers offer online courses and certificates developed in partnership with a range of universities. The ecosystem of massive online open course providers includes both large, international providers such as edX, Coursera, and FutureLearn, which partner with a range of universities worldwide to offer large numbers of courses. The ecosystem also includes a range of regional, national, or more specialised providers. This creates new use cases for credentials through blockchain.

Customer Relationship Management Systems. Customer relationship management systems, which originated outside of education, and were originally used for the purpose of sales, are now used in educational systems management as well. These systems track individuals' interactions with an educational institution over time – who they interacted with, and how they interacted. Some online universities and programmes integrate these systems with early warning systems to track how an at-risk student is supported. At universities where academic advisors regularly contact students, such as Southern New Hampshire University and Liberty University, an academic advisor might look to such a system to get a weekly update of the student's progress, look at past interactions between that student and their instructors or other academic advisors, and then track their own interaction with the student after calling them on the phone.

Resource Allocation and Planning. An increasing number of school districts and local education agencies now use algorithmic systems for estimating their future needs for equipment, staffing, and other resources. Systems of this nature are also used, often with support from consulting firms, to determine how resources such as government funding can be applied for and/or leveraged at the right time to fill future resource gaps.

Future potentials

Artificial intelligence has emerged as a powerful tool for improving education in recent years. The use of these technologies has expanded, albeit at different paces and in different ways for different technologies. Some technologies have expanded in use quickly, such as the explosion of early warning systems in the United States over the last few years, and some have expanded gradually, such as the slow and sometimes back-and-forth expansion of use of personalised learning technologies, class by class. Some technologies, particularly for studying classroom interaction and supporting classroom orchestration, have been slow to emerge from research classrooms and need greater support for the development of technology (and better ways to secure privacy) that enable their greater emergence.

This book discusses the many different applications and uses that have emerged for artificial intelligence in education. The text discusses them almost in isolation from each other – as separate and separable emerging trends. There is a reason for this: though they emerge from the same types of technology, they largely *have* been separate trends. They have emerged one by one, brought about by different stakeholders, with different goals, sometimes even in opposition to each other. For instance, the various forms of personalised learning technology have often competed with each other for sales and uptake, rather than trying to find ways to work in concert.

The result is a fragmented learning ecosystem. A school may use several different artificially intelligent technologies, but not together. A student may even use five or six different technologies within a single class, within the course of a semester. There are major costs to this lack of integration – multiple different learning technologies may each discover something about the student that the teacher already knows. Developing integration between AIED learning technologies, as called for in Baker (2019[39]), may reduce inefficiency and improve students' learning experiences.

Going further, if we can develop an ecosystem where various artificially intelligent technologies coordinate between each other and communicate information to teachers and other stakeholders, we can substantially improve student outcomes. Prediction of whether a student is at risk of dropping out will be facilitated through continual data on student use of personalised learning systems. Integrating formative assessments with classroom orchestration technologies will facilitate measurement of 21st-century skills while empowering teachers with real-time information on how they are developing. The possibilities are combinatorial – almost every possible pair of the technologies discussed in this chapter creates new opportunities when they are integrated together. There is the potential for the school of the future to move towards an integrated learning experience for students, where data is combined not just across learning platforms, but across every aspect of the learning experience. In this situation, teachers of different classes could coordinate to support each student's development of 21st-century skills, working in tandem with a variety of learning platforms to create an integrated, unified learning experience. A student struggling with seeking help, for instance, could be encouraged to do so (appropriately) in group activities in class within a personalised learning platform used by homework, and by an educational robot. Teachers could collaboratively review an integrated dashboard to understand the student's progress and its implications for his/her risk of dropping out of high school. The student's success at building this 21st-century skill could be assessed both formatively and summatively by assessment systems. Such a vision requires solving several challenges – perhaps the first is using policy to develop incentives to encourage the developers of this disparate systems to work together. Ultimately, the success of such a vision also requires the re-shaping of several systems – platform design, school practices, teacher professional development – to accommodate the opportunities that the new technology brings.

One driving force behind integrating information across technologies may be the increasing interest among teachers in high-quality data and reporting on student performance and progress. This trend was already building prior to 2020 but has amplified with the shift to home learning during the COVID-19 pandemic. Dashboards containing information on what students struggle with are already available for some advanced learning platforms, but are nowhere near universally deployed and available. This type of information becomes more essential to teachers when they cannot interact with students in person. As the demand for this type of functionality goes up, it creates opportunities to connect data sources and provide better information to teachers. It also creates a need for policy that increases support for teacher professional development in data-driven decision-making. Dashboards have generally been more widely-used by teachers with higher levels of data literacy. Fully capitalising on this opportunity will require improvements in the design of dashboards so that they are easier to understand by non-expert users, but also better support for teacher professional learning (both pre-service and in-service) in data literacy and learning to use data dashboards as part of instructional practice.

This shift matches broader shifts in the field's thinking on the uses of artificial intelligence and education as the technologies have matured. It is often hard to see how thinking has changed; the idea that AIED will completely replace teachers seems obviously wrong to most researchers and practitioners working in the field, and it can be difficult to believe that this view was once dominant. To illustrate, research on the design of teacher dashboards for AIED systems was rare as recently as 15 years ago (see Feng and Heffernan (2006[23])). This has been part of a broader shift from considering AIED systems as something a student uses to part of a broader ecosystem that also involves teachers, school leaders, and parents. Take, for example, the five visions for the future of artificially intelligent learning systems given 25 years ago by Shute and Psotka (1996[40]). Each of these five visions involved compelling, rich learning experiences. None of them involved teachers or parents (except as someone to say hello to on the way to a virtual reality cubicle). Increasingly, the field is aware that it does not have to choose between AI and humans as teachers; they can work together.

The next 20 years of changes to educational practice will be shaped in no small part by the greater uptake of artificial intelligence. For this shift to achieve its full potential, it will need to be driven not just by technology and research but in full partnership with teachers, school leaders, and the learners themselves. Putting the right policies in place can create a future for vision that matches – that exceeds – this book's optimistic vision (OECD, 2021[41]).

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