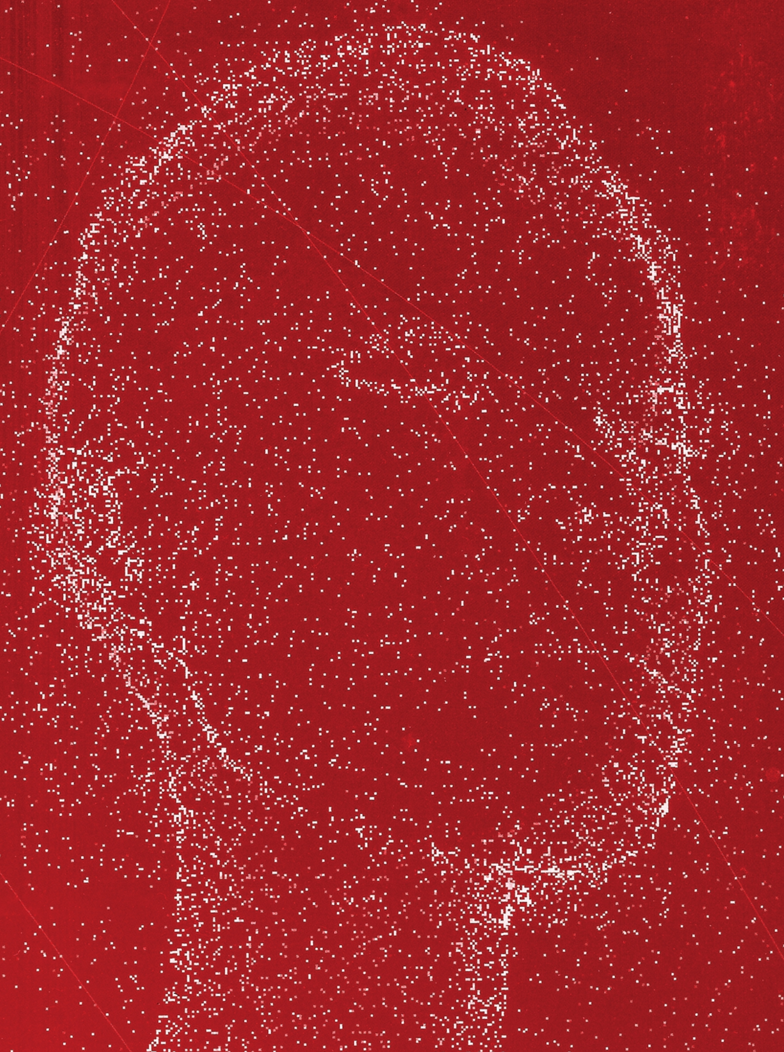
Wayne Holmes, Maya Bialik, Charles Fadel



Artificial Intelligence in Education

Promises and Implications for Teaching & Learning

"... a must read for educators and all stakeholders interested in how the future of education will be impacted—and more than likely transformed—by AI... provides a critical lens on both the potential benefits and risks of AI without hyping the technology."

—Jim Flanagan, Chief Operating and Strategy Officer, **ISTE**

Praise for *Artificial Intelligence in Education*

From International Organizations

"**Artificial intelligence will be disruptive, but few people understand that education is going to be in the first frontline.** This brilliantly reflective and forward-looking book helps the education community in navigating the storm, avoiding both the Scylla of fashionable denial of teaching knowledge and the Charybdis of romantic restoration of the old disciplinary canon. **Quite a daring intellectual undertaking!**"

—Dirk Vandamme, Deputy Director, Directorate for Education and Skills, **Organization for Economic Cooperation and Development (OECD)**

"This **is a must read for educators and all stakeholders interested in the future of education which will be impacted—and more than likely transformed—by AI**. The book is enjoyable and accessible as it models interdisciplinary learning by weaving in examples from domains including philosophy, science, engineering and popular culture. **By staying rooted in the science of learning, the authors provide a critical lens on both the potential benefits and risks of AI without hyping the technology.** I'll also keep it handy as a ready reference to the many 'what' and 'how' frameworks and models that will help me to map a course forward though an uncertain but exciting future."

—Jim Flanagan, chief operating and strategy officer, **The International Society for Technology in Education (ISTE)**

"**A must-read resource that enables you to cut through the hype around AI in education and think deeply about designing the future of teaching and learning.** Balanced and clearly written for easy understanding, this is an essential guide to this early moment in the fourth Industrial Revolution."

—Keith Krueger, CEO, **Consortium for School Networking (COSN)**

"*Artificial Intelligence in Education* is a breakthrough that delves into two very important and related subjects: moving to a more modern personalized curriculum and the role of AI in teaching and learning. The book provides an excellent overview of both of these areas, establishing a foundation to serve as a basis for bringing these two fields together towards improving education for every student."

—Rob Abel, CEO, **IMS Global Learning Consortium**

"*Artificial Intelligence in Education* is **the first internationally comprehensive attempt to help policy makers and educators to read through the lines of artificial intelligence and find what is in there for them**. Readers will certainly welcome the analytical perspectives and, even more, the value propositions that reaffirm the value of education in a world where many spheres of daily life, from work to culture and social life, could be dramatically challenged by artificial intelligence."

—Francesc Pedró, chief, education policy, **UNESCO**

"*Artificial Intelligence in Education* is an important, if at times disturbing, contribution to the debate on AI and provides a detailed analysis on how it may affect the way teachers and students engage in education. The book **describes how artificial intelligence may impact on curriculum design, on the individualization of learning, and on assessment, offering some tantalizing glimpses into the future** (the end of exams, your very own lifelong-learning companion) while not falling victim to tech-hype. The enormous ethical, technical and pedagogical challenges ahead are spelt out, and there is a real risk that the rapid advances in artificial intelligence products and services will outstrip education systems' capacity to understand, manage and integrate them appropriately. As the authors conclude: "We can either leave it to others (the computer scientists, AI engineers and big tech companies) to decide how artificial intelligence in education unfolds, or we can engage in productive dialogue." **I commend this book to anyone concerned with the future of education in a digital world**."

—Marc Durando, executive director, **European Schoolnet**

From Corporations

"The fourth Industrial Revolution will impact both K–12 education and what we need to learn later in life in an unprecedented way. This is **a comprehensive and elaborate synthesis of how AI will change *what* we need to learn, but also *how* we will learn it in the future**."

—Ulrik Juul Christensen, chief executive officer—**Area9 Lyceum**; executive chairman—**Area9 Group**

"To begin to realize the potential of AI in education, education leaders and stakeholders globally need a much deeper and shared understanding of how AI intersects with curriculum modernization as we shift towards competency-based learning models. This book provides the strongest foundation available for deepening that understanding. **It is a must-read for anyone seeking to go beyond the hype of AI towards appropriate, precise, and empowering uses of these tools for learning**."

—Maria Langworthy director of Worldwide Education Research, **Microsoft**

"The new book ***Artificial Intelligence in Education*** **provides readers with both a view on what people should know to thrive in the era of AI, as well as how AI will impact the education industry and society more broadly**. In addition to traditional knowledge and skills, learners in the future will need more meta-learning skills and character building experiences to be successful. The education industry will use AI to help both learners and teachers be more successful in adapting to rapid change, and advancing AI systems will have better and better models of users' knowledge and goals. **A recurring theme/warning in the book is that individuals must actively engage to shape these technological and economic forces towards desirable outcomes, or be prepared to be shaped by the forces in ways that are less desirable than they may wish**."

—Jim Spohrer, director of Mapping AI Progress with **Cognitive Opentech Group IBM**

"In these turbulent times with increasingly complex problems to solve, the need for better talent is essential for success, and survival. The role of AI as a means to leverage human intelligence is widely being explored. The application of AI to accelerating learning and making it more widely available is the very complex subject of this book. It is **an extensive and comprehensive collection of frameworks and tutorials with appendices that make it usable by experts and novices alike**. It is an essential tool for any leader or researcher exploring this field."

—John Abele, chairman emeritus and co-founder **Boston Scientific**

From Foundations and Non-Profit Organizations

"In a world where information is readily available online, how can schools continue to be relevant? The emergence of artificial intelligence (AI) has exacerbated the need to have these conversations. *Artificial Intelligence in Education* immerses the reader in a discussion on what to teach students in the era of AI and examines how AI is already demanding much needed updates to the school curriculum, including modernizing its content, focusing on core concepts, and embedding interdisciplinary themes and competencies with the end goal of making learning more enjoyable and useful in students' lives. The second part of the book dives into the history of AI in education, its techniques and applications—including the way AI can help teachers be more effective, and finishes on a reflection about the social aspects of AI. This book is **a must-read for educators and policy-makers who want to prepare schools to face the uncertainties of the future and keep them relevant**."

—Amada Torres, Vice President, Studies, Insights, and Research, National **Association of Independent Schools (NAIS)**

From A.I., EdTech, and Education Thought Leaders

"This book provides **a benchmark for understanding the impact of AI on the goals and methods of education in the 21st century**."

—Henry Kautz, founding director**, Goergen Institute for Data Science**; past-president, **Association for the Advancement of Artificial Intelligence (AAAI)**

"**AI is changing the knowledge and skills students need for success** in a global, knowledge-based, innovation centered civilization. To accomplish these ambitious educational outcomes, **AI is also enabling novel, powerful methods of teaching and learning**. This valuable book also describes AI in education in the larger context of shifts in society."

—Chris Dede, Timothy E. Wirth Professor in Learning Technologies, Technology, Innovation, and Education Program, Graduate School of Education, Harvard University

"*Artificial Intelligence in Education* is the best synthesis to date of the implications of code that learns—**both the new aims it demands of secondary education and how educators can incorporate it into learning experiences**."

—Tom Vander Ark, CEO ,**Getting Smart**, first director of education for the **Bill & Melinda Gates Foundation**

"**We are experiencing the fourth Industrial Revolution**. We are increasingly living in a world of AI & robotics—a digitized and globalized world. As educators, particularly as educators, we need guidance to navigate our way in this complex and uncertain age of artificial intelligence. *Artificial Intelligence in Education: Promises and Implications for Teaching and Learning* is **a guide that was worth waiting for**."

—Anthony Mackay, CEO, **National Center for Education and the Economy (NCEE)**

"The authors of *Artificial Intelligence in Education* **brilliantly provide a 'How to' roadmap to harness the power of AI in education**. This book should be required reading for every educator, policymaker, and curriculum designer."

—Robert Martellacci, EdTech Pioneer & co-founder & president, **C21**

"*Artificial Intelligence in Education* is really two books in one: the first presents a comprehensive curriculum framework for 21st century learning; the second is a thorough survey of the uses of AI in learning. It is **an invaluable resource for those concerned with the future of education**."

—Tony Wagner, best-selling author of *The Global Achievement Gap* and *Creating Innovators*

Artificial Intelligence in Education

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Dedications and Thanks

From Wayne

To Tracey, Cate and Oliver: thank you for being in my life. And to my friends and colleagues Denise, Diego, Doug, Duygu, Eileen, Ig, Juliette, Kaska, Laurie, Manolis, Maria, Mark G., Mark N., Rose, Seiji, and Stamatina: thank you for your kindness, guidance and support.

From Maya

To the students who have asked "why do we need to learn this?" and to those who will continue to ask it for as long as it takes for education systems to change.

To my teachers, especially my father, who taught me how to think conceptually and critically. And to all teachers, working to make learning meaningful for their students.

From Charles

To the benevolent AI in our future (remember me! ;-)

To the countless people yearning for a fulfilling life—you are my inner motivation, thank you!

To (alphabetically) Aline, Carole, and Nathalie, for their love, and with all of mine.

To Ellen Koshland for her trust and camaraderie on this education adventure.

To Claude Cruz, my co-founder on the early Neurodyne journey, during the neural networks winter (timing is everything!).

To my wonderful co-authors, for their significant patience and numerous expert contributions.

The authors also wish to thank all the reviewers for their kind endorsements.

CCR wishes to thank all the following colleagues for their insights, ideas and contributions to this writing and to CCR's work in general (alphabetically by last name):

John Abele, the Alfond family (Barbara, Bill, Justin, Kat, Ted), Lee Batchelor, Michele Bruniges, Annamaria Diniz, Pat Farenga, Eron Gjoni, Brendan Griffen, Danny Hillis, Jim Koshland, Siva Kumari, Rose Luckin, Leticia Lyle, Rick Miller, Henri Moser, Attilio Oliva, Greg Powell, Robert Randall, Todd Rose, Cathy and Harry Rubin, Courtney Sale-Ross, Bror Saxberg, Andreas Schleicher, Morgan Silver-Greenberg, Ray Stata, and all the foundations that support us.

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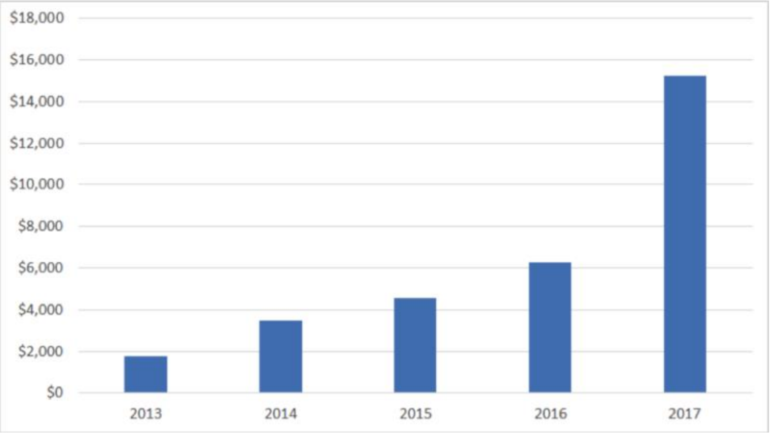
Introduction: The Context

Artificial intelligence (AI) is arguably *the* driving technological force of the first half of this century, and will transform virtually every industry, if not human endeavors at large.[1] Businesses and governments worldwide are pouring enormous sums of money into a very wide array of implementations, and dozens of start-ups are being funded to the tune of billions of dollars.



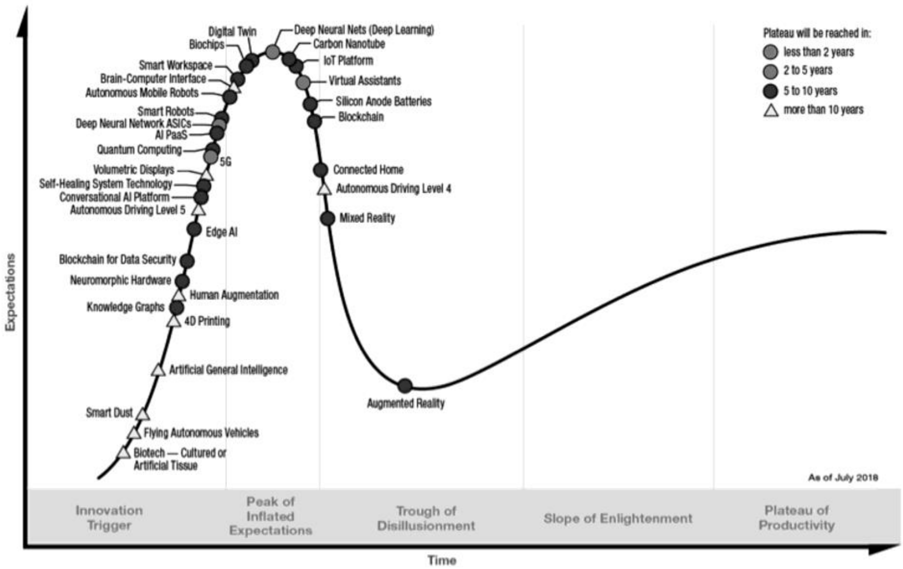
Funding of AI startup companies worldwide, from 2013 to 2017
(in millions of U.S. dollars). *Source*: Statista[2]

It would be naive to think that AI will not have an impact on education—*au contraire*, the possibilities there are profound yet, for the time being, overhyped as well. This book attempts to provide the right balance between reality and hype (per the Gartner diagram that follows), between true potential and wild extrapolations. Every new technology undergoes a period of intense growth of reputation and expectations, followed by a precipitous fall when it inevitably fails to live up to the expectations, after which there is a slower growth as the technology is developed and integrated into our lives. As visualized in the Gartner diagram, each technology can be said to reside somewhere on the curve

[1] Possibly matched only by biotechnology.

[2] https://www.statista.com/statistics/621468/worldwide-artificial-intelligence-startup-company-funding-by-year

at any given time (for example Deep Learning, which is part of AI, is currently peaking).



Source: Gartner Inc.[3]

It is of course a risky proposition then, in a field moving so fast, to attempt to predict the future. As such, this work will likely be updated periodically to keep up with the developments (just as you would expect from software/apps).

This book is organized around a somewhat glib quote: "There are only two problems in education: What we teach, and how we teach it."[4] Hence this book is divided into two parts, one focused on the *What*, and one on the *How* of AI in education.

[3] http://www.Gartner.com/SmarterWithGartner

[4] Dr Roger Schank, https://www.rogerschank.com/

The What

> *We're headed for a world where you're either going to be able to write algorithms … or be replaced by algorithms.*
>
> —Bridgewater hedge-fund billionaire Ray Dalio

The first part of this book explores the question: *What* should students learn in an age of AI? And all the corollary, provocatively phrased questions: "If you can search, or have an intelligent agent find, anything, why learn anything? What is truly worth learning?"

It is widely expected that AI will have an enormous impact on what we teach, as it will impact many occupations. Take for instance the Organization for Economic and Co-operative Development (OECD) Programme for the International Assessment of Adult Competencies (PIAAC)[5] survey, which measures adults' proficiency in key information-processing skills—literacy, numeracy and problem solving in technology-rich environments—and gathers information and data on how adults use their skills at home and at work. Already, AI is matching more than 50% of adult human-proficiency levels, and closing in on another 36%.

Proficiency Level	OECD Adults	Artificial Intelligence
2 and below	53%	Yes
3	36%	Close
4–5	11%	No

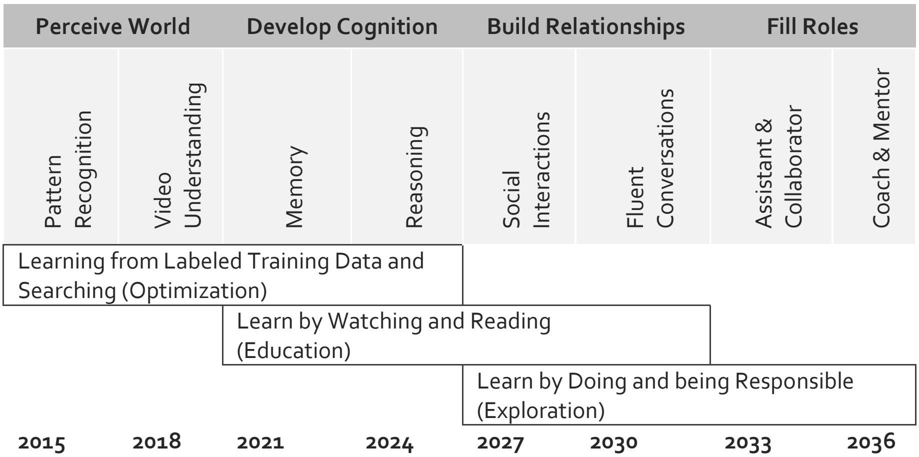
Source: Elliott Stuart, "Computers and the Future of Skill Demand."[6]

Such progress is bound to continue at an accelerating, pace. IBM's Open Leaderboard effort attempts to understand the progress being made by tracking many variables. According to IBM's Leaderboard, AI should be getting into the realm of deeper self-learning by the early 2020s

[5] https://www.oecd.org/skills/piaac/

[6] https://read.oecd-ilibrary.org/education/computers-and-the-future-of-skill-demand_9789264284395-en#page1

and become capable of assisting, collaborating, coaching and mediating by the early 2030s.



Source: Jim Spohrer, IBM[7]

Given all the above, the *What* section makes a case for the necessity to focus on a broad, deep, and versatile education as a hedge against uncertain futures, which in turn means a reinvigorated focus on the *deeper learning goals* of a modern education:

- Versatility, for robustness to face life and work.
- Relevance, for applicability, and student motivation.
- Transfer,[8] for broad future actionability.

All of which are to be developed via:

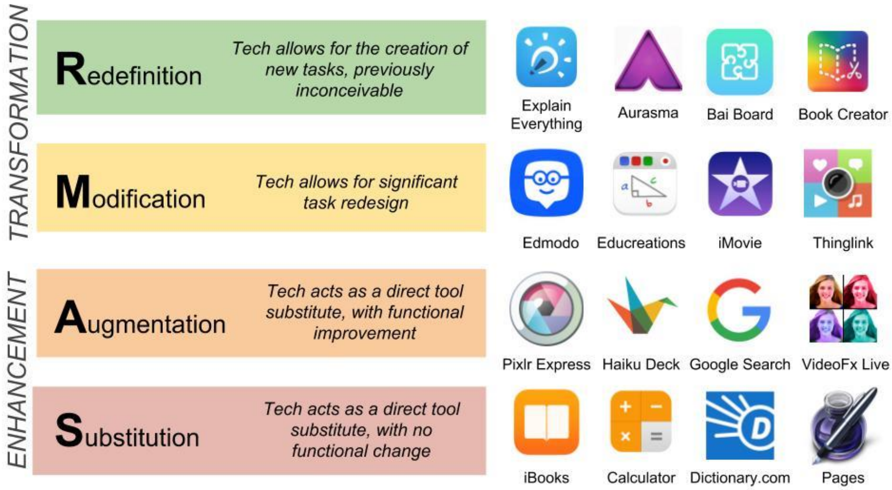
- Selective emphasis on important areas of traditional knowledge.
- The addition of modern knowledge.
- A focus on essential content and core concepts.
- Interdisciplinarity, using real-world applications.
- Embedded skills, character, and meta learning *into* the knowledge domains.

[7] IBM, 2017, Cognitive Opentech Group.

[8] This refers to the transfer of knowledge from a domain it was learned in to another domain.

The How

The second part of this book addresses the question: How can AI enhance and transform education? First, it is important to make the distinction between education technology (EdTech) at large and artificial intelligence in education (AIED) specifically. A quick summary of the affordances of EdTech is appropriate at this stage, as the taxonomy and ontology of the field is quite murky. Using the SAMR[9] model that follows, the How section showcases how AIED will span all layers, with its maximum impact growing as it moves up the stack.



Substitution, augmentation, modification, and redefinition model (SAMR).

Note that the examples shown in the preceding figure represent today's apps, not tomorrow's, and only serve to help explain the model. Often these apps are collapsed under one term, technology, and then there is much confusion about the potential of technology. This model helps us to delineate the different types of impact that technology can have, from mere substitution with no functional changes, all the way through the creation of new, previously inconceivable tasks as a result of technology.

[9] Dr. Ruben Puentedura, http://www.hippasus.com/

The Role of Assessments

> *What gets measured gets managed.*—Lord Kelvin

Assessments have been the hidden villain behind a lot of education debates, and a powerful one at enshrining institutional inertia. Repurposing the famous Aristotelian syllogism:[10]

> Lack of, or poor, education is at the root of many human problems.
> Assessments define the education we get.
> *Therefore*, assessments are the root of many human problems.

Although not a focus of this book, it is clear that assessments have an oversized role to play in the change process, and as part of the AI-driven systems of (mostly formative) assessments.

Andreas Schleicher, director of the OECD's Directorate of Education and Skills, publicly stated "What is easy to measure is also easy to automate," thereby throwing the gauntlet to the assessment world to readjust its focus and thus *drive* change.

Lastly

Readers will have different priorities and interest in this topic. Policymakers and curriculum designers may initially favor the What section, while teachers and IT specialists may at first favor the How section.

The What and How sections are therefore written to be independent of each other; the appendices also reflect an emphasis on digestibility, particularly for the technical details.

Further, we are all pressed for time, so our writing philosophy is, to use Antoine de Saint-Exupéry's words, "Perfection is attained not when there is no longer anything to add, but when there is no longer anything to take away." This book is therefore not meant to be an in-depth

[10] "All men are mortal. Socrates is a man. Socrates is mortal." https://en.wikipedia.org/wiki/Syllogism

academic piece, but rather it is meant to be concise and to the point, and adhere to Yuval Harari's philosophy: "In a world deluged with irrelevant information, clarity is power."[11]

We wish you all very pleasant reading, and invite your feedback at: info@CurriculumRedesign.org

[11] Harari, Y. (2018). *21 Lessons for the 21st Century.* Spiegel & Grau.

Part 1
What Should Students Learn? The Impact of AI on Curriculum

Education is slow to change. Students are still hearing outdated justifications for curriculum choices that even the teachers find difficult to believe. While we are told that we won't have a calculator with us every day, we all have extremely powerful calculators in our pockets. And not just calculators, but dictionaries, encyclopedias, books, papers, instructional videos, and platforms to ask questions and get answers. Access to powerful technology leads us to ask the question: if you can Google everything, why learn anything? Or, put less flippantly, what is truly worth learning?

The Purposes of Education

As with any discussion of value, context is highly important. To answer the question of what is worth learning, one must first ask about the purpose of the entire endeavor.

This question is far from new, and the answers have changed over time. The purposes of education systems originally evolved around creating laborers, imparting religious knowledge, and the basic skills of literacy and numeracy. As the structure of society changed, education began to take on other practical, social, and emotional functions.

Practically, school is now seen as a gateway to higher education and ultimately financial independence. In this view, education serves primarily as a seal of approval, signaling to future employers that prospective employees have met some minimum social standards of quality control.

The social conception of educational systems has slowly matured as the needs of individuals in society, and society itself, have evolved; education is both a way to mold students to fulfill the needs of society, and a means by which students may become empowered to best fulfill their own needs. Finally, school is also perceived in emotional terms, as a place to be inspired and fall in love with learning (which, in a world requiring ever-more continuous adaptation, becomes an essential characteristic).

Because learning is a lifelong endeavor, it is reasonable to consider the differences between the goals of education at the primary and secondary (K–12) levels, and the goals of learning later in life. Learning later in life tends to be necessary for three reasons:

1. Economic: Specialization for careers, as the opportunities of available jobs continue to shift.
2. Civic: Staying informed about voting issues as the explosion of information continues to grow, and facts continue to become more difficult to pin down.
3. Personal: For the personal pleasure of picking up new hobbies and continuing to grow and challenge oneself and relate to others.

Primary and secondary school learning, by contrast, is specifically focused on developing the foundation for all future learning, both in terms of knowledge and competencies:

1. Foundational knowledge: A solid foundation of knowledge on which to build when it comes time to learn more, or from which to apply what was learned in a real world setting.
    a. Core concepts: The most important concepts for students to understand in order to be able to make connections and meaning resulting in transfer.[12]
    b. Essential content: The most important content knowledge that students must learn in order to internalize concepts and make informed decisions throughout their lives.
2. Foundational competencies: The motivation and the ability to effectively activate knowledge when relevant and to learn more when it becomes necessary.

[12] Transfer: The process of making use of knowledge outside of the context in which it was learned.

a. Skills: What we do with what we know; how we use our creativity, critical thinking, communication, collaboration skills.
b. Character: How we behave and engage in the world using our mindfulness, curiosity, courage, resilience, ethics, and leadership.
c. Meta learning: How we reflect and adapt, i.e. with metacognition or a growth mindset.

When we run workshops about twenty-first century education, whether our audience is educators, school leaders, policy makers, or industry representatives, the answers we get are very similar when we ask, "What will be important for students to learn to be prepared for the future?"

Rarely does someone speak up with a particular book from English class or a particular period from History class. Nor do they speak up with a branch of mathematics or a topic from biology. Not one time has anyone said that it's important for students to learn that mitochondria are the powerhouse of the cell. No, unequivocally the answers we receive over and over are things like "how to think critically," "systems thinking," "ethics," "communication," "learning how to learn," and so on.

Intuitively, we know that content knowledge may be the least important thing that students retain from their schooling (and that they mostly don't retain it![13]), and yet time and again, well-intentioned educational efforts result in a never-ending bloat of material in the curriculum, with no time left to spend on that which is most important.

It begins innocently enough. "Students need basic literacy and numeracy knowledge to learn higher level material." But the issue is that it becomes very unclear how to draw the boundaries around what is

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[13] Subirana, B., Bagiati, A., & Sarma, S. (2017). "On the forgetting of college academics: At 'Ebbinghaus Speed'"? *Center for Brains, Minds, and Machines Memo* (68): 1–12.

enough for the majority of people who are not going to become experts, and whether someone will go on to be an expert.

Meanwhile, educators are teaching competencies such as collaboration, but often only as a byproduct, not in a way that is deliberate, systematic, demonstrable, and comprehensive. Because these competencies are harder to measure than content knowledge, assessments rarely focus on them, and it is that much more tempting to spend time on content, and hope that competencies are implicitly learned along the way.

According to UNESCO: "Quality education systems have to enable learners to continuously adapt their competencies while continuously acquiring and even developing new ones. These competencies are diverse in scope; ranging from core skills, content knowledge, cognitive skills, soft skills, to occupational skills, they enable us to meet a complex demand or carry out a complex activity or task successfully or effectively in a certain context. Their typologies and approaches are as diverse as the entities—countries, organizations and individuals—that define them."[14]

In *Four-Dimensional Education*[15] the Center for Curriculum Redesign (CCR) synthesizes the curricula from 35 jurisdictions and organizations around the world, and together with input from teachers and administrators, as well as reports on expectations of employers, economists and futurists, creates a unifying framework that is:

Comprehensive. There are no major elements missing.
Compact. It is actionable and deployable.
Uncorrelated. No duplication or confusion.
Abstracted to the appropriate level. It is organized.
Globally relevant. For broad acceptability.

This framework breaks educational goals into four dimensions.

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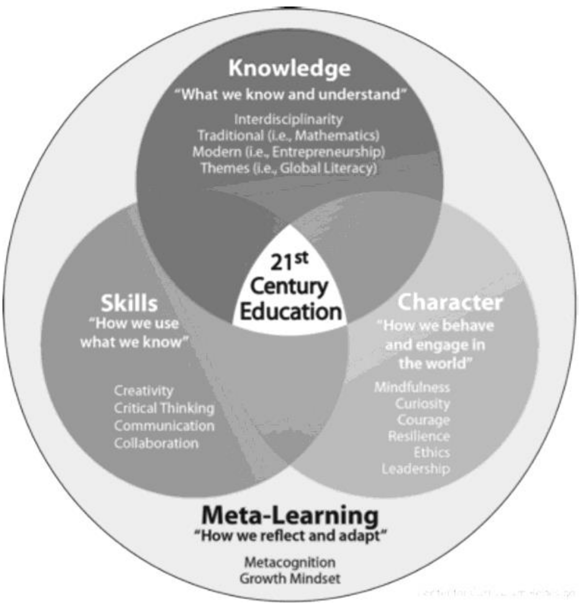
[14] UNESCO, http://www.unesco.org/new/en/education/themes/strengthening-education-systems/quality-framework/desired-outcomes/competencies

[15] Fadel, C., Bialik, M., and Trilling, B. (2015). *Four-Dimensional Education: The Competencies Learners Need to Succeed.* Center for Curriculum Redesign.

1. Knowledge—what we know and understand.
2. Skills[16]—what we can do with what we know.
3. Character[17,18]—how we behave and engage in the world.
4. Meta learning[19]—how we reflect and adapt.

By looking across research, frameworks, and standards from around the world, we were able to create a list of 12 total competencies (in addition to knowledge) to represent the goals of a twenty-first century education. They are visualized through the following Venn diagram.



Because the competencies (skills, character, and meta-learning) can be pretty complex, we conducted an in-depth analysis of the way they have been conceptualized, and broke them down into subcompetencies.[20] Our

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[16] Bialik, M., & Fadel, C. (2015). "Skills for the 21st century: What should students learn?" Center for Curriculum Redesign.

[17] Alternatively called socio-emotional skills, non-cognitive skills, soft skills, etc. for more info see: http://curriculumredesign.org/wp-content/uploads/CCR-Decision-matrix-for-Character-terminology-FINAL.pdf

[18] Bialik, M., Bogan, M. Fadel, C., Horvathova, M. (2015) "Character Education for the 21st Century: What Should Students Learn?" Center for Curriculum Redesign.

[19] Bialik, M., & Fadel, C. (2015) "Meta-Learning for the 21st century: What should students learn?" Center for Curriculum Redesign.

[20] https://curriculumredesign.org/framework-of-competencies-subcompetencies/

current work involves translating these subcompetencies one step further: into classroom actions and habits.

An extra challenge to this work is that realistically, there cannot be a class created to teach each one of these independently. In fact, the case could be made that they are actually *best* taught in the context of knowledge! Therefore, we are now working on identifying the most conducive combinations and gathering ideas from experts in order to further expound on the competencies.

This book, however, concentrates on the knowledge component. After all, it is the dimension that is the most directly and immediately affected by technological changes, and it deserves to be examined carefully in its own right.[21]

Foundational Knowledge: What Do Students Need to Learn?

Let us briefly consider an example. Although high school calculus is helpful for the 20–30% of bachelor's degree students who enter college with a STEM major and are expected to take calculus,[22] what is the experience of the other 70–80%? Further, what is the experience of the nearly 30%[23] of high school graduates who do not enroll in college? What about the large number of students who do go to college and must take calculus as a prerequisite for their major, even if that career path does not include calculus? Currently, even in the best-case scenario, students are still spending the majority of their time on material they will never use again once they choose a specialization. The same thought experiment can be done with almost any subject matter.

Knowledge taught in schools must be reorganized such that it is relevant to all students, while at the same time giving each student the opportunities to study in depth the prerequisite knowledge they will need

[21] For the other three dimensions please visit http://www.curriculumredesign.org/our-work/papers.

[22] Chen, X. (2013). *STEM Attrition: College Students' Paths into and out of STEM Fields. Statistical Analysis Report*. NCES 2014-001. National Center for Education Statistics.

[23] National Center for Education Statistics, https://nces.ed.gov/fastfacts/display.asp?id=51

for whatever career trajectory they choose. This is a balance well worth striving for.

Overview of Core Concepts

What is learned in school ought to be useful to people well after they finish school. Approaching any new situation that requires using one's knowledge, whether it is a real-world application or learning a more advanced topic in a given discipline, it involves leveraging what one has already learned. In either case, existing knowledge must be effectively used in a new context. The more robust a mastery one has developed of the fundamentals of a topic, the easier it is to leverage it to learn even more.[24] The question thus becomes, how can students' understanding be developed in such a way that it is useful?

In his book, *Future Wise*,[25] Harvard professor David Perkins makes the case that curriculum should work toward "expert amateurism" rather than try to instill expertise within subjects. While expertise privileges technical depth, expert amateurism aims for "a robust and flexible understanding of the fundamentals." By internalizing the most important concepts of each discipline and across disciplines, which we will call *core concepts*, students are better equipped to deal with multifaceted problems and have a more diverse set of tools with which to interpret the world.[26]

But the trap of the coverage mindset "in which students march through a textbook, page by page (or teachers through lecture notes) in a valiant attempt to traverse all the factual material within a prescribed time" is difficult to avoid.[27] Even frameworks that start with the important concepts typically break them down into minute topics that are

[24] Bower, G. H., & Hilgard, E. R. (1981*) Theories of Learning*. Eaglewood Cliffs, NJ; Prentice-Hall

[25] Perkins, D. (2014). *Future Wise: Educating Our Children For A Changing World*. John Wiley & Sons.

[26] One important consideration, then, is that the world is changing rapidly, and the knowledge that is necessary to interact with the world is thus changing accordingly (more on that later).

[27] Wiggins, G., & Mctighe, J. (2005). *Understanding by Design*, Expanded 2nd Ed. ASCD.

not taught in the context of the broader disciplinary or subject concepts, and assessments often cover material only at the most granular level.[28]

While experts readily understand the connections between content details and higher-level concepts, novices do not automatically make those connections. In fact, seeing connections between pieces of information in a field is a defining feature of what it means to be an expert.

If novices are only taught and assessed on detailed fragmentary knowledge, they may appear to understand the material but are unlikely to be able to make use of what they have learned. In order to transfer knowledge to a new setting or to use knowledge to build larger understandings that will be useful and transferable, content should be connected with concepts in a way that helps students to create meaning. (See appendix 1 for an example of tying topics to important concepts).

One difficulty is that the most useful knowledge is that which experts apply without a second thought, the knowledge that defines their field and is usually left unsaid. This is what makes it difficult for experts to create a curriculum that is truly geared toward developing expert amateurism. They know how to expertly work with the content, but they cannot necessarily state the concepts that lead to that expertise explicitly.[29] Imagine being asked to explain how to balance while walking, or how to chew. This is one of the greatest and most overlooked difficulties in creating a K–12 curriculum that builds a foundation for learning in students.

Overview of Essential Content

If students are expected to build on the foundation of knowledge they develop in school, one important characteristic of this foundation is that it be sufficiently representative of all the ways students could choose to build on it. In other words, by exposing students to many fields of

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[28] Cooper, M. M, Posey, L. A, Underwood, S. M. (2017). "Core ideas and topics: Building up or drilling down?" *Journal of Chemical Education.*

[29] https://en.wikipedia.org/wiki/Curse_of_knowledge

human endeavor through pairing core concepts with essential content, schooling can allow children to survey the different possible life and career paths and make informed decisions as to which endeavors they would be best suited to.

In the slightly less long-term view, content must be reconsidered on the basis of society's new relationship with information. Storage of information was scarce for most of human history, but became abundant with the mass production of books. With personal computers, and finally the internet, there became an abundance of resources to manipulate information as well. Any simple piece of information can be found quickly online, and powerful computational tools are easily accessible. In addition, the evidence suggests that individuals forget academic content at the rate of 50% every two years,[30] and that what is known in a given field changes over time such that a predictable fraction of what is learned in school will be outdated by the time it would be useful in a professional setting.[31] In such a context, what is the essential content that is worth knowing, and not just searching for when it is needed, or learning if one chooses to specialize?

Some content will be the medium that the concepts are taught through, and some limited, appropriate amount of content is worth internalizing to automaticity to build up more complex knowledge later, or to use in daily life. Content may serve as the way a concept is introduced because it is most exemplified in that context, or, it may demonstrate the generality of a concept in near or far. This will allow students to abstract and apply concepts to relevant situations they encounter in the future without being explicitly prompted (as authentic environments tend not to do).

In order to maximize its relevance for a rapidly changing world and society, content needs to be modernized in two ways. First, key modern disciplines (engineering, wellness, sociology, etc.) that haven't had time to be included into the curriculum must be added, and decisions must be

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30 Subirana, B., Bagiati, A., & Sarma, S, "On the forgetting of college academics," 1–12.

31 Arbesman, S. (2013). *The Half-Life Of Facts: Why Everything We Know Has an Expiration Date*. Penguin.

made about what parts of the current curriculum should be de-emphasized or eliminated. Second, the way in which (both traditional and modern) disciplines are taught should be modernized. For example, the pedagogical notion of a flipped classroom relies on the idea that technology can fundamentally change the structure of learning. As we will see in Part 2 of this book, there should be a push to move from mere technology acting as a mere substitution with no functional changes, to the creation of new, previously inconceivable tasks as a result of technology.

Beyond these practical goals, it is generally deemed valuable that students have some capacity to appreciate the fields they are not actively pursuing, for civic engagement as well as for developing a multifaceted sense of personal meaning and connecting with others.

This is a large set of goals, and in the process of making sure students are exposed to the wide range of ideas and topics in a given discipline, classes are often accordingly designed to be sweeping surveys of the field. This in itself is not necessarily problematic, but presenting students with fragmented information (a common consequence of such a course design) makes it difficult for them to develop conceptual frameworks that they can later use to understand new information or to build upon existing information.

The opposite of fragmented information is meaning. In his book, *Realms of Meaning*,[32] Philip Phenix makes the argument that making meaning is the essential human activity, and that education should help students learn the different ways that humanity has successfully developed to make different kinds of meanings. In this view, it may be said that students should get sufficient exposure to the different realms of making meaning.[33]

In building a foundation for future learning and appreciation, meaning is a useful guiding principle, as it is closely related to feelings of

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[32] Phenix, P. H. (1964). R*ealms of Meaning a Philosophy of the Curriculum for General Education*. McGraw–Hill.

[33] Realms of meaning are related but independent of each other

purpose,[34] understanding,[35] and engagement.[36] This type of meaning-making and deep understanding of the logic of a field of study is exactly the type of thing that one cannot simply search for when needed, but rather, must know intuitively when and how to apply (in fact it is needed to know what to search for!). It is also the type of thing that, unlike fragmented knowledge, is not easily forgotten, or changed, with time.

Making Meaning and the Impact of Algorithms

Since ancient times, schools have been tasked with helping students build a foundational understanding on which they can later rely when they hone their expertise. Relevance, which determines how well students will be able to make meaning, has always been crucial for making sure that what is learned in school is transferrable. And yet, there is a particular urgency to the question now, especially as it relates to climate change, social disruptions, technological breakthroughs, and the changing landscape of employment opportunities. Although not the only important consideration (consider personal and civic functions described above), one of the most worrying implications of this question has to do with the changing landscape of occupations as algorithms become more prevalent.

Employability

One difficulty with designing curricula to expose students to what they will need to know for their careers is the rapid change in the landscape of available professions due to automation and offshoring; preparations we make to ready students for the world of today will be outdated by the time they graduate. However, automation is not affecting all types of jobs

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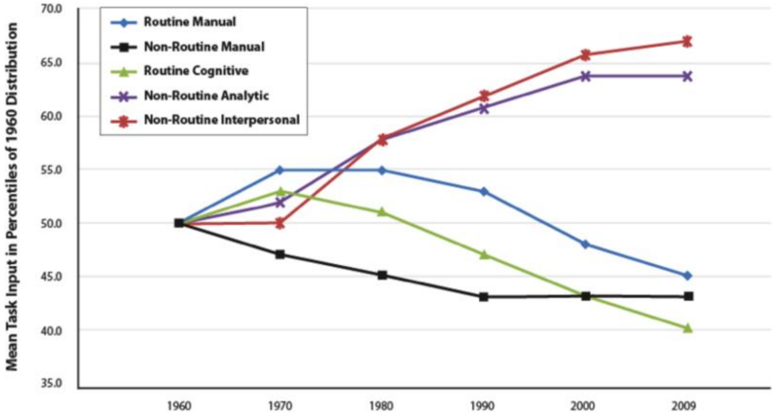
[34] Frankl, V. E. (1985). *Man's Search For Meaning*. Simon and Schuster.

[35] Understanding is in a very real sense equivalent to making meaning, since it must always be active on the part of the learner.

[36] Shernoff, D. J., Csikszentmihalyi, M., Schneider, B., & Shernoff, E. S. (2003). "Student engagement in high school classrooms from the perspective of flow theory." *School Psychology Quarterly*,18 (2): 158–176.

equally. So far, the types of jobs that can be automated are ones that involve routine tasks.[37]



Changing prevalence of types of tasks required for work over time.
Source: Autor and Price

Tasks that are routine are easily automatable, since a computer program can learn to execute a series of steps and follow rules (an algorithm). This is evident in the changing proportions of types of jobs in the figure below; the two types of jobs that have increased have been non-routine interpersonal (such as a consultant) and non-routine analytic (such as an engineer). Routine manual (such as factory jobs) have decreased, as have non-routine cognitive (such as filing paperwork). Non-routine manual jobs (such as plumbing) did decrease but then seem to have hit a plateau, as there continues to be a baseline need for them.

Several organizations (Oxford University,[38] OECD,[39] PwC,[40] McKinsey,[41] and others) have tried to quantify the impact of automation

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[37] Autor, D. and Price, B. (2013). "The changing task composition of the US labor market: An update of Autor, Levy, and Murnane." MIT Mimeograph.

[38] Frey and Osborne. (2013). *The Future of Employment: How Susceptible are Jobs to Computerization?* University of Oxford.

[39] Arntz, M., T. Gregory and U. Zierahn. (2016). *The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis*. OECD Social, Employment and Migration Working Papers, No. 189, OECD Publishing.

[40] Berriman, R. and Hawksworth, J. (2017). *Will Robots Steal Our Jobs? The Potential Impact Of Automation On The UK And Other Major Economies*. UK Economic Outlook. https://www.pwc.co.uk/economic-services/ukeo/pwcukeo-section-4-automation-march-2017-v2.pdf

[41] McKinsey Global. (2017)."Automation and the future of work—briefing note prepared for Necker Island meeting on education."

on occupations, with a growing concern about *jobsolescence*. Their numbers range from 9% (OECD) to about 50% (Oxford University). The subject has also recently gained the public's attention, with articles ranging from a doomsday scenario to a cheerful utopia, and those trying to describe various nuanced positions in between.[42]

The progress of AI has been nothing short of stunning to a large segment of even the technologically literate.[43,44] One way to examine this trend is through the lens of Bloom's taxonomies, extended to the cognitive,[45] affective,[46] and psychomotor[47] domains. These were made to understand and categorize increasing complexity in thought, emotion, and movement, respectively. The following figure shows that existing algorithms already encroach on significant portions of human capabilities, and that is only the beginning of the impact.

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[42] See: Brooks, Rodney. (2017) "The seven deadly sins of AI predictions." *MIT Technology Review*. See also: Chui, Michael, Manyika, James, and Miremadi, Mehdi. (2015) "Four Fundamentals of Workplace Automation." *McKinsey Quarterly*. http://www.mckinsey.com/business-functions/digital-mckinsey/our-insights/four-fundamentals-of-workplace-automation
Hensel, A. (2017) "How robots will really take our jobs." *VentureBeat*.
Jones, M. (2017) "Yes, the robots will steal our jobs. And that's fine." *The Washington Post*.
Shewan, D. (2017) "Robots will destroy our jobs—and we're not ready for it." *The Guardian: Technology*
Surowiecki, J. (2017) "Robopocalypse Not" The Great Tech Panic of 2017. *Wired*.

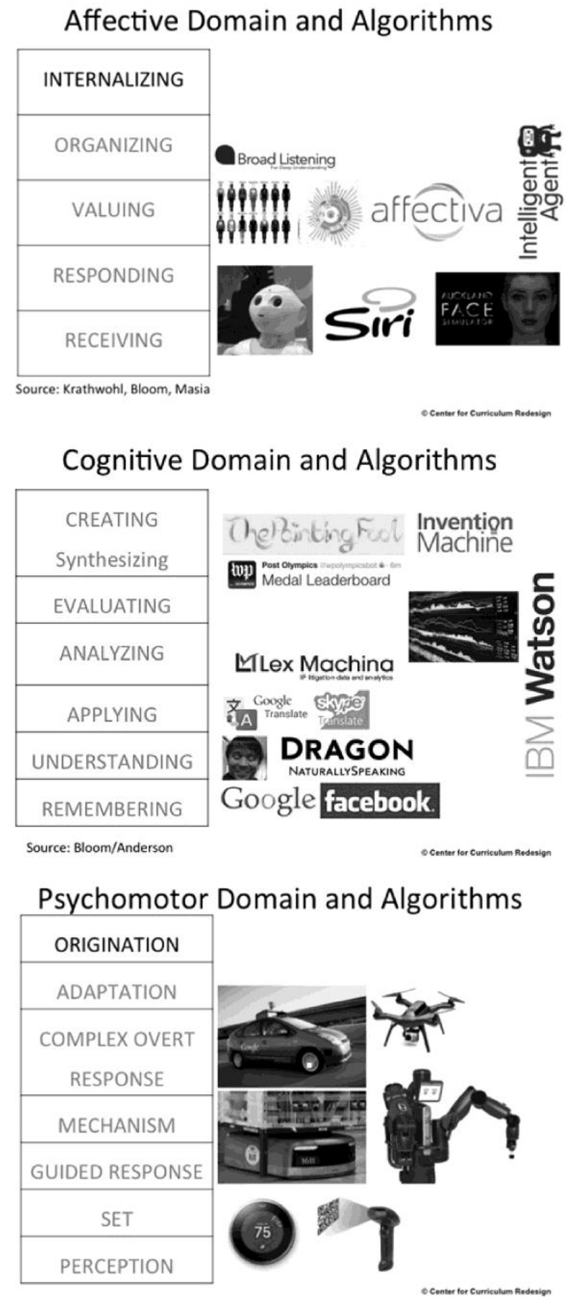
[43] It is estimated that historically the exponential acceleration of technology is due to three main factors: about 66% due to hardware speed, about 20% due to solid data sets, and about 10% to the algorithms themselves. But now, advances in the fundamental algorithms for learning are becoming the main driver of progress.

[44] Anthes, G. (2017) "Artificial intelligence poised to ride a new wave." *Communications of the ACM* 60 (7): 19–21. https://cacm.acm.org/magazines/2017/7/218862-artificial-intelligence-poised-to-ride-a-new-wave/fulltext

[45] Krathwohl, D. R. (2002). "A revision of Bloom's taxonomy: An overview." *Theory Into Practice* 41 (4): 212–218.

[46] Krathwohl, D. R., Bloom, B. S., & Masia, B. B. (1964). *Taxonomy of Educational Objectives, Handbook II: Affective Domain.* David McKay Co.

[47] Simpson, E. (1971). "Educational objectives in the psychomotor domain. Behavioral objectives in curriculum development: Selected readings and bibliography." 60 (2).
https://files.eric.ed.gov/fulltext/ED010368.pdf
See also Hill, K., Fadel, C., and Bialik, M. (2018). *Psychomotor Skills For The 21st Century: What Should Students Learn?* Center for Curriculum Redesign. https://curriculumredesign.org/wp-content/uploads/Psychomotor-Skills-CCR-May2018.pdf



Developments in the automation of the affective, cognitive, and psychomotor domains. *Source*: CCR

Augmented Intelligence

How clean is this divide between human tasks and computer tasks? Once a task has been automated, is there any role left for humans? Chess is a good example to consider because it is a game that one could imagine playing in a human, holistic way using intuition, or in a robotic, algorithmic way using powerful calculation. When in 1997 the computer Deep Blue beat the world champion, Garry Kasparov, at chess, it seemed to add chess to the list of activities in which humans have been outpaced by computers. Similarly, the game of Go has been conquered in recent times, to the point of algorithms even using innovative strategies that have not been used by human players.[48]

However, while it is true that computers can now beat humans at chess, combinations of the two—computers and humans working together—appear to be more effective than either alone. The results of freestyle chess competitions have shown that amateur chess players using computers can beat computers alone, grandmasters alone, and even grandmasters using a weaker computer.[49] This is a great example of a situation which appears on the surface to be yet another case of computers encroaching on what was once deemed a uniquely human challenge, but turns out to be an opportunity for humans to use algorithms as tools for doing what humans do best, even better. This idea has been referred to as "augmented intelligence" and it is the key to understanding the role of humans with regard to computers, and thus holds implications for the goals of an education.

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[48] https://en.wikipedia.org/wiki/AlphaGo

[49] Brynjolfsson, E., & McAfee, A. (2014). *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*. WW Norton & Company.

Entity	Advantage	However...
Computer	—Fast generation and testing in big search space of solutions. —Fast processing over big data.	—Solution generator is incomplete in the open world. —Data is not a full representation of the open world.
Human Team	—Life experience in the open world. —Diverse experience of cross-disciplinary teams in multiple domains.	—There are coordination costs.
Human–Computer Team (highest performance):	—Complementary kinds of cognition compensate for each other's failure modes and enhance performance.	—We need a better theory and practices for building human-computer teams.

Comparison of computers humans and human-computer teams.
Source: Adapted from PARC.[50]

A similar process applies to many professional shifts. Calculators didn't replace mathematicians, but rather boosted their abilities. Word processors did not replace writers, but rather gave them more power as they wrote and edited their work. Even though the changes taking place due to AI are likely more transformative than those shifts, that does not mean that AI will not also be used best as a tool, if the next generation is effectively trained to make best use of it.

So where are machines best suited, and where could humans expect an enduring role, and leverage the power of machines? Our summary based on the current state of affairs is as follows:

Areas Where Machines Best Humans

- Repetitive/predictive tasks.
- Tasks that hinge on computational power.
- Classifying huge amounts of data and inputs.
- Making decisions based on concrete rules.

[50] Kefik, M. (2017). "Half-human, half-computer? Meet the modern centaur." PARC Blog.

Areas Where Humans Best Machines

- Experiencing authentic emotions and building relationships.
- Formulating questions and explanations across scales and sources.
- Deciding how to use limited resources across dimensions strategically (including which tasks machines should be doing and what data to give them).[51]
- Making products and results usable for humans and communicating about them.
- Making decisions according to abstract values.

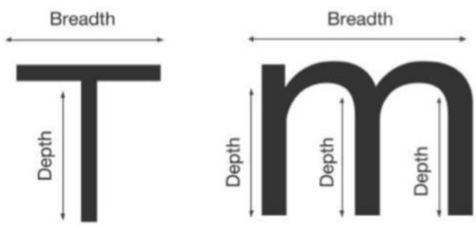
If all tasks were perfectly algorithmic and able to be subdivided, algorithms could handle it all. But most of the time, humans are required to frame the problem, choose the data, decide how the pieces fit together, communicate its value to others, make judgments according to values, and so on. Even AI, while it may be free of the constraint of algorithms, will still need to be designed, trained, and situated within a larger process. Although many *parts* of jobs are likely be automatable, there are still important roles for humans to play, if they are properly prepared.

[51] Additionally, humans have biases, and their algorithms and data sets can reflect them, so it will be important to account for unintended consequences of the way information is structured and combined.

Implications for Education and What Students Need to Know

Considering the exponential advances of AI and its disruptive nature on occupations and tasks, as well as all the other factors of social and personal instabilities, what is a wise strategy for humans to adopt, when it comes to education?[52]

Logic would indicate that, in times of unpredictable change, adaptability and resourcefulness would be essential. This in turn makes a case for a more *versatile* education, where one could be broadly trained in a number of domains, and learn the skills and character qualities needed to thrive and adapt to other endeavors. This is in a sense what education has always tried to achieve—a solid foundation that translates to preparedness for future challenges—but this has to be done more effectively than ever, given the magnitude of the disruptions.



T-shaped and M-shaped person, for comparison.
Source: CCR based on Spohrer.

IBM's Jim Spohrer coined the term *T-shaped person*[53] to indicate the cognitive profile of someone whose knowledge is both broad and deep, not one or the other. To include the projected changes in the workforce, we expand this model by describing an *M-shaped person*, who develops several depths over their lifetime.

[52] Certainly education cannot solve everything—there are political and legislative discussions that must be had—but our focus here is on education.
[53] https://www.slideshare.net/spohrer/t-shaped-people-20130628-v5

Two ways of reaching the goal of K–12 education: the traditional method, which assumes that transfer can only be a result of expertise (curved line) and the proposed method (wavy line) that alternates between gaining transfer and expertise. *Source*: CCR.

Education is always about transfer (the process of making use of knowledge outside of the context in which it was learned) and expertise (a highly developed understanding of some domain of knowledge, including particular ways of perceiving and interpreting information).[54] But now, more than ever, there is the need to reconsider the relationship between expertise and transfer and to make them the focus of an education[55] in a deliberate, systematic, comprehensive, and demonstrable way.[56]

The diagram that follows shows how increasing technological processes provide the opportunity for the emphasis of curriculum to be flipped[57] so students spend more time focused on transfer and expertise via concepts rather than on learning content that can now be easily accessed and manipulated. This is similar to the way that flipped classroom pedagogy incorporates technology for learning content so that

[54] For example, see: Simonton, D. K. (2000). "Creative development as acquired expertise: Theoretical issues and an empirical test." *Developmental Review* 20 (2): 283–318.

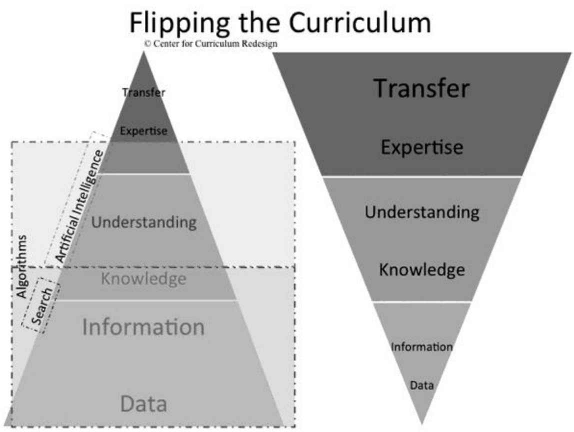
[55] Expertise was always understood to be important to focus on, but in the ideal balance, both expertise and transfer would be emphasized.

[56] One of CCR's key mantras: Yes, here and there, now and then, to a certain extent, such efforts take place. CCR's goal is to make them considerably more "deliberate, systematic, comprehensive, and demonstrable."

[57] Here we are adapting the language of flipped classroom but actually referring to a flip in the value placed on different priorities, rather than on classroom strategies.

class time can be used for activity-based concept learning, but with a focus on "the what" rather than on "the how."[58]

This is directly related to technological changes; search and AI algorithms first encroached on the more fundamental aspects of knowledge (basic facts and processes), but are now reaching the level of specific expertise. Algorithms are expanding upward in their abilities to provide meaning, which can be seen as very beneficial rather than threatening. Rather than spend undue amounts of classroom time amassing information, the time can now be much better spent reaching the more profound goals of an education, namely expertise and transfer, preparing students for the types of tasks they will actually be expected to do in the workforce.[59]



Flipping the curriculum to account for the encroachment of search and AI. *Source*: CCR

Considering the changes taking place, we are reminded that content must be modernized as well. One way to approach this is to remove portions of the curriculum that are outdated. A useful metaphor might be one of the game Jenga,[60] where players remove the non-load-bearing blocks without weakening the edifice, thereby keeping the essential structure. (Of course, it is possible to remove too much; the goal is to

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[58] https://en.wikipedia.org/wiki/Flipped_classroom

[59] This is important but, as a reminder, it is not the only aim.

[60] https://en.wikipedia.org/wiki/Jenga

keep what is essential). Additionally, valuable contemporary topics should be added to the classic content to update its relevance. Finally, the way content is taught should be modernized, making use of new educational as well as professional tools—although using old tools is still preferable to using new tools mindlessly.

Just as content can overpower concepts, expertise can become the focus of education, at the expense of transfer. Consider an example from mathematics: drilling procedures for solving trigonometric equations involving arc secants by hand was useful for training land surveyors in a non-digital world, or might have been useful for those who went on to study engineering, just as memorizing the Krebs cycle was once useful for those who went on to a career in biology. But for the majority of modern students, both examples often end up serving no real purpose and, in fact, can be easily accomplished by using computers for search or calculation.

This approach, which focuses on expertise and eventually leads to transfer, is not the only way to reach the goal of combining transfer and expertise, and it has significant drawbacks. Namely, if one stops the development of knowledge within a subject early (as many do, and in most cases K–12 encourages by design), then the potential for transfer remains incredibly low. The detailed understanding remains limited to the domain in which it was learned, and is not useful. It is possible, as the preceding transfer/expertise figure illustrated, to alternate between teaching for transfer (breadth) and teaching for expertise (depth), such that if one stops early, they've still gained important and transferrable understandings.[61]

For example, it is possible to gain an understanding of the scientific way of viewing the world by earning a PhD in a scientific field, painstakingly developing expertise by learning the relevant background knowledge, reading dense primary research articles, and designing and executing research studies. But shouldn't the ability to consider the

[61] It may be the case that different disciplines have slightly different curves.

testability and uncertainty of claims—something inherent to science—be internalized sooner rather than later? Shouldn't it be conveyed in every relevant example of scientific knowledge that is taught? Most practitioners of a field will claim that no one piece of information is as important as learning to think in a particular way. Additionally, this "thinking in a particular way" is something that remains inaccessible to computers. Certainly, we are now bombarded with information we are expected to be able to evaluate, for which we need to have learned the general frameworks that would allow us to ask the right questions. Education needs to be restructured to reflect that.

The Importance of Meaning

What makes a foundation of knowledge solid? What makes it fragile? The key lies in making meaning.

A useful understanding is one that is meaningful: ideas are connected according to their relationships and applicability. In some sense, making meaning and understanding can be said to be synonymous. Experts, who have studied their field in great depth and have devoted their lives to a particular way of making meaning, develop an understanding so deep that they are often able to use their intuition to understand how to approach new challenges in their field. Of course, once one has learned a particular concept in great depth from many angles, it is natural that they will have developed an intuition for it.

But can intuition be developed in those who will not go on to specialize in a subject? Can students be educated to recognize situations to which their knowledge may be applicable, and have informed strategies for how to approach the unknown from relevant perspectives, without developing full technical expertise in all subjects?[62] We believe that they can, if knowledge is presented in ways that facilitate making meaning, and that which is most fundamental is made explicit.

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[62] Which is, of course, not possible.

Intuition

Suppose you are a local in a particular city, and you have walked the streets your entire life and know them without having to think about it. No matter where you find yourself, you understand the general area you are in and how it relates to other areas you have visited. You might be an expert in the layout of that city.

Now, suppose you are trying to teach someone who is new to the city how to get around. You could provide them with a map and start at the top and have them memorize it square by square or pixel by pixel. After all, once you've finished this exercise, they would presumably have a very deep, detailed understanding of the city. Or you can just tell them the exact directions and local landmarks to get from one place to another every time they need to go anywhere, and if they stay in the city long enough they will probably put together a reasonable mental map.

Alternatively, you could simply convey to them the largest scale of organization and the useful landmarks of the city. For example, you could tell them the river divides the town into north and south, there is a main street with neighborhoods that branch off of it, and there is a bus that loops along the perimeter of the city. This method provides a foundation of knowledge that is more meaningful and able to be expanded as the stranger learns more about the city, whether they plan on moving to the city or are there as a tourist. The description that provides the most essential components of the city is more useful, as it helps the stranger to develop an intuition for how to approach making meaning from the layout and landmarks of this city. If they find themselves in an unknown neighborhood, they can look for the river, and find their way, adding what they learn from the experience to their understanding of the city.

That is truly the test of a foundation: can it be built upon, or is it going to collapse under the pressure of new material? If all the pieces have been added in a way that creates meaningful relationships with all the existing pieces, then it is clear where new pieces ought to be connected. If all the pieces are being collected together in the hope of an emergent meaning arising in the future, any addition to this collection will just be another fragment of an idea to remember, and could be easily lost or confused.

It may seem like some topics are so technical that there is no way to preserve meaning in the majority of the pieces as they are added, or to develop an intuition without developing comprehensive expertise; experts built their understanding in the current system, after all, and therefore may often default to believing that their own journey should be the journey of anyone learning their discipline.

It may be, however, that an expert is in the worst position to decide how to introduce students to their discipline. It is common for them to succumb to the "curse of knowledge,"[63] by which they are unable see how novices perceive material, and thus how it should best be presented. Someone with a deep passion for the material and to whom it came easily may have particular trouble imagining the experience of someone who just wants a handle on the foundation, or a struggling learner.

Relevance: Mobilizing Knowledge

Research shows that information is filtered through our perception based on our frameworks for understanding it and our goals. This applies to the lowest levels of perception[64] as well as to the higher levels of cognition.[65] If students' brains cannot find the usefulness of information, it is more likely to be difficult to integrate (understand) the information in a meaningful way. For knowledge to be relevant, it does not necessarily have to be useful in a concrete way; it may be useful for solving an abstract problem or understanding a confusing idea.

Furthermore, relevance has a direct relationship with student motivation. The information gap theory of curiosity[66] posits that a

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[63] Wieman, C. (2007). "The 'curse of knowledge,' or why intuition about teaching often fails." *APS News* 16 (10).

[64] For example: Gauthier, I., Skudlarski, P., Gore, J. C. & Anderson, A.W. (2000). "Expertise for cars and birds recruits brain areas involved in face recognition." *Nature Neuroscience* 3 (2):191–197.

[65] For example: Mack, A. and Rock, I. (1998). *Inattentional Blindness*. MIT Press.

[66] Loewenstein, G. (1994). "The Psychology of curiosity: A review and reinterpretation." *Psychological Bulletin* 116 (1), 75–98.

powerful form of motivation arises when there is awareness of a gap in one's understanding. The gap, however, must be of manageable size; if it is too big or too small, students will be uninterested or intimidated, respectively.[67] Additionally, people like to seek out information on topics they enjoy thinking about, and avoid information on topics they don't enjoy thinking about. This last phenomenon, the ostrich effect,[68] is particularly interesting, as it shows that relevance is highly subjective, taking into account emotional valence that may sway the way someone approaches potentially relevant but unpleasant information.[69]

David Perkins says "Knowledge is like a bicycle. That is, knowledge is for going somewhere. If we know something about the French Revolution or the nature of democracy or Bayesian probability or opportunity cost, we want to go somewhere with it. Maybe we want to understand an issue in the headlines or think about a medical decision or get a project off the ground in the most effective way. For any of these missions and thousands more, we want to go somewhere with what we know."[70] Even going on a leisurely bike ride for pleasure requires the bicycle to be functioning. Put another way, knowledge should not be in a void, rather it should be useful for something. Acquiring this kind of knowledge is critical for complementing, rather than competing with, computers, which are not able to spontaneously see connections and transfer knowledge to new contexts; humans must do this formulation work by defining the problem, and then recruit computers to do the work within each of the problems that requires computational power.

The idea of functional knowledge is often connected to various pedagogies that focus on active learning.[71] As John Dewey said, "only in education, never in the life of a farmer, sailor, merchant, physician, or

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[67] McClelland, D. C., Atkinson, J. W., Clark, P. W., and Lowell, E. L. (1953) *The Achievement Motive*. Appleton–Century–Crofts.

[68] https://en.wikipedia.org/wiki/Ostrich_effect

[69] Golman, R.and Loewenstein, G. (2015). "Curiosity, information gaps, and the utility of knowledge." Available at SSRN: https://ssrn.com/abstract=2149362 or http://dx.doi.org/10.2139/ssrn.2149362

[70] Perkins, D. *Future Wise*.

[71] Including self-directed learning, experiential learning, expeditionary learning, learning-by-doing, inquiry learning, hands-on learning, project based learning, problem based learning, discovery learning, and so on.

laboratory experimenter, does knowledge mean primarily a store of information aloof from doing."[72] This was reinforced by the seminal work by Benjamin Bloom,[73] discussed above; in this framework, higher levels of cognitive complexity require greater mobilization of knowledge on the part of the learner, from remembering, to understanding, to applying, to analyzing, to evaluating, to creating.[74] Thus, many people have worked to solve the problem of imparting usable knowledge through pedagogical approaches that focus on the students' active construction and application of knowledge. These approaches shift the focus from information transfer to student learning, and from "knowing" to "doing." After all, learning knowledge in a context of its application ensures that it has at least that meaning for the student to use in their conceptual organization. As we will see, however, this is just part of the picture.

Developing a Toolbox of Concepts

Any particular piece of knowledge could in theory be useful in a variety of situations, but it is ultimately up to the student to know how and when to use it, and this is key to the type of understanding that ought to be the aim of education. For example, what use is the knowledge of the definition of confirmation bias if a student never checks whether they are succumbing to it? This fits with the common way of describing learning as developing a toolbox, meaning each student is honing their proficiency with a set of tools, which are in this case concepts they have learned to use appropriately.

There are some concepts, however, that are more powerful than others. The concept of brute force versus elegance in mathematics, for example, crystallizes an important idea about the possible approaches to

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[72] Dewey, J. (1916). *Democracy and Education*. https://www.gutenberg.org/files/852/852-h/852-h.htm

[73] Bloom, B. S., Engelhart, M. D., Hill, H. H., Furst, E. J., & Krathwhol, D. R. (1956). *Taxonomy of Educational Objectives. The Classification of Educational Goals, Handbook I: Cognitive Domain*. David McKay Company. Inc, New York.

[74] Anderson, L. W., Krathwohl, D. R., and others. (2001). *A Taxonomy For Learning, Teaching, and Assessing: A Revision Of Bloom's Taxonomy Of Educational Objectives*. Pearson; and Krathwohl, D. R. (2002). "A revision of bloom's taxonomy: An overview. *Theory Into Practice* 41 (4): 212–218.

solving a problem; being aware of the type of strategy one is employing (by using this concept as a tool) will help all students, regardless of whether or not they specialize in a science, technology, engineering or math (STEM) field. For this reason, this can be thought of as a power tool of thought. Although it is learned in a particular context, it has a disproportionate amount of utility for all students.

Core concepts are the power tools of knowledge and should be of high priority in the curriculum, compared to concepts that offer less leverage for future learning, or worse, fragmentary knowledge that is inappropriately tied to the context it was learned in, and thus difficult to use as a tool in new contexts.

Transfer: Using Learned Knowledge in New Circumstances

Another way to frame this challenge is as transfer (the process of using a conceptual tool outside of the context in which it was learned). A lot of research[75] has focused on the puzzling findings around the cases in which transfer does and doesn't occur, but recently, research has suggested that a more productive way to conceptualize transfer is that it is almost always occurring, but it is not always being done in the ways that teachers hope for.

In essence, transfer can be conceptualized simply as activating a set of mental resources to understand some new information.[76] It is a natural process of learning, in which one leverages what they already understand to figure out something they do not yet understand.[77,78] If students are applying the tools incorrectly or failing to apply them when they are appropriate, that is an indication that the meaning that they've made is not complete or accurate in some way. Rather than "failing to transfer,"

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[75] For example: Barnett, S. M., & Ceci, S. J. (2002). "When and where do we apply what we learn? A taxonomy for far transfer." *Psychological Bulletin* 128 (4): 612–637.

[76] Bransford, J. D. & Schwartz, D. L. (1999). "Rethinking transfer: A simple proposal with multiple implications." *Review of Research in Education* 24: 61–100.

[77] Billett, S. (2013). "Recasting transfer as a socio-personal process of adaptable learning." *Educational Research Review* 8: 5–13.

[78] Wiser, M., Smith, C. L., Doubler, S., & Asbell-Clarke, J. (2009). *Learning Progressions as a Tool for Curriculum.* Paper presented at the Learning Progressions in Science (LeaPS) Conference, June 2009, Iowa City, IA.

these students are simply transferring a tool in a way or to a context that does not apply. It also happens to be exactly what computers cannot do: figure out how to do something they have not been trained on without learning it from scratch.

How does transfer take place? When confronted with some new problem, situation, or information, the first thing our brains do is try to find a pattern that matches a pattern they have already learned. They might find an abstract pattern for which they have tools, such as word problem, division, or poems, and activate appropriate tools to that category. This is called high road transfer. By contrast, low road transfer is when our brains notice a pattern match between the superficial features of the new information, and some superficial features of previous experiences.[79]

For example, suppose a student is asked to solve this word problem: "Four children have 16 blocks. Their teacher asks them to share the blocks equally between them. How many blocks will each child receive?" To solve the problem, the student might use high-road transfer and realize that to share the blocks equally, they must use division. Or, if the student uses low-road transfer, they might notice that the problem structure or vocabulary are similar to other problems that they have solved in the past and know to follow the same procedure to solve the problem. Assuming the students have seen a similarly worded problem in the past, both types of transfer would successfully get the correct answer (4 blocks). However, high-road transfer allows the student to organize experiences based on their deeper meaning, and thus will ultimately be more useful for transferring knowledge learned in school to questions and experiences after school.

In terms of potential for transfer, core concepts, as described in the previous section, can have a high return on investment, in that they are applicable to many contexts, without needing to be learned in each one separately. If the goal of the curriculum is to allow students to construct

[79] Sometimes this happens cleanly, but often a particular situation will somewhat match several patterns. This accounts for students' inconsistent application of certain concepts that are so puzzling to teachers.

transferrable knowledge, then core concepts should be central to the construction of the curriculum. In fact, one way of conceptualizing core concepts is that they are what allow transfer to take place.

It is tempting to think that all learning could be as painless as learning one's native language. This process happens naturally as children engage with the world, and the result is a truly impressive, complex knowledge base. However, learning another language in school does not usually include the option of sending students to a foreign country, and subjects such as math don't have an equivalent construct of math country that students could visit even if they wanted to. Learning a foreign language in school involves the explicit discussion of grammar rules, declensions, conjugations, and so on. This is because hoping that one absorbs an entire language without being shown the lines along which transfer can take place is clearly inefficient. In a class of Spanish as a foreign language, a core concept may be situated around "verbs that end with -ar". This way, when a student studies -ar verbs they are not only learning those words, they are learning how to treat certain words they have not yet encountered, and how to spot those situations in which their knowledge is transferrable.

Realms of Meaning

In the 1964 book *Realms of Meaning,*[80] Philip Phenix makes the argument that curriculum design should prioritize opportunities for students to make meaning, and that disciplines should thus be grouped by the ways in which they make meaning: their typical methods, learning ideas, and characteristic structures. For example, math and linguistics both make meaning using systems of symbols and agreed upon rules. This way of making meaning has been a successful approach and it is worthwhile for students to understand what it means to make meaning in that particular way. Newer disciplines can be sorted into the same categories (for example, computer science would belong to the symbolic realm).

[80] Phenix, P. H. (1964). *Realms of Meaning a Philosophy of the Curriculum for General Education*. McGraw-Hill.

This is the most abstract level of meaning, in that it is an entire approach to making meaning. Someone who is a scientist has internalized the empiric way of making meaning, and will likely look for evidence and consider alternate explanations even in matters of their personal lives. It is along these lines that interdisciplinary work is often most difficult; when values and methods of inquiry do not align it is hard to find a starting point or see each other's position through their eyes. If a K–12 education is to provide a foundation, that foundation should include an intuition for the different possible ways of making meaning. *The Realms of Meaning* are:

> **Symbolic**: Systems of symbolic structures with socially accepted rules of formation and transformation (for example, math, linguistics, computer science, etc.).
> **Empiric**: Probable empirical truths framed in accordance with certain rules of evidence and verification, and using certain systems of analytical abstraction (for example, physics, biology, etc.).
> **Aesthetic**: Patterns of the inner lives of humans (for example,Visual arts, Musical Arts, Arts of Movement, and Literature).
> **Personal**:[81] Knowledge of self and others, learned through experience (for example, psychology, philosophy, literature, religion, in their existential aspects).
> **Ethical**: Personal conduct that is based on free, responsible, deliberate decision (philosophy, psychology).
> **Integrative**:[82] Synthesized from multiple perspectives into coherent integrated wholes (for example, philosophy, history, religion, etc.).

Some disciplines fit into multiple realms, because there are different traditions within them. For example, psychology can be a way to make personal meaning, a way to make ethical meaning, or a rigorous empirical practice that makes meaning through experiments and analysis. Even disciplines that seem to fit squarely within one realm can be crucially important to consider in other realms; for example, mathematicians

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[81] In *Realms of Meaning* this was called "Synnoetic."

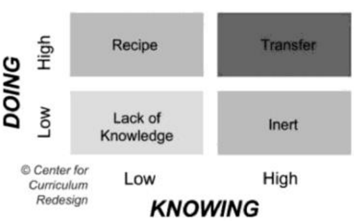
[82] In *Realms of Meaning* this was called "Synoptic."

would likely consider math as not only belonging to the symbolic realm, but also perhaps the integrative and even the aesthetic.[83] Rather than strict delineations, these categories provide a way of discussing high-level patterns in ways of producing knowledge. This abstract way of thinking about formulating questions or making decisions according to abstract values of a community is the exact kind of thing that computers cannot be trained to grasp.

Problematic Knowledge

The results of learning without meaning, or problematic knowledge, have been conceptualized in many different ways: fragile knowledge, rote or recipe knowledge, inert knowledge, and the prevalence of misconceptions. These types of problematic knowledge stem from slightly different ways of losing meaning in the learning process.

Fragile knowledge, the most broad category, describes knowledge based on its behavior: it is not a good foundation, because when there is any stress added to it, it collapses and ceases to be useful. As the following figure shows, rote or recipe knowledge, is that which is based too heavily on doing, and not closely enough connected to conceptual understanding, such that students seem to be able to complete the activity that would require certain knowledge, but do not have a deep understanding that could result in high road transfer. Inert knowledge is the reverse; students seem to know some information when asked, but fail to apply it when necessary.



A deficiency of either knowing or doing results in problematic knowledge (recipe and inert, respectively). *Source*: CCR

[83] Lockhart, P. (2009). *A Mathematician's Lament: How School Cheats Us Out of Our Most Fascinating and Imaginative Art Form.* Bellevue Literary Press.

If students simultaneously do not know about a concept abstractly and cannot execute a solution practically, this is simply a lack of knowledge, as shown in the bottom left corner of the figure. In order for students to adequately transfer knowledge from one situation to another, they need to both have a high understanding and a high ability to make use of their understanding.

There is a multitude of popular pedagogical perspectives, all with the general underlying paradigm of constructivism,[84] and the general underlying goal of creating active-learning experiences for students. This balancing of top–down traditional learning (in which meaning is explicitly told to the students but may not effectively connect to student conceptions and experiences) with bottom–up progressive pedagogy (in which meaning is constructed by the students but may be limited in complexity) is an important part of the implementation of curriculum; if a particular curriculum focuses too much on the side of the top–down, the result will be inert knowledge, whereas if it focuses too much on the side of the bottom–up, the result will be recipe knowledge. Both of these types of knowledge do not transfer properly to new contexts for different reasons. The key here is to balance the need for both bottom–up approaches and top–down approaches, to create a learning experiences in which children create meaningful, useful, understandings.

Misconceptions are simply understandings in which the meaning is not properly constructed.[85] Often there are counterintuitive understandings that a student must learn, but their original ways of making meaning of the world are more solidly established, and they inadvertently rely on them, instead of the more tenuously established complex ones they recently learned in school. Consider the following example that explores why students seem to drop robust conceptions of force mid-explanation.

[84] The popular pedagogical paradigm created by Jean Piaget in which students actively construct understanding and cannot simply have it given to them.

[85] These are often called "alternate conceptions" to preserve the idea that they still have meaning, they just do not match the standard.

> … Thinking about the rising ball, students are likely to activate maintaining agency, the idea that effort must be continued in order to maintain the effect ("if you stop pushing, it'll stop moving"). [The idea of] maintaining agency causes students to think that a continued upward "influence" must act on the ball to keep it moving upward. Asked about forces, students unconsciously map "influence" onto "force," leading to an explanation that's consistent with the motion requires force misconception. Thinking about the motionless peak of the trajectory, however, students' intuitive sense of balancing turns on; an upward something seems to be balancing a downward something. Asked again about forces, students map that "something" onto force and say the forces balance.[86]

Ultimately, how a student will interpret a given problem or situation will depend on how robustly they have constructed various understandings, and how the context triggers or fails to trigger these understandings to be used as tools for approaching the question.

Optimization

This helps explain the classic finding when it comes to forgetting knowledge: the Ebbinghaus forgetting curve. In 1880, Ebbinghaus published a paper (that has since been well replicated)[87] about the rate of forgetting, in which he showed that our memories had a steep decline and then levels off.

The interesting thing to note here is the content that was being remembered. Since any idiosyncrasies in the material could throw off the results in unpredictable ways, these studies tested the retention of a string of nonsense syllables. If the goal was to design the materials so as to result in the most fragile possible knowledge, this is what would result, since the fact that they are nonsense allows no footholds for the brain to use. That makes this classic finding an interesting baseline measure for learning, but far from representative of learning.

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[86] diSessa, A. (1993) as cited in Hammer, D., Elby, A., Scherr, R. E., & Redish, E. F. (2004) in J. P. Mestre (Ed.) *Transfer of Learning from a Modern Multidisciplinary Perspective*. IAP. 89–119.

[87] https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0120644

What would it look like to design material with the exact opposite goal: to provide as many footholds and routes of transfer as possible? There is a large opportunity for adaptive intelligent tutoring systems to help craft the ordering of material to optimize for transfer, both generally, and specific to each student.

Core Concepts

Any piece of information can serve as a tool for understanding any other piece of information. So how do we use the idea of knowledge being a tool as we design curriculum? The key lies in identifying and explicitly focusing on core concepts, the most powerful tools, both within each discipline and across disciplines.

What is Most Important?

The most complex aspect of curriculum design is to determine the most essential complex abstractions that should be taught to all students, within disciplines and across disciplines.

There have been a number of efforts that have worked to highlight abstract concepts to help students build intuitions, make connections, and create more generalized understandings. Although they differ in framing and conceptualization, these frameworks are all pointing to the need for structuring curriculum to facilitate robust and flexible understandings via deliberate organization of concepts.

Knowing and Doing

As discussed in the previous section, transfer is really the process of knowing with an understanding that allows one to use or leverage previously learned information as a resource. It is thus no wonder that the distinction between knowing and doing has been of interest in curriculum design. In the context of that dichotomy, knowing on its own is synonymous with having knowledge that one cannot necessarily transfer, or use in a new context, whereas doing involves necessarily mobilizing some knowledge to make something happen, even if that knowledge is superficial and procedural rather than deeper and conceptual.

It is not a coincidence, then, that various literacy[88] and fluency[89] efforts that extend these words beyond language have been increasing in popularity. After all, literacy is the ability to use your existing knowledge (of language, usually) to understand new information (by reading); in other words, to "know with" some set of information.[90] It thus conveys the idea of striving for expert amateurism and preparation for future learning.[91] Mastering the core concepts of a given discipline is the equivalent of being literate in that discipline, or "thinking like a [practitioner of that discipline]."[92] Unfortunately, as discussed above, these concepts are so foundational to the thinking that they often go without saying, making them difficult to enumerate.

Key Knowledge Frameworks

The CCR framework is highly informed by those frameworks that came before it. Rather than reinventing the wheel, the goal was to create a framework that was as comprehensive as possible, while remaining as simple as possible. Many concept-based frameworks were reviewed, and the ones most key to the final synthesis can be found in the table that follows.

What all of these frameworks have in common is a "less is more" approach to content, by placing concepts first. Instead of adding yet another element the curriculum must cover, it is consolidating content, structuring it more efficiently, leveraging transfer along the way.[93] As discussed, in order to facilitate transfer, a balance must be struck between

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[88] For example, financial literacy, media literacy, scientific literacy, graphic literacy.

[89] For example, math fluency.

[90] To be fluent, a certain level of proficiency must be internalized to the degree of automaticity.

[91] It is even evident in our clichés, like when a scientist explaining something to a non-scientist who looks slightly annoyed and says "in English, please," meaning that they are not fluent or literate, in this scientific topic.

[92] Wineburg, S., Martin, D., & Monte-Sano, C. (2014). *Reading Like A Historian:* Teaching Literacy in Middle and High School History Classrooms—Aligned with Common Core State Standards. Teachers College Press.

[93] An argument has been made that all reasoning/learning is at some level transfer (metaphor, analogy).

doing and knowing. The extreme form of doing results in recipe knowledge, in which one knows how to do something, but they are not in fact leveraging deep understanding, rather they are simply remembering the superficial actions necessary to achieve their goal. Therefore, many of these frameworks explicitly try to pair knowing and doing in order to get to the heart of useful knowledge. Similarly, being able to think outside the scope of one discipline entails transfer to a new context, and is therefore also often noted in knowledge frameworks. The following table summarizes how the various knowledge frameworks relate to each other within the two dichotomies of knowing versus doing and disciplinary versus non-disciplinary.[94]

For example, a type of essential question in the disciplinary, big picture category is one that deals with what is foundational: these point to big ideas and frontiers in a discipline: "How many dimensions are there in space–time?"

A type of essential question in the disciplinary, small picture category is one that deals with that is necessary for deep dives into content: "In what ways does light act wavelike?"

A type of essential question in the non-disciplinary, big picture category is one that deals with what is timeless. These questions are interesting to debate and continue to change, such as, "What is justice?"

[94] We use the word "non-disciplinary" as opposed to interdisciplinary, cross-disciplinary, or transdisciplinary to avoid a discussion about exactly which kinds of connections outside the traditional confines of disciplines we mean. It is intended in the very general sense.

	Know		Do	
	Big Picture	**Small Picture**	**Big Picture**	**Small Picture**
Disciplinary	Big Ideas[a] Essential Questions[a] Theories[b] Principles[b] Central Ideas[c] Disciplinary Core Ideas[d] Representative Ideas[e] Threshold Concepts[f] Enduring Understandings[g]	Essential Questions[a] Microconcepts[b] Generalizations[b]	Core Tasks[a] Processes[b] Core Tasks[c] Practices[d]	Strategies[a] Skills[a]
Non-Disciplinary	Lines of Inquiry[c] Essential Questions[a]	Macroconcepts[b] Concepts[c] Cross-Cutting Concepts[d]	Transdisciplinary[c] Skills[c]	Subset Skills[c] © Center for Curriculum Redesign

Summary table of types of terms used to describe Knowledge. Understanding by Design (a), Concepts Based Education (b), International Baccalaureate (c), Next Generation Science Standards (d), Realms of Meaning (e), Meyer and Land (f), and Rubicon (g). *Source*: CCR

Separating knowing and doing into a dichotomy may not actually be productive in the construction of a curriculum. After all, neglecting either one results in fragile knowledge. We therefore do not include this distinction in our framework, and simply focus on designing a process to determine which concepts and content to teach, and how to organize them. Truly learning a concept necessarily entails both the knowing and doing aspects.

Concept Inventories as a Tool

Attempts to start collecting, organizing, and assessing the deeper concepts for each discipline have also emerged. At the college level, there have been various efforts to create concept inventories for the sciences to assess how well students are learning the key concepts of a discipline. A concept inventory is created by collecting input from experts and educators of a given discipline, and constructing multiple-choice tests that diagnose students' particular conceptual structures using distractor answers to identify common misconceptions. Look at the following example question[95] and its corresponding answer choices to get a sense.

> **Imagine that you are an ADP molecule inside a bacterial cell. Which best describes how you would manage to "find" an ATP synthase so that you could become an ATP molecule?**
>
> This question is designed to test whether students understand that diffusion is caused by random motion of molecules.
>
> **a. I would follow the hydrogen ion flow.**
>
> Students who choose this answer think that ADP somehow can identify where a hydrogen ion gradient is.
>
> **b. The ATP synthase would grab me.**
>
> Students who select this answer think that an ATP synthase senses the presence of ADP and actively grabs it.

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[95] Garfield, J., & Ooms, A. (2006). *Assessment Resource Tools for Assessing Students' Statistical Literacy, Reasoning, and Thinking*. Proceedings of the National STEM Assessment Conference.

c. My electronegativity [is the main factor that] would attract me to the ATP synthase.

Students who select this answer think that charges cause the ADP and ATP synthase to be attracted to each other.

d. I would be actively pumped to the right area.

Students who select this answer think that the ADP is somehow placed in the correct area so that it is close to the ATP synthase.

e. Random movements would bring me to the ATP synthase.

This is the correct answer. In other words, ADP finds ATP synthase by the random motion of ADP molecules.

Through an intensive process of student interviews and iterative question development, these diagnostic tools are developed to be a diagnostic tool of student conceptions on a given topic. The first concept inventory was The Force Concept Inventory (FCI),[96] created in 1992. By 2008, twenty-three concept inventories had been developed in the sciences, and stirred discussion around the best teaching practices of higher education STEM subjects.

We believe that this effort needs to be expanded in three ways to be effective.

1. It should be used as a curriculum design tool, not just a diagnostic tool.
2. It should include subjects outside of STEM.
3. It should be adjusted (if necessary) for K–12 students.

This expanded project would likely be most effective if conducted in a digital format, which would allow for continued growth, multiple contributors, interconnected organizational systems, etc.[97]

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[96] Hestenes, D., Wells, M., & Swackhamer, G. (1992). "Force concept inventory." *The Physics Teacher* 30: 141–158.

[97] One promising project is Ed's Tools, which offers a computer program to help construct concept inventories for any subject. https://edstools.colorado.edu/

Levels of Organization

As concept-focused knowledge frameworks and concept inventories expand to become the basis for entire curricula, we must consider the hierarchy of concepts and how content are paired with concepts. Some of the frameworks that we drew from identified concepts that exist at different levels of content (for example, interdisciplinary, discipline specific, branch specific, or subject specific). We propose making this content/concept relationship explicit so students can most efficiently and effectively make meaning from the core concepts that exist across and within all K–12 disciplines.

Structuring Content through Concepts

As concept inventories expand to become the basis for entire curricula, they must be organized across different levels of content. If a piece of content is not connected to any concept in the curriculum, it will not be connected to a concept in the students' minds, and will therefore not be a useful, transferable, piece of knowledge. Too often, courses are designed to hit the main content areas within a discipline to give students exposure to the range of subjects; however, organizing with this goal in mind will almost certainly lead to fragmented, disjointed content.

But how can concepts be organized within disciplines and across them? The seminal Force Concept Inventory refers to a taxonomy that groups sets of items into categories, such as kinematics, impetus, and action/reaction pairs.[98] Others have referred to concept clusters,[99] use subtests,[100] mentioned macro and micro level[101] concepts, or explored interdisciplinary concepts such as maturity.[102] Many frameworks also

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[98] Hestenes, Wells, & Swackhamer, G., "Force concept inventory," 141–158.

[99] Steif, P. S. (2004). "An articulation of the concepts and skills which underlie engineering statics." In *Frontiers in Education*, *2004*. FIE 2004. 34th Annual (pp. F1F-5). IEEE.

[100] Evans, D. L., Gray, G. L., Krause, S., Martin, J., Midkiff, C., Notaros, B. M., & Streveler, R. (2003). "Progress on concept inventory assessment tools." In *Frontiers in Education, 2003, Vol. 1*. IEEE.

[101] Kinchin, I. M. (2010). "Solving Cordelia's dilemma: Threshold concepts within a punctuated model of learning." *Journal of Biological Education* 44 (2): 53–57.

[102] Peter, M., Harlow, A., Scott, J. B., McKie, D., Johnson, E. M., Moffat, K., & McKim, A. M. (2014). "Threshold concepts: Impacts on teaching and learning at tertiary level." *Teaching & Learning Research Initiative.*

mention the inter-relationships among concepts. The exact conceptualization depends on the way each framework is organized, but there is general consensus that concepts are interrelated such that your understanding of one is affected by and affects your understanding of the others.

We propose a structure that disentangles content and concepts, and identifies a handful of core concepts at each level of content organization (with many interdisciplinary connections). Topics are the lowest level of granularity and contain the content itself; they can be taught directly and should be used to exemplify, explore, and apply core concepts from across the higher levels. One of the advantages of this approach is that specific content (such as parts of a cell) can inherit high-level core concepts (such as scientific reasoning) and even concepts from other disciplines (such as division of labor). This organization helps curriculum designers keep track of the difference between learning objectives and the content used to teach them, facilitating a structure that revisits important concepts from different perspectives.[103]

Content Structure

Although there may be useful ways of organizing meaning in each discipline, it is ultimately not crucial to embark on the logistical challenge of reorganizing classes themselves. Rather, the keys to making meaning will be incorporated as core concepts at the various levels of organization. For many schools, a massive restructuring is not possible, and the CCR framework is designed to be as simple to implement as possible.

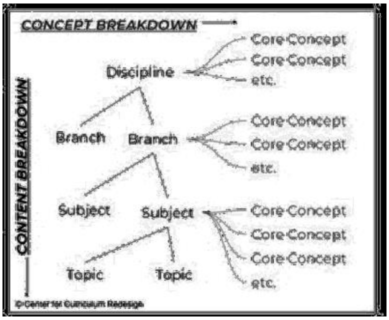
We therefore identify a set of names that correspond to groupings. Each one is made up of those below it (for example, disciplines are made up of branches).

- Disciplines—Mathematics, history, science, etc.
- Branches—Algebra, Western civilization, biology, etc.

[103] This can be through a spiral curriculum, a strand curriculum, curriculum mapping, etc.

- Subjects—Game theory, the Russian revolution, ecology, etc.
- Topics—Prisoner's Dilemma, execution of the Romanovs, foraging, etc.

It should be understood that no ontology and taxonomy can be perfectly coherent all the time and for all uses. For example, it may be useful to count both science and biology at a discipline level, therefore making two layers of the discipline type. At each level, the categories denote a particular grouping of content, and a particular set of defining core concepts.



Schematic of core concepts at each level of content organization (only topics can be taught directly, and thus must contain the core concepts of the higher level categories). *Source*: CCR

Biology (a branch) as a grouping of content is the study of life and living things; its core concepts may be "Structure and function are interrelated," "Natural phenomena tend to take the form of complex systems," and so on. It is part of the scientific approach to knowledge, or science, (a discipline), which has its own core concepts, which may be something like "Scientific explanations, theories, and models are based on collective evidence and always contain a degree of uncertainty," "Applications of science often have ethical, social, economic and political implications," and "Science assumes that for every effect there is one or more causes." This focus on empirical and collective knowledge construction is distinct from, for example, the focus on beauty in the arts, or the focus on morals or narratives in the humanities.

By assigning core concepts to each level in the taxonomy, a large and common mode of confusion is avoided. Curricula often choose just a few of these levels and try to encompass all the relevant core concepts or big ideas within them, resulting in a redundancy, incompleteness, and a confusing mixture of levels. For example, an otherwise rigorous study of core concepts in physiology[104] synthesized responses from faculty members to determine the core concepts of their field. Though the list was not initially structured based on how broad or narrow the core concept is, the following figure shows how we have organized these fifteen ideas into three content-based categories: the discipline, the branch, and the subject.

[104] Michael, J., & Mcfarland, J. (2011). "The core principles ('big ideas') of physiology: Results of faculty surveys." *Advanced Physiology Education* 35: 336–341.

Science
(Discipline)

Causality: [Living organisms] are causal mechanisms (machines) whose functions are explainable by a description of the cause-and-effect relationships that are present.

Scientific Reasoning: [Physiology is a science.] Our understanding of [the functions of the body] arises from the application of the scientific method; thus, our understanding is always tentative.

Levels of Organization: Understanding [physiological functions] requires understanding the behavior at every level of organization from the molecular to the social.

Mass Balance: The contents of any system or compartment in a system is determined by the inputs to and the outputs from that system or compartment.

Biology
(Branch)

Physics/Chemistry: The functions of living organisms are explainable by the application of the laws of physics and chemistry.

Energy: The life of the organism requires the constant expenditure of energy. The acquisition, transformation, and transportation of energy is a crucial function of the body.

Evolution: The mechanisms of evolution act at many levels of organization and result in adaptive changes that have produced the extant relationships between structure and function.

Homeostasis: The internal environment of the organism is actively maintained constant by the function of cells, tissues, and organs organized in negative feedback systems.

Interdependence: Cells, tissues, organs, and organ systems interact with one another (are dependent on the function of one another) to sustain life.

Structure/Function: The function of a cell, tissue, or organ is determined by its form. Structure and function are intrinsically related.

Physiology
(Subject)

Cell-to-Cell Communication: The function of the organism requires that cells pass information to one another to coordinate their activities. These processes include endocrine and neural signaling.

Cell Membrane: Plasma membranes are complex structures that determine what substances enter or leave the cell. They are essential for cell signaling, transport, and other processes.

Cell Theory: All cells making up the organism have the same DNA. Cells have many common functions but also many specialized functions that are required by the organism.

Genes to Proteins: The genes (DNA) of every organism code for the synthesis of proteins (including enzymes). The functions of every cell are determined by the genes that are expressed.

Flow-Down Gradients:[105] The transport of "stuff" (ions, molecules, blood, and air) is a central process at all levels of organization in the organism, and this transport can be described by a simple model.

Categorizing physiology core concepts into three layers of abstraction of content. *Source*: CCR adapted from Michael & Mcfarland

[105] Flow-down gradients may be a lower level core concept than physiology.

By organizing core concepts according to levels, their number for each topic becomes manageable, as high-level concepts apply to all of their low-level elements. In this case, while the subject is physiology, there is no need to choose between scientific reasoning and flow-down gradients, because they are organized by scale. The other concept-focused frameworks only partially divide concepts based on the taxonomy of concepts. The following table shows a crosswalk that summarizes the way that CCR's approach compares to similar concept-focused frameworks.

	Concept-Based Education	Big Ideas	Threshold Concepts (TCs)	Concept Inventories	Inquiry Project	CCR
Interdisciplinary	Macro-concepts	Some Essential Questions: Important/Timeless Interesting to debate Continue to change e.g., "What is justice?"	Cross-disciplinary threshold concepts (e.g., phase transition). TCs can be integrated vertically or horizontally in the curriculum.	None	There are interrelationships among concepts, e.g., math is closely related to science. Some important concepts e.g., epistemological concepts are naturally interdisciplinary.	Core Concepts (Theme)
Discipline	Theories Principles Generalizations Micro-concepts	Some Essential Questions: Elemental/Foundational Point to big ideas and frontiers in discipline e.g., "How many dimensions are there in space-time?"	TCs are generally defined within disciplines: Concepts that are transformative integrative, irreversible, bounded, and potentially troublesome to students.	CIs are developed within discipline, but the concepts tested may or may not be broadly applicable to the whole discipline.	Learning progressions are determined empirically and cover concepts at different scales systematically.	Core Concepts (Discipline)
Branch		Some Essential Questions: Vital or necessary for learning core content? For deep dives into content? e.g., "In what ways does light act wavelike?"	Little differentiation is made between branch and subject TCs—these are collectively referred to as micro-TCs.	Most concept inventories are at the branch or subject level (i.e., the Electrical Engineering CI has 3 sub-assessments in fields, waves, and fields and waves)		Core Concepts (Branch)

Crosswalk of curricula that place concepts first, and how CCR compares. *Source*: CCR

Essential Content

When asked what teachers hope their students take away from their class, attendees at CCR keynotes around the world as well as teachers in CCR seminars rarely mention specifics of content. In the real world, any particular piece of content is available for search instantaneously. This leads to the question: What content is essential to include in a curriculum? To answer this, we must first look at the purposes of content.

If You Can Search Anything, Why Learn Anything?

Learning happens in a context, and over time it is generalized and abstracted, but isolated information found online cannot fully capture the context in many cases. Daniel Willingham[106] compares this to studying vocabulary words. Students are asked to use new words in sentences when they are learning them, in order to learn not just a definition, but how the word is used in context. When students simply look up synonyms online, they often end up using them incorrectly, such as saying "he meticulously balanced on the edge" (using the definition of "meticulous" to mean "careful"). The same reasoning, he argues, should be applied to all content learning. Just having the ability to look up a fact may not be enough to use and apply that fact properly.

Avoiding the Dunning–Kruger Effect[107]

One important use of knowledge is to guide us to what we don't know, and should learn more about. As adults, there is a critical mass of knowledge that we use to create a rough map of our understanding and its gaps. Actor John Cleese humorously explains the Dunning–Kruger effect as "if you're very, very stupid, how can you possibly realize that you're very, very stupid? You'd have to be relatively intelligent to realize how stupid you are." Without a minimum understanding of a subject

[106] Willingham, D. (2017). "You still need your brain" *Gray Matter*. http://nyti.ms/2rKoSPt

[107] Kruger, Justin; Dunning, David (1999). "Unskilled and unaware of it: How difficulties in recognizing one's own incompetence lead to inflated self-assessments." *Journal of Personality and Social Psychology*. 77 (6): 1121–1134.

area, the trap one is likely to fall into is not just ignorance (which can be cured with an internet search), but "meta-ignorance," ignorance about one's ignorance,[108] which can be far more pernicious.

For example, when reasoning about economic policies, citizens must implicitly estimate various economic realities in order to compare them to an ideal and consider possible changes. In a 2014 Gallup survey, 63% of Americans said they believed the crime rate was on the rise, despite the crime rate being at a 20-year low. Those who thought crime rates were rising were 8 percentage points less likely to support stricter gun control laws.[109,110]

If one doesn't know that their estimates are not representative of reality, they may not think to look up the true numbers. In fact, in this study, participants who identified with both major US political parties misrepresented the inequality in the same way and agreed on the ideal distribution. Factual information, therefore, serves a crucial role in one's ability to think critically and creatively.

In fact, having the ability to look things up may exacerbate the effect. In one study,[111] participants who were allowed to use Google to answer trivia questions perceived themselves as smarter than did those who were not allowed to use Google (even when the percent of questions answered correctly was artificially equalized).

Speed, Fluency, and Automaticity Used in Daily Life

There is a basic level of each discipline that is necessary for day-to-day living. For example, there is a level of understanding that is necessary for basic math fluency with constructs such as weight, temperature, and

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[108] Poundstone, W. (2016). *Head in the Cloud: Why Knowing Things Still Matters When Facts are so Easy to Look Up*. Little, Brown.

[109] Interestingly, 20 years prior, in 1994, people who thought crime rates were increasing were 9 percentage points more likely to support stricter gun laws, so there is some interaction with rhetoric.

[110] Kohut, A. (2015). "Despite lower crime rates, support for gun rights increases." Pew Research Center. http://www.pewresearch.org/fact-tank/2015/04/17/despite-lower-crime-rates-support-for-gun-rights-increases/

[111] Wegner, D.M., & Ward, A,F. (2013). "The internet has become the external hard drive for our memories." *Scientific American* 309 (6): 58–61.

money.[112] In neurotypical children this level is achieved without any concerted effort, but it is important to keep in mind which parts of the curriculum will be truly useful for all students' lives.

Part of a Shared Social Background

Consider giving directions to a local compared to a tourist. When speaking to a tourist, we naturally understand that we cannot rely on any shared information or assumptions, and take much more time to explain things that we otherwise would take for granted.[113] Similarly, news and media are not written in a way that explains every single idea; there is a collection of background information that is assumed and relied upon. E.D. Hirsch has worked to identify what content falls into this category for the U.S. (such as cholesterol, absolute zero) in his work on *Cultural Literacy*.[114] Although this list would need to be adjusted for people from various sub-communities and other cultures around the world, it is an important exercise and useful starting point.

Necessary for More Complex Concepts

Every complex concept is made up of smaller pieces of information, which require automaticity to reach the more complex understandings. While anyone can look up anything at any time, having to look up everything would slow down future learning and problem solving. For example, although one could look up any unfamiliar words, this process is distracting from reading. Generally, the more vocabulary one knows, the greater their reading comprehension.[115] This problem is exacerbated in settings where students have to process information in real-time, such

[112] Patton, J.R., Cronin, M.E., Bassett, D.S., & Koppel, A.E. (1997). "A life skills approach to mathematics instruction: Preparing students with learning disabilities for the real-life math demands of adulthood." *Journal of Learning Disabilities* 30: 178–187.
[113] Poundstone, W. *Head in the Cloud*.
[114] Hirsch Jr., E.D., Kett, J.F., and Trefil, J.S. (1988) *Cultural Literacy: What Every American Needs to Know*. Vintage.
[115] Schmitt, N, Xiangying J, and Grabe. W. (2011). "The percentage of words known in a text and reading comprehension." *The Modern Language Journal* 95 (1): 26–43.

as lectures or group works, and do not have the option to look things up at their own pace when they need to.

In such cases, a lack of fluency or automaticity (the combination of accuracy and speed) in low-level components can serve as a bottleneck to learning high-level concepts.[116] More broadly, research has shown that fluency "increases retention and maintenance of skills and knowledge, endurance or resistance to distraction and application or transfer of training."[117]

But learning a concept is usually not simply the process of amassing the smaller pieces of information that comprise it. This is the thinking behind the research exploring learning progressions: Mosher's *A Hitchhiker's Guide to Thinking about Literacy, Learning Progressions, and Instruction* notes, "curricula should be designed to provide students with a systematic exposure to increasingly complex meanings ... and grounding them in experiences with particular content and topics".[118] It may be that learning topics in a certain order or through a certain pathway will lead to the knowledge being represented and stored differently, and to serve as preparation for different types of future learning. Therefore, another reason some knowledge may be included in a curriculum is that it is part of a particularly effective learning progression.

Content as Substrate for Core Concepts

If the majority of what teachers want students to take away takes the form of concepts that can be applied to new situations, there is still a decision to be made about what content best illustrates the concepts, such that students learn them and are able to transfer that understanding. The context in which a particular concept is learned deeply affects the way it is structured in the learner's mind.[119]

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[116] Binder, C. (1993). "Behavioural fluency: A new paradigm." *Educational Technology*.

[117] Ibid.

[118] Mosher, F. (2017). *A Hitchhiker's Guide to Thinking about Literacy, Learning Progressions, and Instruction.* Consortium for Policy Research in Education. http://www.cpre.org/hitchhikers-guide-thinking-about-literacy-learning-progressions-and-instruction

[119] https://en.wikipedia.org/wiki/Situated_cognition

When content is organized in a curriculum, it is constructed as a progression with a scope and sequence. Based on this sequence, later elements can leverage understanding built earlier, and the curriculum can build to cover greater complexity over time efficiently. It is within the context of a curriculum that content elements take on a relative scope, in terms of what elements they tie together. According to Mosher's *Hitchhiker's Guide*, "curricula should be designed to provide students with a systematic exposure to increasingly complex meanings … and grounding them in experiences with particular content and topics." The same paper says, "no particular order of instruction is necessary, but we argue that picking a reasonable order across a school or school system (and even more widely if possible) is wise, and likely to be more effective than leaving the choice solely to individual teachers."

Therefore, when a concept is first introduced, it should be through an exemplar[120]—content that naturally demonstrates the concept, such that the student can internalize a set of intuitions. This means it is not merely an example, but it exemplifies:[121] it makes salient the features that are relevant to the concept. The exemplar content should be stable, accessible, and have minimal distracting properties.[122] Since each topic is full of information and what is signal for one concept is noise for another, this step often involves some amount of setting the stage and orienting students to the relevant features. By seeing the same concept through different content, the elements that are part of the deeper structure and the elements that are incidental to the context become apparent.[123]

After that, however, the concept should be explored in less straightforward contexts, with less scaffolding from the teacher. At this

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[120] This aligns with the use of the term in psychology: https://en.wikipedia.org/wiki/Exemplar_theory

[121] Elgin, C. Z. (2017). *True Enough*. MIT Press.

[122] Ibid.

[123] For example, Quilici, J.L., & Mayer, R.E. (1996). "Role of examples in how students learn to categorize statistics word problems." *Journal of Educational Psychology* 88 (1): 144–161. http://doi.org/10.1037//0022-0663.88.1.144 and Tenenbaum, J.B., Kemp, C., Griffiths, T. L., & Goodman, N.D. (2011). "How to grow a mind: statistics, structure, and abstraction." *Science* 331 (6022): 1279–85. http://doi.org/10.1126/science.1192788

stage, the particular topic might be an exemplar of a different set of concepts, but still be an instantiation of a concept that has already been introduced. As the word suggests, the topic is an instance of the concept, but being just one instance of many, it also has many other features. In other words, the topic is an example of the concept, but not an exemplar.

If the color red has been covered in the context of the color wheel as an exemplar, it may be useful to point out all of the things on the street that are red, (even though this topic—the reason you are on the street—may be the exemplar for learning cardinal directions). That the concept may not be salient (camouflaged, occluded, overshadowed, or a borderline case[124]) allows students to practice generalizing the concept and fine-tune their understanding.

This structure naturally makes use of one of the most robust findings of the learning sciences: interleaving information that should ultimately be integrated leads to more long-term learning than studying the information sorted into its natural categories.[125] Normally, this is applied to content, but in this case the explicit untangling of content and concepts leads to the inevitable grouping by content and thus interleaving of concepts.[126]

Finally, the concept can be an application to a conceptually distant topic. The challenge may be that the teacher does not explicitly prompt the application of the concept, more closely simulating real life scenarios, and/or that the concept is not salient in the context. In the example of teaching the concept of the color red, the application topic may not

[124] "Camouflaged: a tiger who blends into the surrounding jungle instantiates being striped but would in that circumstance be unlikely to exemplify stripedness. (It might, however, exemplify how stripes—even orange stripes—can camouflage in a jungle of green.)" "Occluded: a bald man wearing a hat is ill positioned to exemplify his baldness." "Overshadowed: the fearsome timbre of a lion's roar may block its effectively exemplifying its pitch." "Borderline case: even though a chartreuse fire hydrant is a vivid instance of greenness, its color is too close to yellow to be a good exemplar." In Elgin, C. Z. (2017). *True Enough*. MIT Press, 1–91.

[125] Rohrer, D. (2012). Interleaving helps students distinguish among similar concepts. *Educational Psychology Review*, 24(3): 355-367.

[126] Those who have had experience working with Spiral Curricula may recognize that this framework would fit well with the notion of revisiting concepts, but that is just one way of conceptualizing this underlying structure.

include anything that is red, but the student can learn to see that red is part of what makes orange and purple, which are in the application topic. By interweaving contexts that make salient different concepts, a scaffold for conceptual understanding can be constructed that enables complex concepts to be built up simultaneously and systematically, in a way that is likely to transfer to real life contexts. While this is the same process by which experts eventually gain this conceptual understanding, there is no reason that it can't also be explicitly and systematically used as a curriculum-design guideline for students.

This idea is discussed in The Inquiry Project in the context of always teaching more than one concept at a time: "One always is considering portions of several concepts (foregrounding some, backgrounding others), working on successive subconcepts, such as scale weight, each of which involves relations among parts of concepts, revisiting concepts and amplifying the subconcepts and contexts considered."[127]

Knowledge as Substrate for Competencies

Although we have not discussed competencies in detail in this book (please see *Four-Dimensional Education: The Competencies Learners Need To Succeed*[128] for further details), knowledge cannot be discussed completely in a vacuum. The perceived importance of teaching students how to think, how to learn, and how to apply socio-emotional skills, often overshadows discussions about which content should be taught in the first place. However, it is important to note that learning is highly situated and context-dependent, and competencies are thus best taught through some fitting content substrate, or medium.[129] And there is reason

[127] Wiser, M., Smith, C.L., Doubler, S., & Asbell-Clarke, J. (2009). "Learning progressions as a tool for curriculum development: Lessons from the Inquiry Project." Paper presented at the Learning Progressions in Science (LeaPS) Conference, June 2009, Iowa City, IA

[128] Fadel, C., Bialik, M., and Trilling, B. (2015). *Four-Dimensional Education: The Competencies Learners Need to Succeed.* Center for Curriculum Redesign.

[129] Garner, R. (1990). "When children and adults do not use learning strategies: Toward a theory of settings." *Review of Educational Research* 60 (4): 517–529.

to believe that some content may be better aligned for teaching some competencies than others.[130]

For example, it is unclear whether mathematics is a good vehicle for teaching critical thinking (as is often supposed) since the same features that make it very rigorous when mastered, make it difficult to grasp and thus practice for novices.[131] It may be that a more concrete domain, such as social studies, and a more accessible learning mechanism, such as debate, would be more effective. This points to the need for further research into proving/disproving the explicit and implicit claims of various disciplines regarding their role in the development of cognitive competencies.

Modernized Knowledge

When choosing content to include in a curriculum, it is important to make sure that it is not outdated. This is challenging for a few reasons.

First, consensus on facts changes as more information is gathered, and observing the aggregate scale, there can be said to be a predictable rate of decay of facts within a given discipline.[132] Therefore, even if one could learn all of the most relevant facts, as their life continues, a growing fraction of that knowledge will become incorrect. Learning is never finished; it is always setting up a foundation for future learning.

Second, the types of jobs available are changing. Forecasting new professions has always been a difficult endeavor since the tendency to think linearly prevails, and discontinuities in progress, and thus needs, cannot be forecast. Some accounts conclude that automation is fundamentally changing the workforce by eliminating jobs, while others conclude that automation creates almost as many jobs as it replaces.

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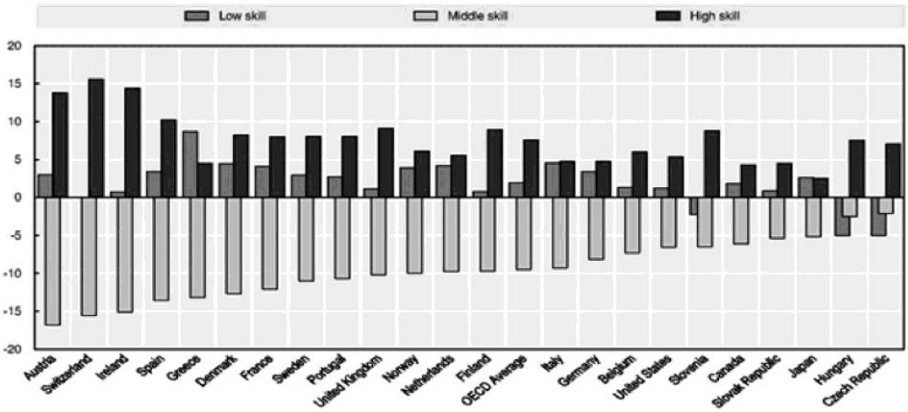
[130] Lehman, D.R., Lempert, R.O., & Nisbett, R.E. (1988). "The effects of graduate training on reasoning: Formal discipline and thinking about everyday-life events." *American Psychologist* 43 (6): 431–442.

[131] Bialik, M., & Kabbach, A. (2014). "Mathematics for the 21st Century: What should students learn? Paper 4: Does mathematics education enhance higher-order thinking skills?" *Center for Curriculum Redesign.*

[132] https://en.wikipedia.org/wiki/Half-life_of_knowledge and, in particular, Thierry Poynard's article in *Annals of Internal Medicine* 136: 888.

Regardless, the types of jobs available to workers worldwide look different today than they did 20 years ago.[133]

Looking at the change in the types of jobs held by workers from 1995–2015 in the figure below, the polarization of jobs is apparent. The number of high-skill jobs (i.e. managerial and professional) and to a lesser extent low-skill jobs (service and retail) is increasing while middle-skill jobs (trade work, machine operation, and assembly) are disappearing. Given these trends, there is ever-greater urgency to help students to build a strong foundation for complex content areas, and to prepare them for the situation that they will need up-skilling during their lifetimes.



Job polarization by country: Percentage point change in share of total employment, 1995 to 2015. Across all countries, the number of middle-skill jobs (gray) decreased by an average of about 10%. High-skill jobs (dark gray) increased by about 8% and low skill jobs (light gray) increased by about 2% on average. *Source*: OECD

Specifically, tasks that involve predictable physical work, data processing, and data collection are the most susceptible to being automated, while also accounting for about 50% of all work activity in the US.[134] The jobs least likely to be automated are those that require expertise, interacting with other people, and in particular, management

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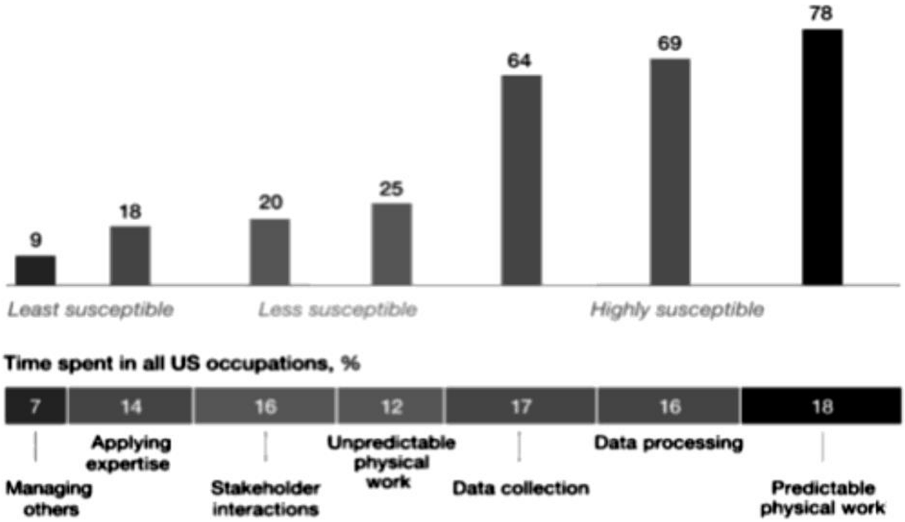
[133] OECD. (2017). OECD Digital Economy Outlook 2017, OECD Publishing. http://dx.doi.org/10.1787/9789264276284-en

[134] Chui, M., Manyika, J. and Miremadi, M. (2016). "Where machines could replace humans—and where they can't (yet)." *McKinsey Quarterly*. https://www.mckinsey.com/business-functions/digital-mckinsey/our-insights/where-machines-could-replace-humans-and-where-they-cant-yet

skills. This makes intuitive sense, since algorithms will take over the most rote tasks first, people will need to manage these computers just as they managed those tasks when humans were performing them.



Top chart: Percent of time spent on activities that can be automated by adapting currently demonstrated technology. Bottom chart: Percent of time spent in all US occupations. *Source*: McKinsey

Third, it is important to consider the larger trends taking place. The world is changing at an increasing rate along multiple fronts: technology, environment, globalization, and advances in our understanding, which ought to change the content that should be included in the curriculum. Ideally, education reform would minimize the lag between human progress and preparation for people to enter the changing landscape of the workforce, society, and life. Each of these will require different content areas to be added to the now outdated curriculum, and various updates to be made to the focus of what students ought to take away from those content areas.

These trends will affect what is important in the entire range of ways of making meaning and can be summarized into the following major changes:

1. Technology: Trends that are forecast to be particularly transformative are: [135]
    a. The rise of smart machines and systems (robotics etc.).
    b. Massive data and new media (big data, social networks/media, etc.).
    c. Amplified humans (artificial intelligence, robotics, gene editing, etc.).
2. Environment: Climate change is a new and large-scale challenge, whose stresses and demands must be addressed.[136]
3. Globalization: People and organizations are increasingly interconnected, and creating previously unforeseen emergent patterns.[137]
4. Social Unrest: With greater inequality, polarization, distrust and large-scale changes, there is global social unrest that must be addressed.
5. Advances in the disciplines: Curriculum often fails to include new findings due to already being full; it should be updated to include the important recent discoveries.

One way to capture these changes is through the six realms of meaning mentioned earlier. Each of the realms roughly encapsulates a set of disciplines, making it a simple way to make sure that the full range of content is considered. Cross-referencing these two sets of categories produces a table that illustrates the types of topics or disciplines that need to be emphasized or added wholesale. The following table illustrates some examples at their appropriate intersections.

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[135] Davies, A., Fidler, D., Gorbis, M. (2011). "Future work skills 2020." *Institute for the Future.*
[136] Ibid.
[137] Ibid.

Major Change / **Realm of Meaning ↓**	**Technology**	**Environment**	**Globalization**	**Social Unrest**	**Advances in the Fields**
Symbolic	Statistics, Big Data, Programming.	Data Analysis, Modeling.	Natural Language Processing for translation, International law, International economics.	Political Science, Social Justice Theory, Philosophy, Law.	Game Theory, Logic.
Empiric	Robotics, Engineering, Household electronics.	Solar Panels, Wind Turbines, Climate Change.	Natural language processing for different languages.	Information Literacy for Social Science.	Quantum Physics.
Aesthetic	Private vs. Public Self-Image.	Appreciation of nature's beauty, landscape art.	Developing taste for different cultures (food, art, music, way of life, etc.).	Exposure to inner life of humans different from ourselves.	New Media; New art movements.
Personal	Social Media, Communication, Marketing.	Awareness of ecological footprint, citizenship and activism.	Entrepreneur-ship, Cultural sensitivity.	Practice proper debate, based on understanding, community organizing.	Wellness.
Ethical	Autonomy and accountability as we become more merged with machines; Distributed Trust.[138]	Leaving the earth better than we found it for future generations.	Cultural sensitivity.	Clear ethical framework regardless of tribe.	Moral Psychology.
Integrative	Triangulating sources.	Interconnected systems (economics, ecological, psychological, etc.) work together to create the large-scale trends we find ourselves in.	Multiple perspectives, e.g., international view on the history of intellectual discovery.	Integrating different perspectives on social issues.	Post-modernism and reactions to it.

[138] Botsman, R. (2017). *Who Can You Trust: How Technology Brought Us Together and Why It Might Drive Us Apart*. PublicAffairs.

What Content Should be Added

In order to reflect the changes that are occurring in society, it is important to add modern disciplines, branches, subjects, and topics where appropriate, and not be constrained by inertia. Currently, these disciplines have been crowded out by the traditional disciplines, and yet they are becoming increasingly useful and deserving of space in the curriculum. Below is a (non-exhaustive) list of modern content areas that should be integrated into curriculum, as they are now widespread in use and in importance.

Technology and Engineering

This includes computer science, in particular: coding, robotics and artificial intelligence; bioengineering, in particular, genome editing and synthetic biology; as well as advanced manufacturing including CAD, 3-D printing.

Media

The changes that the internet has made to society have just begun, and already they have been transformative. Everyone constantly consumes and creates media, and this has become inextricable from the social world. And yet, no one is taught how to properly and healthily use this media. Curricula must change to keep up. This includes journalism, including the different forms it is now beginning to take, and audio/video. If everyone can make a video about anything, what does this mean to interact with this world in a productive way? How can one discover their voice?

Entrepreneurship and Business

As jobs continue to become more polarized by the skill levels they require, as the landscape of what is needed in the workforce continues to change, and as the economy nevertheless continues to grow, students will need to be prepared to take advantage of opportunities that present themselves throughout their lives. It is often no longer enough to find a job out of college and work there until retirement. Students must be prepared to approach their careers from a business perspective.

Personal Finance

As jobs become less stable and opportunities become more varied, while the laws are becoming more complex, and personal debt continues to grow, those entering the workforce need to have some preparation on how to organize their financial lives. This is perhaps the most applicable knowledge students will learn, and is relevant to all students.

Wellness

Rather than only treating problems when they become a serious issue, students should be taught how to proactively take care of themselves mentally, emotionally, and physically. This has come to be known as *wellness* and is a very broad category, and often spanning some sort of space from physical education to health education. In a society with problems like depression, anxiety, obesity, and chronic back pain, students should be informed and empowered to keep themselves well. They should also be taught about interpersonal wellness—what constitutes emotional or psychological abuse, how to navigate relationships, and be given practice developing their own foundation of emotional awareness.

Social Sciences

The social sciences study humans as their topic, but use systematic methods to do so. This may include sociology, anthropology, psychology, political science, future studies, civics, etc. This area of research has not only made great advances and become very important in many professions that deal with humans, but it also entails an important and unique way of making meaning of the social world. The world students need to be prepared for is increasingly interpersonal, and the social sciences address these topics.

Naming the disciplines, branches, subjects, and topics that may become more relevant due to the trends in progress is only the first step.

As this material gets integrated it will be necessary to identify the core concepts and an effective scope and sequence through them. It is also important to note that while modern disciplines need to be added, this does not mean that traditional disciplines must be abandoned. Adding modern disciplines can be an act of consolidation, as the important concepts from previously separate subjects may unite new and old material, while strengthening and deepening the potential for understanding.

What Content Should be Removed

The method of consolidating does, however, also mean that some content must be removed. The redesigned curriculum should be more efficient, doing more with less, as discussed above. In many ways, the curriculum has been extremely stagnant, even since ancient times (See appendix 1). It is an important part of the redesign process to comb through the content of the curriculum and remove anything that is obsolete, or redundant and not an efficient use of time. This is often the hardest part, since it may feel risky to remove something that has been present for so long and is present in so many other curricula (and when done well, may be useful as an example of a concept). According to Perkins, "Curriculum suffers from something of a crowded garage effect; it generally seems safer and easier to keep the old bicycle around than to throw it out."[139] But the point of the curriculum, as discussed, is not to cover as much content as possible. Without this process of removal, change cannot happen.

Non-Disciplinary Structures

So far the discussion of curriculum structure has been under the assumption that disciplines are relatively distinct, as is their teaching. However, this does not have to be the case.

Disciplines have been a convenient way of organizing knowledge, but if change is to happen and deep, relevant, transferrable concepts are to be

[139] Perkins, *Future Wise.*

learned, it is likely that a less discipline-focused approach will be needed. After all, if the most important things about knowledge are its relational qualities—mapping ideas and activating resources—more relationships across more disciplines will be a powerful way to bolster mental models of concepts (as well as consolidate content). For instance, exponentials (from mathematics) can be taught alongside compound interest (from finance) and financial bubbles (history, sociology), as well as bacterial growth (biology) and resource exhaustion (environmental literacy).

Additionally, interdisciplinary approaches can be a powerful motivational tool, as students may explore different contexts, meanings, and applications of concepts, and find angles they are personally curious about. This allows students to be guided by intrinsic motivation, or interest, rather than extrinsic motivation like grades or performance.

A report issued by the National Academy of Sciences[140] in the United States identifies four primary drivers of interdisciplinarity today:

1. The inherent complexity of nature and society.
2. The desire to explore problems and questions that are not confined to a single discipline.
3. The need to solve societal problems.
4. The power of new technologies.

Accordingly, the interest in interdisciplinarity and its analogues has rapidly emerged since the 1960s.

Trends in articles with the term "interdisciplinary" in the title 1990–2007. *Source*: Jacobs, Jerry, and Frickel

[140] National Academy of Sciences (2004). *Facilitating Interdisciplinary Research*. Washington, DC: National Academies Press, 2, 40.

Interdisciplinary studies is now a major area of study, and interest in it continues to grow as the preceding charts show. In order to get a more clear sense of the entire landscape of knowledge and how disciplines relate to one another fluidly, it may be possible to make use of new analysis and imaging tools, such as what is discussed in the first half of this book.

Embedding Interdisciplinary Themes in Curriculum Design

Running through disciplines are crosscutting themes, which can be drawn from as a source of examples for any disciplinary content. These can be applied to any other body of knowledge, as a way of seeing it in a particular perspective with its particular focal points.

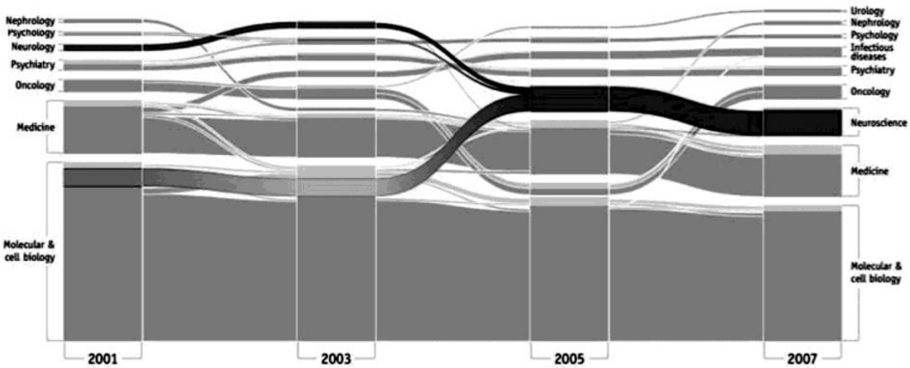
As discussed earlier, these are often thought of as different types of literacies, which naturally convey the ideas of "knowing with" and preparing for future learning. In this sense, they are at the same scale as disciplines, but inherently trans-disciplinary. Like disciplines, they each have their own set of core concepts, which encapsulate the habits of mind that each theme comprises. CCR has identified the following as fruitful themes (See appendix 1 for a deeper discussion of each):

- Environmental Literacy
- Global Literacy
- Civic Literacy
- Information Literacy
- Digital Literacy
- Systems Thinking
- Design Thinking
- Computational Thinking

These are simply important categories to consider when designing curriculum to develop knowledge that will be useful across disciplines. Like disciplines, each lens would have its own set of core concepts that students would be expected to internalize, through a range of different sources of content.

Changes in Disciplines

The exact connections and lines between disciplines are always shifting, if slowly. Over time, disciplines branch to create subfields and merge to create interdisciplinary fields. For example, in the following image,[141] the field of neuroscience emerges as a synthesis of molecular & cellular biology, psychology, and neurology, whereas urology emerges as a subfield that splinters off of medicine.



The emergence of neuroscience as a discipline.
Source: Roswall, Martin, and Bergstrom

By disregarding the directionality of time, all disciplines can be conceived of as interdisciplinary, either because they are at the root and thus contribute to other disciplines,[142] or because they are composites of other disciplines. Newer disciplines tend to be in some ways composite of older disciplines (for example, optogenetics comprises optics, neuroscience, and genetics) or they may be sub-disciplines, splintering off from existing ones (such as civil engineering).

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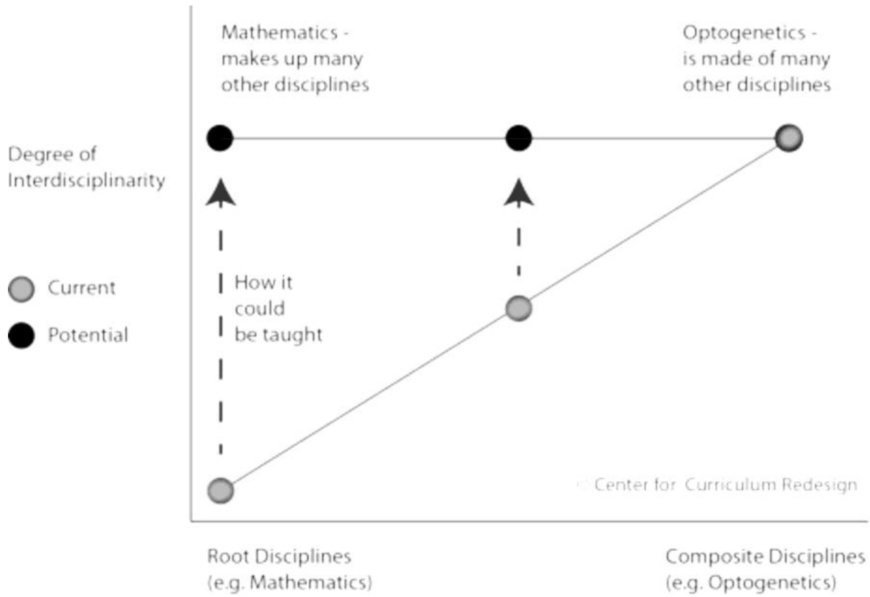
141 Rosvall, M., and Bergstrom, C.T. (2010). "Mapping change in large networks." *PloS ONE 5.1*. https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0008694

142 Crease, R.P. (2010). "Physical Sciences." In *The Oxford Handbook of Interdisciplinarity*.



Interdisciplinarity in all disciplines, root and composite.
Source: CCR

Curricula tend to focus on root disciplines (especially under pressure, such as assessments that test root disciplines in isolation). The goal then becomes to teach more of the newer interdisciplinary subjects, and to highlight the interdisciplinarity in the root disciplines.

Interdisciplinarity is likely to become more viable as curricula place concepts at the center, and content is designed to serve those more abstract elements, to achieve transfer. In that case, examples can be chosen deliberately, preparing students for learning across disciplinary lines.

Practical Considerations

There are three options for how to redesign the curriculum's treatment of disciplines:

1. Traditional: Disciplines are organized into departments directly, and modern disciplines are simply added either as units to their related discipline, or as an elective.
2. Hybrid: Disciplines are intact, but the departments are novel categorizations. These can be Themes or Realms of Meaning as discussed earlier in the document.
3. Redesigned: Disciplines are no longer the organizational backbone of the curriculum and classes are mostly on hybrid topics, such as systems thinking. This makes adding new disciplines natural.

The route each school chooses to go will be a result of their goals, capabilities, buy-in, pressures, and so on. Even a traditional organizational structure can go quite a long way toward teaching interdisciplinarity through projects and the interconnectedness of core concepts. However, the exact organizational structure is not as important as aiming for a robust and flexible understanding of the fundamentals, by identifying the essential content and core concepts and structuring learning experiences around them.

Decision Making

One of the main tensions with organizing curriculum is the level at which the various decisions are made. At the highest level are disciplinary experts and policymakers, followed by curriculum designers, then teachers, and finally students. It is possible to completely prescribe all elements, or to leave all elements completely up to the students, and of course, most organizations fall somewhere in between. The particular configuration of responsibility depends on the constraints and preferences of a given jurisdiction, but they should be made explicit[143] and used as a guideline for appropriate division of labor and corresponding expectations and communication channels.

Conclusion

Once the levels of core concepts have been established, the particular pieces of content must be considered for inclusion or exclusion, one by one.[144] There should be no content that does not serve concepts. Most content will exemplify a specific concept that has a high potential for being leveraged to understand many aspects of the world. It should also serve as a good instantiation or application of concepts that are exemplified elsewhere.

In addition to serving concepts, content across all levels of primary and secondary education should be:

1. Modernized with the addition of new disciplines and new approaches to old disciplines, including interdisciplinarity.
2. Systematically increasing in complexity so that as students learn more they are asked to make more and broader.connections to increasingly abstract (but relevant) concepts.
3. A substrate for teaching competencies which include skills, character, and meta learning.

The goal is to rid the curriculum of obsolete, irrelevant information, while simultaneously modernizing, systematically sequencing, and infusing the content with competencies. Students should learn the useful ways of seeing the world developed by different disciplines, as well as particularly important topics and discoveries within and across the disciplines. In other words, the goal is to maximize the potential for making meaning in the curriculum. This is not just so that students find school more enjoyable, but also to make their learning more useful to

[143] Bialik, M. & Fadel, C. (2017). "Overcoming system inertia in education reform." Center for Curriculum Redesign. https://curriculumredesign.org/wp-content/uploads/Inertia-in-Education-CCR-Final.pdf
[144] In practice, this process will likely be more iterative than we suggest here.

them later in life. Without meaning, a structure of understanding is not built, and learning does not get internalized in a way that applicable outside of its original context.

This idea can be exemplified through an analogy to learning to play an instrument. There is nothing wrong with beginning with drilling scales, as long as more meaningful learning takes place not long afterwards. It is possible to get sucked into the minutiae of music and never get to the meaning of it, just as it is possible to get sucked into any other minutiae. In this excerpt from *A Mathematician's Lament*,[145] a dystopian world is described where music is taught the way math is taught now:

> Since musicians are known to set down their ideas in the form of sheet music, these curious black dots and lines must constitute the "language of music." It is imperative that students become fluent in this language if they are to attain any degree of musical competence; indeed, it would be ludicrous to expect a child to sing a song or play an instrument without having a thorough grounding in music notation and theory. Playing and listening to music, let alone composing an original piece, are considered very advanced topics and are generally put off until college, and more often graduate school. As for the primary and secondary schools, their mission is to train students to use this language—to jiggle symbols around according to a fixed set of rules: "Music class is where we take out our staff paper, our teacher puts some notes on the board, and we copy them or transpose them into a different key. We have to make sure to get the clefs and key signatures right, and our teacher is very picky about making sure we fill in our quarter-notes completely …"

To avoid mistreating other subjects like this, it is important that each piece of curriculum is there for a reason, and that meaning is never too far away. Students can continue to practice scales and notation, even as they begin to play solo pieces, play pieces as part of an orchestra, compose their own pieces, and even learn to improvise. Ultimately, they are never going to need to play a perfect scale (or the equivalent in

[145] Lockhart, P., *A Mathematician's Lament.*

another subject) but they are going to rely on the automaticity of their scales in order to do higher level processes such as composition and improvisation. It is therefore crucial that meaning is the primary concern, and all else is in service of that, as that is what will effectively get internalized and prepare students for the future, whatever it may hold.

Part Two
The How: Promises and Implications of AI for Teaching and Learning

Seldom a day goes by without at least a mention in the news or entertainment media of AI. Perhaps an AI program has just beaten the world's leading player in a complex strategy game; perhaps a new Hollywood feature film depicts a dystopian future in which robots have overtaken the world; or perhaps a pair of leading tech entrepreneurs have a public disagreement.[146]

> I have exposure to the very cutting-edge AI, and I think people should be really concerned about it. … AI is a rare case where we need to be proactive about regulation instead of reactive. Because I think by the time we are reactive in AI regulation, it's too late.
>
> —Elon Musk

> I think people who are naysayers and try to drum up these doomsday scenarios … I just, I don't understand it. It's really negative and, in some ways, I actually think it is pretty irresponsible.
>
> —Mark Zuckerberg

In fact, as the exchange between Mark Zuckerberg (Facebook) and Elon Musk (SpaceX, Tesla) suggests, the future impact of AI remains very unclear (indeed, is artificial intelligence little more than the latest technical hype?).[147] Nevertheless, investments and developments continue to grow exponentially, such that AI has become an integral, pervasive and inescapable, although often hidden, part of our daily lives:

[146] E.g., https://www.nytimes.com/2018/06/09/technology/elon-musk-mark-zuckerberg-artificial-intelligence.html

[147] "Highly-publicized projects like Sophia [http://www.hansonrobotics.com/robot/sophia] [try to] convince us that true AI—human-like and perhaps even conscious— is right around the corner. But in reality, we're not even close. The true state of AI research has fallen far behind the technological fairy tales we've been led to believe. And if we don't treat AI with a healthier dose of realism and skepticism, the field may be stuck in this rut forever." Dan Robitzski quote (2018) at https://futurism.com/artificial-intelligence-hype

from Siri[148] to auto-journalism,[149] from forecasting stock movements[150] to predicting crime,[151] from facial recognition[152] to medical diagnoses[153] and beyond.

But of particular interest here, artificial intelligence has also quietly entered the classroom.[154] Whether students, teachers, parents and policy makers welcome it or not, so-called intelligent, adaptive, or personalized learning systems are increasingly being deployed in schools and universities[155] around the world, gathering and analyzing huge amounts of student big data, and significantly impacting the lives of students and educators.[156] However, while many assume that artificial intelligence in education (AIED) means students being taught by robot teachers, the reality is more prosaic yet still has the potential to be transformative. Nonetheless, the application of AI to education raises far-reaching questions.

> We should ask what happens when we remove care from education.... What happens to thinking and writing when... the whole educational process is offloaded to the machines—to "intelligent tutoring systems," "adaptive learning systems," or whatever the latest description may be? What sorts of signals are we sending students?
>
> —Audrey Watters[157]

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148 https://www.apple.com/uk/ios/siri

149 E.g., https://www.washingtonpost.com/pr/wp/2018/06/12/the-washington-post-plans-extensive-coverage-of-2018-midterm-elections/?utm_term=.e66d88e4a716

150 E.g., https://equbot.com

151 E.g., http://www.predpol.com

152 E.g., https://www.cbp.gov/newsroom/national-media-release/cbp-deploys-facial-recognition-biometric-technology-1-tsa-checkpoint

153 E.g., https://www.babylonhealth.com

154 Luckin, R., et al. (2016). *Intelligence Unleashed. An Argument for AI in Education*. Pearson. https://www.pearson.com/content/dam/one-dot-com/one-dot-com/global/Files/about-pearson/innovation/Intelligence-Unleashed-Publication.pdf

155 "The time-to-adoption for adaptive learning technologies and artificial intelligence is estimated within two to three years, acknowledging the advances in these technologies and their promise to positively impact teaching and learning." Becker, S.A., et al. (2018). "Horizon Report: 2018." *Higher Education Edition 2*.

156 Holmes, W., et al. (2018). *Technology-Enhanced Personalised Learning. Untangling the Evidence*. Robert Bosch Stiftung.

157 http://hackeducation.com/2015/08/10/digpedlab

In fact, AI technologies have been researched in educational contexts for around fifty years.[158] More recently, companies as influential as Amazon, Google and Facebook have invested millions of dollars[159] developing AIED products, joining well-established multimillion dollar-funded AIED companies such as Knewton[160] and Carnegie Learning,[161] while the $15 million Global Learning XPrize[162] called for software that empowers children to take control of their own learning (AIED by another name). Meanwhile, AI is being introduced into some mainstream schools as a curriculum in its own right,[163] is being developed to improve online tutoring,[164] and is being researched as a way of enhancing teacher training.[165] In short, the application of AI in educational contexts is growing exponentially,[166] such that by 2024 it is predicted to become a market worth almost $6 billion.[167]

While we may have some limited knowledge or experience of mainstream AI, either from the media or in our daily lives, for many the use of AI in education remains a mystery. A multitude of yet-to-be-answered questions spring to mind. How exactly can AI work in classrooms, and what can be achieved? With AI requiring so much data, how is student privacy maintained? What will be AI's long-term effects on teacher roles? Are the proponents of AIED promising more than can

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158 Woolf, B. (1988). "Intelligent tutoring systems: A survey.' In *Exploring Artificial Intelligence*: 1–43; Cumming, G., and McDougall, A. (2000). "Mainstreaming AIED into education?" *International Journal of Artificial Intelligence in Education* 11: 197–207; du Boulay, B. (2016). "Artificial intelligence as an effective classroom assistant." *IEEE Intelligent Systems* 31 (6): 76–81. https://doi.org/10.1109/MIS.2016.93

159 https://www.linkedin.com/pulse/tech-giants-quietly-invest-adaptive-learning-system-rd-drew-carson

160 http://www.knewton.com

161 http://www.carnegielearning.com

162 https://learning.xprize.org

163 http://www.gettingsmart.com/2018/07/coming-this-fall-to-montour-school-district-americas-first-public-school-ai-program

164 Following a $300m investment, the Chinese online tutoring company Yuanfudao has set up a research institute for artificial intelligence, which aims to train its homework app to be smarter. https://techcrunch.com/2018/12/26/yuanfudao-raises-300-million/

165 O'Connell, S. (2018). "New Project Aims to Use Artificial Intelligence to Enhance Teacher Training." Center for Digital Education. http://www.govtech.com/education/higher-ed/New-Project-Aims-to-Use-Artificial-Intelligence-to-Enhance-Teacher-Training.html

166 https://www.eschoolnews.com/2017/05/22/brace-ai-set-explode-next-4-years

167 https://www.gminsights.com/industry-analysis/artificial-intelligence-ai-in-education-market

be delivered? What is the impact of AI on student agency and outcomes? And what are the social and ethical consequences?

However, we begin with a tentative response to an ostensibly simpler question: what does AIED actually look like?

AI in Education

As a brief review of AIED conference and journal papers will confirm, AIED includes everything from AI-driven, step-by-step personalized instructional and dialogue systems, through AI-supported exploratory learning, the analysis of student writing, intelligent agents in game-based environments, and student-support chatbots, to AI-facilitated student/tutor matching that puts students firmly in control of their own learning. It also includes students interacting one-to-one with computers, whole-school approaches, students using mobile phones outside the classroom, and much more besides. In addition, AIED can also shine a light on learning and educational practices.

The field of AIED is both derivative and innovative. On the one hand, it brings theories and methodologies from related fields such as AI, cognitive science, and education. On the other hand, it generates its own larger research issues and questions: What is the nature of knowledge, and how is it represented? How can an individual student be helped to learn? Which styles of teaching interaction are effective, and when should they be used? What misconceptions do learners have?[168]

While AIED tools necessarily instantiate specific learning theories (such as Gagné's "instructionalism"[169] or Vygotsky's "zone of proximal development"[170]), some AIED researchers question the assumptions behind those theories, applying AI and data analysis techniques to try to open the "black box of learning."[171] In other words, AIED effectively

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[168] Woolf, B.P. (2010). *Building Intelligent Interactive Tutors: Student-Centered Strategies for Revolutionizing e-Learning*. Morgan Kaufmann, 11.

[169] Gagné, R.M. (1985). *Conditions of Learning and Theory of Instruction, 4th Revised Edition*. Wadsworth Publishing Co Inc.

[170] Vygotsky, L. S. (1978). *Mind in Society: Development of Higher Psychological Processes*. Harvard University Press.

[171] Luckin, R., et al. *Intelligence Unleashed. An Argument for AI in Education*.

involves two main complementary strands: developing AI-based tools to support learning, and using these tools to help understand learning (how learning happens and other questions that have long been investigated by the learning sciences, and which might be applied in classrooms whether or not AI is being used). For example, by modeling how students go about solving an arithmetic problem and identifying misconceptions that might have been previously unknown to educators, researchers and teachers can begin to understand much more about the process of learning itself, which might then be applied to mainstream classroom practices.

In fact, new AIED applications and approaches, addressing old and newly identified problems, are being researched and released all the time—such that, what AIED looks like and can do is still emerging. Accordingly, here we adopt an alternative approach. Rather than trying to define AIED, within some relatively easy-to-identify broad areas we will discuss a wide range of AIED examples—existing AIED tools and AIED tools that might be available in the not-too-distant future.

What this book does not include, but what might nonetheless have a major impact on education, is the use of AI to support school and university administrative functions such as class timetabling, staff scheduling, facilities management, finances, cybersecurity, safety and security. Instead, we focus on the use of AI to support learning, what might be called the academic (or system-facing) functions of AIED.

However, before doing so, it will be helpful to have at least a working understanding of AI itself.[172] That is where we go now, before returning to look in more detail at how AI works in educational contexts. We conclude by considering the various challenges, pragmatic and ethical, from the perspectives of AIED researchers and developers, as well as of educators, students, funders and policy-makers.

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[172] It has been argued that "Artificial Intelligence should be accessible to all of us, even without a math background." https://www.youtube.com/watch?v=LqjP7O9SxOM&list=PLtmWHNX-gukLQlMvtRJ19s7-8MrnRV6h6

The Background of AI

AI is one of those aspects of modern life about which most of us have some awareness, and yet recognize we have little knowledge.[173] In fact, for many AI is synonymous with humanoid robots,[174] which might be because news about AI is almost always illustrated with a picture of a robot or a digital brain. However, while robotics (embodied AI, that can move and physically interact with the world) is a core area of AI research, AI is being applied in many different ways and different contexts. Meanwhile, the dystopian images of futuristic robots remain firmly in the realm of science fiction (which is why for the most part we leave robotics well alone). In the next few pages, we provide a brief background to artificial intelligence; interested readers will find more information about the origins and development of AI and its various techniques in appendix 2.

However, first, we should acknowledge that the very name artificial intelligence is sometimes seen as unhelpful. Instead, some researchers prefer augmented intelligence, which retains the human brain as the source of intelligence, and positions the computer and its programs as a sophisticated tool with which humans might enhance or augment our intellectual capabilities. In this approach, computers are employed to do what humans find more difficult (such as finding patterns in huge amounts of data). The debate contrasting augmented and artificial will inevitably run and run, with artificial intelligence winning at least on popular usage even if augmented intelligence is more accurate or useful. Accordingly, hereafter we will take the ultimate pragmatic approach and refer almost exclusively to AI, leaving the reader to decide for themselves what the A in AI represents.

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173 E.g., "What is artificial intelligence?" https://www.brookings.edu/research/what-is-artificial-intelligence

174 The question "When you think of AI, what is the first thing that comes into your head?" has been posed in numerous lectures and surveys about AI in education. The evidence is anecdotal, but overwhelmingly participants answer: robots.

A 1956 workshop held at Dartmouth College, a US Ivy League research university, is widely considered to be AI's foundational event.[175] It was where what is thought to be the first AI program, the Logic Theorist, was presented and discussed. Over the following decades, AI developed in fits and starts with periods of rapid progress (for example, rule-based expert systems) interspaced with periods known as AI winters where confidence and funding all but evaporated.

In recent decades, thanks to three key developments (the advent of faster computer processors, the availability of large amounts of big data, and advances in computational approaches) AI has entered a period of renaissance—AI has now become an integral, pervasive, and inescapable, although often hidden, part of our daily lives. In fact, paradoxically, the more that it is integrated, the less we tend to think of it as AI.

> A lot of cutting edge AI has filtered into general applications, often without being called AI because once something becomes useful enough and common enough it's not labeled AI anymore.[176]

Instead, AI is often known as an advanced computer program (such as email spam filtering),[177]a personal assistant (such as Cortana),[178] a recommendation system (such as in Netflix),[179] or perhaps a language-learning app (such as Duolingo).[180] Having said that, recent voice-activated smart speakers, such as Google Home[181] and Amazon Echo,[182] have made AI more visible in our living rooms. In fact, many recent developments in AI are both groundbreaking and in many ways transformative. Relatively recent AI computational approaches, such as

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175 Crevier, D. (1993). *AI. The Tumultuous History of the Search for Artificial Intelligence*. Basic Books.

176 http://edition.cnn.com/2006/TECH/science/07/24/ai.bostrom/index.html (Professor Nick Bostrom, director of the Future of Humanity Institute, University of Oxford).

177 E.g., https://www.mailwasher.net uses Bayesian techniques to learn which emails are spam and which are not.

178 https://www.microsoft.com/en-us/cortana

179 https://help.netflix.com/en/node/9898

180 https://www.duolingo.com

181 https://store.google.com/gb/product/google_home

182 https://www.amazon.com/b/?ie=UTF8&node=9818047011

machine learning (supervised, unsupervised, and reinforcement learning), neural networks (including deep learning), and evolutionary algorithms have all been used in a diverse range of applications (interested readers will find more information about these techniques in appendix 2).

For example, recent advances in face recognition (ensuring that faces in smartphone photographs are always in sharp focus, and identifying travelers at e-passport gates) are thanks to the application of neural networks and machine learning. Google researchers presented a brain-inspired AI neural network with 10 million randomly selected video thumbnails from YouTube.[183] By using deep-learning techniques, and despite not being told how to recognize anything in particular, this machine learning system soon learned how to detect human faces in photographs. Two years later, Facebook introduced a nine-layer deep AI neural network, involving more than 120 million parameters, to *identify* (not just detect) faces in timeline photographs.[184] It was trained on a dataset of four million images of faces that had previously been labeled by humans (the Facebook users, who had been happily labeling their friends in uploaded photographs over several years).

Another area that has seen much AI development in recent years is autonomous vehicles, with neural networks being used to enable cars, trucks, and taxis to drive without human intervention. A complex rig of cameras and sensors collate massive amounts of real-time data (the road's edges and markings, road signs and traffic lights, other vehicles including bicycles, other potential obstacles, and pedestrians), while a neural network-driven intelligent agent, drawing on massive of computing power, controls the car's steering, acceleration, and braking. A probably less well-known use of AI is in journalism. News organizations around the world are developing AI technologies to support their news gathering and news reporting. For example, AI agents continually monitor global

[183] https://www.nytimes.com/2012/06/26/technology/in-a-big-network-of-computers-evidence-of-machine-learning.html?_r=1

[184] Facebook introduced a nine-layer deep AI neural network, involving more than 120 million parameters, to identify (not just detect) faces in timeline photographs. It was trained on a dataset of four million images.

news outlets and use semantic analysis to automatically extract key information that is made available to the journalists to write their stories.[185] There are even some AI technologies that go one step further and automatically write the stories themselves.[186]

Another application of AI is in law, where e-Discovery tools are being used by lawyers to help process the huge amounts of documentation that need to be reviewed as potential evidence in civil or criminal legal cases.[187] One technique involves a machine learning analysis of a sample of documents that have been reviewed and labeled by an expert. The outcomes enable the AI to then identify which of the remaining documents need to be prioritized for in-depth review. A final brief example is the use of AI in medical diagnoses. For example, AI techniques are used by radiologists to help them identify anomalies in medical images more quickly while making fewer mistakes.[188] One system looks for irregularities in X-ray images. If, for example, it finds nodules on an image of a pair of lungs, it sends it to a pulmonary radiologist for further checks.

AI Techniques and Terminology

While it is relatively straightforward to understand what the applications of AI outlined in the previous section are doing, understanding how they are doing it can require some highly technical knowledge—exacerbated by the fact that any one AI application might draw on several different AI techniques. This is one reason why many people involved in AI have advanced degrees in mathematics or physics (although AI is increasingly being offered as a service: for example, Amazon's Machine Learning on AWS,[189] Google's TensorFlow,[190] IBM's Watson,[191] and Microsoft's

185 E.g., http://bbcnewslabs.co.uk/projects/juicer
186 E.g., https://narrativescience.com/Products/Our-Products/Quill
187 E.g., https://talkingtech.cliffordchance.com/en/emerging-technologies/artificial-intelligence/ai-and-the-future-for-legal-services.html
188 Hosny, A., et al. (2018). "Artificial intelligence in radiology." *Nature Reviews Cancer* 18 (8): 500–510. https://doi.org/10.1038/s41568-018-0016-5
189 https://aws.amazon.com/machine-learning
190 https://www.tensorflow.org

Azure).[192] Nonetheless, because some AI techniques have already been repeatedly mentioned, and because they play important roles in AIED and so will be mentioned again, some key and closely interlinked AI techniques and terminologies will next be introduced.[193] At times (despite our best efforts) our discussion will be somewhat technical; so please feel free to jump to the next section, to move directly onto our discussion of the application of AI in education (which, after all, is the reason we are all here).

Algorithms

Algorithms are at the core of AI, such that the history of AI might be thought of as the history of the development of increasingly sophisticated and increasingly efficient (or elegant) algorithms. Probably the most famous algorithm of recent times is PageRank,[194] which was developed in 1996 by the founders of Google while they were students at Stanford University. It ranks the relative importance of a website, by counting the number of external links to the website's pages, to determine where the website appeared in a Google search. In fact, all computer programs are algorithms. They comprise hundreds if not thousands of lines of code, representing sets of mathematical instructions that the computer follows in order to solve problems (compute a numerical calculation, grammar-check an essay, process an image, or explain patterns that we see in nature).[195] All that makes AI algorithms distinct from other computer programs is that they involve some specific approaches and, as we have noted, they are applied to areas we might think of as essentially human—such as visual perception, speech recognition, decision-making and learning.

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191 https://www.ibm.com/watson

192 https://azure.microsoft.com

193 Readers wishing to learn more about AI techniques might be interested in Russell, S. and Norvig, P. (2016). *Artificial Intelligence: A Modern Approach, 3rd Edition.* Pearson; and Domingos, P. (2017). *The Master Algorithm: How the Quest for the Ultimate Learning Machine Will Remake Our World.* Penguin.

194 PageRank of Site = Σ [PageRank of inbound link/Number of links on that page].

195 Turing, A. (1952). "The chemical basis of morphogenesis." *Philosophical Transactions of the Royal Society* 237 (641): 37–72.

Machine Learning

Much early, rule-based AI involves writing in advance the steps that the computer will take to complete a task, rules that will be followed exactly. Machine learning, on the other hand, is about getting computers to act without being given every step in advance. Instead of the algorithms being programmed exactly what to do, broadly speaking they have the ability to learn what to do. This is not to suggest that machine learning does not require large amounts of programming, because it does. But rather that, instead of direct commands leading to direct outputs, machine learning involves large amounts of input data to predict novel outcomes.

Machine learning algorithms analyze the data to identify patterns and to build a model which is then used to predict future values (for example, by identifying patterns in historical stocks data, AI predicts future stock movements; by identifying patterns in photographs of named people, it predicts who is shown in other photographs; and by identifying patterns in medical symptoms, it predicts a specific diagnosis). In other words, machine learning may be considered a three-step process (analyze data, build a model, undertake an action) that is continuously iterated (the outcomes of the action generate new data, which in turn amends the model, which in turn causes a new action). It is in this sense that the machine is learning.

Many recent applications (including natural language processing, self-driving cars, and the Google DeepMind AlphaGo program that beat the world's number one player of Go)[196] have all been made possible thanks to machine learning. In fact, machine learning is so widespread today that, for some commentators, AI and machine learning have become synonymous—whereas machine learning is more properly a sub-field of AI. What is true, however, is that the renaissance and exponential growth of AI over the last decade, has come about because of significant

[196] https://www.theguardian.com/technology/2016/mar/15/googles-alphago-seals-4-1-victory-over-grandmaster-lee-sedol

advances in machine learning (based on, as we have noted, faster computer processors, the availability of large amounts of big data, and new computational approaches).[197]

There are three main categories of machine learning: supervised, unsupervised, and reinforcement learning.

Supervised Learning

Most practical machine learning involves supervised learning. The AI is first provided large amounts of data for which the output is already known—in other words, data that has already been labeled. For example, the AI might be given many thousands of photographs of streets in which the numerous visible objects (bicycles, road signs, pedestrians, etc.) have already been identified and labeled by humans. The supervised learning algorithm aims to identify the function that links the data to the labels, from which it builds a model that can be applied to new similar data. This is broadly speaking the approach, mentioned earlier, used by Facebook to identify people in photographs, which used millions of photographs submitted and labeled by Facebook users to identify and label automatically the same people in new photographs.

Unsupervised Learning[198]

In unsupervised learning, the AI is provided with even larger amounts of data, but this time data that has not been categorized or classified, that is to say data that is not labeled. By analyzing this unlabeled data, unsupervised learning algorithms aim to uncover hidden patterns in the underlying structure of the data, clusters of data that can be used to classify new data (this is broadly the approach, mentioned earlier, used by Google to detect faces in photographs). Example applications of unsupervised learning include dividing online shoppers into groups so

[197] Interestingly, the origins of machine learning can be traced back to at least 1959, with the publication of "Some Studies in Machine Learning Using the Game of Checkers" by an IBM researcher.

[198] A comprehensive list of the algorithms available on one of the leading "AI as a service" platforms, Microsoft Azure, is available at http://download.microsoft.com/download/A/6/1/A613E11E-8F9C-424A-B99D-65344785C288/microsoft-machine-learning-algorithm-cheat-sheet-v6.pdf

they can be served tightly targeted advertisements;[199] identifying different letters and numbers from examples of handwriting; and distinguishing between legitimate and fraudulent financial transactions.

Reinforcement Learning

In some senses, reinforcement learning is the most powerful of the machine learning categories. In both supervised and unsupervised learning, the model derived from the data is fixed, and if the data changes the analysis has to be undertaken again (in other words, the algorithm is run once more). However, reinforcement learning involves continuously improving the model based on feedback—in other words, this is machine learning in the sense that the learning is ongoing. The AI is provided with some initial data from which it derives its model, which is evaluated, assessed as correct or incorrect, and rewarded or punished accordingly (to use a computer game metaphor, its score is increased or reduced). The AI uses this positive or negative reinforcement to update its model and then it tries again, thus developing iteratively (learning and evolving) over time. For example, if an autonomous car avoids a collision, the model that enabled it to do so is rewarded (reinforced), enhancing its ability to avoid collisions in the future.

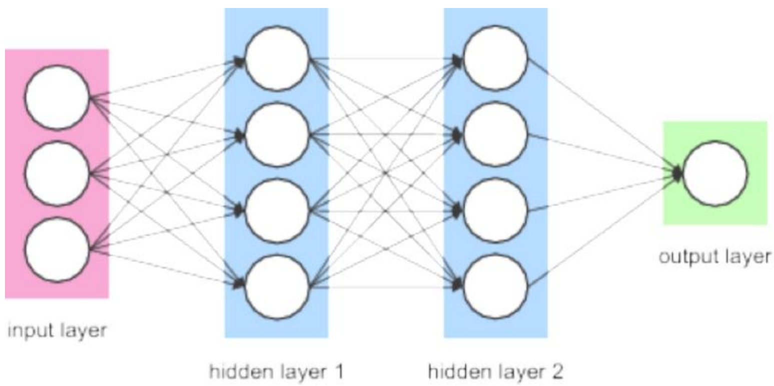
Artificial Neural Networks

An artificial neural network is an AI algorithm that is based on the structure and functions of biological neural networks (i.e. animal brains), that might be applied in advanced supervised, unsupervised, or reinforcement learning. Our brains are made up of billions of individual neurons, each of which is connected to as many as a thousand other neurons, giving trillions of connections. Memory is thought to emerge from complex combinations of these connections across the brain, while learning is thought to involve the strengthening of those connections.

[199] In a now-infamous story, the US retailer Target automatically identified a teenager as being pregnant, before she had told anyone, just by her store purchases, and some unsupervised learning. https://www.forbes.com/sites/kashmirhill/2012/02/16/how-target-figured-out-a-teen-girl-was-pregnant-before-her-father-did/#31650c296668

Although artificial neural networks have been trained to do some incredible things (such as identifying faces in moving crowds of people), they remain primitive in comparison to higher-order animal brains. Unlike for example the human brain's billions of neurons, they usually involve only a few thousand neurons (in some exceptional cases, a few million).

As illustrated in the following figure, artificial neural networks each comprise three types of layers: an input layer that takes stimuli from the environment, in the form of millions of data points, perhaps pixels from images; at least one, but often many more, hidden intermediary layers that together undertake the computation; and an output layer that delivers the result. During the machine learning process, weightings given to the connections are adjusted in a process of reinforcement learning, which allows the artificial neural network subsequently to compute outputs for new stimuli.



A representation of a typical, simple artificial neural network, with two hidden layers.

The hidden layers are the key to the power of artificial neural networks, but they also bring an important problem. It isn't possible (or at the very least it isn't easy) to interrogate an artificial neural network to find out how it came up with its solution—for example, how did it identify a particular person in a photograph? In other words, artificial neural networks can lead to decision making for which the rationale is hidden and unknowable, or un-inspectable, and possibly unjust,[200] a critical issue that is the subject of much research.[201]

Finally, the impressive results of neural networks and other machine learning technologies should not beguile us:

> A neural network of today no more "learns" or "reasons" about the world than a linear regression of the past. They merely induce patterns through statistics. Those patterns may be opaquer, more mediated and more automatic than historical approaches and capable of representing more complex statistical phenomena, but they are still merely mathematical incarnations, not intelligent entities, no matter how spectacular their results.[202]

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[200] O'Neil, C. (2017). *Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy*. Penguin.

[201] Morcos, A.S., et al. (2018). "On the importance of single directions for generalization." ArXiv:1803.06959. http://arxiv.org/abs/1803.06959

[202] https://www.forbes.com/sites/kalevleetaru/2018/12/15/does-ai-truly-learn-and-why-we-need-to-stop-overhyping-deep-learning/#edd206168c02

How AI Works in Education

Having established a working understanding of AI, we will now look in more detail at how AI works in educational contexts, beginning with a brief history. However, what will not be discussed but what might nonetheless have a major impact on education is the use of AI to support school administration (system-facing AI that addresses things like class timetabling, staff scheduling, facilities management, finances, cybersecurity, safety and security).[203] Our focus is the use of AI to support learning (student- and teacher-facing AI).

A Brief History of AI in Education

Precursors of the application of AI in education can be found in the work of the psychologists Sidney Pressey, who was a professor at Ohio State University in the 1920s, and B. F. Skinner, known as the father of behaviorism, who was a professor at Harvard University from 1948 until his retirement in 1974. For Pressey, the challenge was to leverage the potential of multiple-choice tests to consolidate student learning as well as to evaluate it. Drawing on Edward Thorndike's law of effect,[204] he argued that, for tests to support learning, immediate feedback was essential—which is not usually possible when tests are marked by hand. However, a mechanical approach could ensure that no learning opportunities were missed.

> Devices which at once inform a student about the correctness of his answer to a question, and then lead him to the right answer, clearly do more than test him; they also teach him.[205]

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[203] Readers who are interested in the use of AI technologies to support administrative functions might like to read about Ofsted, the UK's school inspection service. Ofsted's use of "artificial-intelligence algorithm to predict which schools are 'less than good'." https://www.tes.com/news/ofsted-use-artificial-intelligence-algorithm-predict-which-schools-are-less-good

[204] Thorndike. E.L. (1927) "The Law of Effect." *The American Journal of Psychology* 39 (1/4): 212–22. https://doi.org/10.2307/1415413

[205] Pressey, S.L. (1950). "Development and appraisal of devices providing immediate automatic scoring of objective tests and concomitant self-instruction." *Journal of Psychology* 30: 417–447.

Pressey made various versions of his machine (and made several unsuccessful attempts to commercialize his idea), the most sophisticated being based on a mechanical typewriter. Inside this device was a rotating drum around which was wrapped a card printed with a list of questions and hole-punched (much like the perforated rolls used in self-playing pianos) to represent the correct answers. Meanwhile, the casing featured a small window, which showed the number of the current question, and five typewriter keys, one for each possible answer. As the student worked through a printed sheet of questions and answers, they would press one of the keys on the device to select their answer for each question. The machine was configured so that the student immediately knew whether they had made the right choice, and it prevented them from moving onto the next question until they had.

Interestingly, Pressey was also one of the first to make the case that, in addition to supporting learning, a teaching machine could make a teacher's life easier and more fulfilling—by relieving them of one of their least interesting tasks (marking tests) and giving them more time to engage with their students.

> Lift from [the teacher's] shoulders as much as possible of this burden and make her [sic] free for those inspirational and thought-stimulating activities which are, presumably, the real function of the teacher.[206]

Pressey's approach was later extended by Skinner, who argued that the techniques he pioneered for training rats and pigeons (in operant conditioning chambers now known as Skinner Boxes) might be adapted for teaching people. Skinner's teaching machine, which he devised in 1958, was a wooden box with a windowed lid. Questions written on paper disks appeared in one window, and the student wrote a response on a roll of paper accessible through a second window (for later marking by a teacher). Advancing the mechanism automatically covered the

[206] Pressey, S.L. (1926). "A simple device for teaching, testing, and research in learning." *School and Society* 23: 374.

student's answer, so that it could not be changed, and simultaneously revealed the correct answer. In this way, Skinner's teaching machine provided automatic, immediate reinforcement. Students were required to compose their own answers, rather than choose from a limited selection (as with Pressey's multiple-choice questions), because Skinner found that learning is more effectively reinforced by recalling a correct response than by simply recognizing it. This approach also gave the student the opportunity to compare their answer with the given model answer, which if properly designed by the teacher and actively undertaken by the student could also contribute to learning.

Skinner argued that his teaching machine in effect acted like a personal tutor, foreshadowing AIED's intelligent tutoring systems.

> The machine itself, of course, does not teach ... but the effect upon each student is surprisingly like that of a private tutor.... (i) There is a constant interchange between program and student.... (ii) Like a good tutor, the machine insists that a given point be thoroughly understood ... before the student moves on.... (iii) Like a good tutor, the machine presents just that material for which the student is ready.... (iv) Like a skillful tutor, the machine helps the student to come up with the right answer.... (v) Lastly, of course, the machine, like the private tutor, reinforces the student for every correct response, using this immediate feedback ... to shape his behavior most efficiently.[207]

Skinner's teaching machine might be thought to have also foreshadowed something else later taken up by AI in education researchers, dividing automated teaching into separate components (in Skinner's case, distinguishing between the subject content, which was pre-programmed into the machine, and the student's achievements, whether or not they answered a question correctly). However, although in a sense Skinner's teaching machine was responsive to individual students, it could not be considered adaptive. That is to say, it did not adapt either the questions, or the order in which they were presented,

[207] Skinner, B.F. (1958). "Teaching machines." *Science* 128 (3330): 969–77.

according to the achievements or needs of the individual students. Instead, question delivery was pre-scripted. While a student could proceed at their own pace, they went through the same list of questions as every other student and in the same order.

Adaptive Learning

Also working in the 1950s, Norman Crowder, who was interested in communication rather than psychology, devised a paper-based alternative to the early teaching machines, known as intrinsic or branching programmed instruction.[208] In Crowder's system (which he developed for training U.S. Air Force engineers to find malfunctions in electronic equipment), the user is presented with a short page of information followed by a multiple-choice question, with each possible answer directing the student to a new page. If the correct answer was chosen, the new page would present new information, building upon that which was correctly understood; if an incorrect answer was chosen, the new page would contain feedback designed to help the student understand the cause of their error, based on what the student had chosen. The system might also branch through one or two additional pages of corrective materials before returning the student back to the main pages. In short, Crowder's system adapted the pathway through the teaching materials according to the individual student's developing knowledge, such that each student might see quite different sets of pages.

However, a British polymath, Gordon Pask, probably developed the first truly adaptive teaching machine in the early 1950s. Known as SAKI (the self-adaptive keyboard instructor), it was designed for trainee keyboard operators learning how to use a device that punched holes in cards for data processing.[209] What distinguished SAKI from the other early teaching machines was that the task presented to a learner was

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[208] Crowder, N.C. (1960). "Automatic tutoring by means of intrinsic programming." In *Teaching Machines and Programmed Learning: A Source Book*. Vol. 116. Lumsdaine, A.A., and Glaser, R. (eds.) American Psychological Association, 286–298.

[209] Pask, G. (1982). "SAKI: Twenty-five years of adaptive training into the microprocessor era." *International Journal of Man-Machine Studies* 17 (1): 69–74. https://doi.org/10.1016/S0020-7373(82)80009-6

adapted to the learner's individual performance, which was represented in a continuously changing probabilistic student model.

When you interact with the system, learning which keys represent which numbers:

> the machine is measuring your responses, and building its own probabilistic model of your learning process. That "7," for instance, you now go to straight away. But the "3," for some obscure reason, always seems to elude you. The machine has detected this, and has built the facts into its model. And now, the outcome is being fed back to you. Numbers with which you have difficulty come up with increasing frequency in the otherwise random presentation of digits. They come up more slowly, too, as if to say: "Now take your time." The numbers you find easy, on the contrary, come up much faster: the speed with which each number is thrown at you is a function of the state of your learning.[210]

Computer-Aided Instruction

SAKI went through many iterations, taking advantage of developments in computers and the new microprocessors, and was one of the first adaptive systems to be commercialized. However, over the following years, other than in the various iterations of SAKI, adaptive learning made few advances, and the focus shifted to what became known as computer-aided instruction (CAI) systems. The 1960s and 1970s saw many CAI systems being built, an early influential example being PLATO (programmed logic for automatic teaching operations), which was developed at the University of Illinois. PLATO involved students accessing standard teaching materials, some of which were interactive, on a central mainframe computer via remote terminals, with as many as a thousand students working at the same time.

This system was also notable for being the first to introduce in an educational technology many tools and approaches still common today, such as user forums, email, instant messaging, remote screen-sharing, and

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[210] Beer, S. (1960). *Cybernetics and Management.* The English Universities Press, 124.

multiplayer games. Around the same time, Stanford University and IBM developed a computer-aided instruction system that was made available via remote terminals to a few local elementary schools. This system involved a linear presentation of teaching materials, for mathematics and language arts, together with drill and practice activities. A third prominent example was TICCIT (time-shared interactive computer-controlled information television), developed by Brigham Young University, which was used to teach freshman-level mathematics, chemistry, physics, English, and various language courses. Each subject area was broken down into topics and learning objectives, which in turn were represented as screens of information. TICCIT then provided a predetermined sequence, although learners could also use the keyboard to navigate through the screens in any order that they found helpful.

Although in other ways successful, during the 1960s and 1970s only very few of these CAI systems were widely adopted, mainly due to the cost and accessibility of the university mainframes that were needed to host the software. The arrival of personal computers in the 1980s changed everything, with the number of CAI programs quickly mushrooming. Very soon, CAI programs addressing every aspect of learning were being widely used in schools, universities and family homes. Nonetheless, of particular relevance for our present purposes, almost all of these systems were severely hampered by the same flaw—a lack of adaptivity. The sequence of topics, the information provided, and the system's response to student actions, were predefined and the same for each student, ignoring the individual student's successes, misconceptions, and interests, and thus inhibiting their potential learning.

AI and CAI

At around the same time that mainstream CAI was developing, other researchers, such as John Self[211] and William Clancey,[212] were wondering

[211] Self, J.A. (1974). "Student models in computer-aided instruction." *International Journal of Man-Machine Studies* 6 (2): 261–76. https://doi.org/10.1016/S0020-7373(74)80005-2

[212] Clancey, W.J. (1983). "GUIDON." *Journal of Computer-Based Instruction* 10 (1–2): 8–15.

how CAI could become adaptive to the needs of individual students, and whether the application of techniques from AI might be useful. The first implementation of AI techniques in computer-aided instruction is usually credited to Jaime Carbonell, who, in his 1970 PhD thesis, introduced a system called SCHOLAR. This novel system was designed to enable a student to review their knowledge of the geography of South America, by means of a dialogue using a subset of English. SCHOLAR was qualitatively different from standard CAI because, unique for the time, it was capable of generating individual responses to student statements by drawing from a semantic network (a way of representing knowledge, in this case knowledge of geography, in which concepts are linked according to their semantic relationships).

> In [a] conventional CAI, the database consists of many "frames" of specific pieces of text, questions, and anticipated answers entered in advance by the teacher. By contrast, [SCHOLAR] is based on the utilization of an information network of facts, concepts, and procedures; it can generate text, questions, and corresponding answers. Because [it] can also utilize its information network to answer questions formulated by the student, a mixed-initiative dialogue between student and computer is possible with questions and answers from both sides.[213]

A SCHOLAR dialogue[214] might look something like this:

> SCHOLAR: Use one of the following: Sucre, French, Argentina, Spanish, to answer the question: What is the language in Chile?
> SCHOLAR: You are taking too much time...
> Student: *Spanich*
> SCHOLAR: You should have written "Spanish." Very good.

Although by today's standards the dialogue (and especially its pedagogy) appears primitive, SCHOLAR is usually considered to be the

[213] Carbonell, J. R. (1970). "AI in CAI: An Artificial-Intelligence Approach to Computer-Assisted Instruction." *IEEE Transactions on Man-Machine Systems* 11 (4): 190–202. https://doi.org/10.1109/TMMS.1970.299942
[214] Carbonell, "AI in CAI," 192.

first example of what came to be known as Intelligent Tutoring Systems, to which we turn next.

Applications of AI in Education

Intelligent Tutoring Systems

> Under the best learning conditions we can devise (tutoring), the average student is two sigma above the average control student taught under conventional group methods of instruction. The tutoring process demonstrates that most of the students do have the potential to reach this high level of learning. I believe an important task of research and instruction is to seek ways of accomplishing this under more practical and realistic conditions than the one-to-one tutoring, which is too costly for most societies to bear on a large scale. This is the 2 sigma problem.[215]

So-called intelligent tutoring systems (ITS) are among the most common applications of AI in education (in any case, as we have seen, they have probably been around the longest). Generally speaking, ITS provide step-by-step tutorials, individualized for each student, through topics in well-defined structured subjects such as mathematics or physics.[216] Drawing on expert knowledge about the subject and about pedagogy, and in response to individual student's misconceptions and successes, the system determines an optimal step-by-step pathway through the learning materials and activities. As the student proceeds, the system automatically adjusts the level of difficulty and provides hints or guidance, all of which aim to ensure that the student is able to learn the given topic effectively.

ITS come in many shapes, although typically they involve several AI models, an approach that we will unpack here. As we saw in our earlier discussion of AI technologies, AI models are highly simplified computational representations (in semantic networks, as used by

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[215] Bloom, Benjamin S. (1984). 'The 2 Sigma problem: The search for methods of group instruction as effective as one-to-one tutoring." *Educational Researcher* 13 (6): 4. Note, however, that according to VanLehn, "human tutors are 0.79 sigma more effective than no tutoring and not the 2.0 sigma found in the Bloom (1984) studies" VanLehn, K. (2011.) "The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems." *Educational Psychologist* 46 (4): 209. https://doi.org/10.1080/00461520.2011.611369

[216] Alkhatlan, A. and Kalita, J. (2018). "Intelligent tutoring systems: A comprehensive historical survey with recent developments." ArXiv:1812.09628. http://arxiv.org/abs/1812.09628

SCHOLAR, in ontologies,[217] or in knowledge graphs)[218] of specific knowledge about the real world (just like a model car is a simplified representation of a real car). The models used by ITS represent knowledge specific to teaching and learning. Typically, knowledge about the topic to be learned is represented in what is known as a domain model, knowledge about effective approaches to teaching is represented in a pedagogical model, and knowledge about the student is represented in a learner model.[219] The ITS algorithm draws on these three models in order to adapt a sequence of learning activities for each individual student. A fourth model found in some ITS is the open learner model, to which we will return later.

The Domain Model

A domain model represents knowledge about the subject that the ITS aims to help the students learn (much like the subject knowledge in a standard, non-educational, expert system). This might, for example, be knowledge about mathematical procedures, genetic inheritance, or the causes of World War I. In fact, over the years, mathematics for primary and secondary school students has dominated ITS. Mathematics, along with physics and computer science, are AIED's low-hanging fruits because they are, at least at a basic level, well-structured and clearly defined.

The Pedagogy Model

The ITS pedagogy model represents knowledge about effective approaches to teaching and learning that have been elicited from teaching experts and from research in the learning sciences (although it should be

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[217] Ontologies are a way of representing a domain's concepts, data, components, entities and properties, and the relationships between them. Sowa, J.F. (1995). "Top-level ontological categories." *International Journal of Human-Computer Studies* 43 (5): 669–85. https://doi.org/10.1006/ijhc.1995.1068

[218] Knowledge graphs are an alternative approach to ontologies, https://ontotext.com/knowledgehub/fundamentals/what-is-a-knowledge-graph

[219] Luckin, R., et al. (2018). *Intelligence Unleashed. An Argument for AI in Education*, 18; Boulay, B. du., Poulovassilis, A., Holmes, W., and Mavrikis, M. (2018). "What does the research say about how artificial intelligence and big data can close the achievement gap?" 4. In Luckin, R. (ed.) (2018). *Enhancing Learning and Teaching with Technology*, 316–27. Institute of Education Press.

acknowledged that some ITS developers falsely assume that they have sufficient expertise in pedagogy).[220] Pedagogical knowledge that has been represented in many ITS include knowledge of instructional approaches,[221] the zone of proximal development,[222] interleaved practice,[223] cognitive load,[224] and formative feedback.[225] For example, a pedagogical model that implements Vygotsky's zone of proximal development will ensure that activities provided by the system to the student are neither too easy nor too challenging, one that implements individualized formative feedback will ensure that feedback is provided to the student whenever it might support the student's learning.

The Learner Model

As we have seen, some CAI effectively (although usually by another name) implemented versions of both domain and pedagogical models: knowledge of what was to be learned and knowledge of how to teach what was to be learned (for example, using linear or branching programmed instruction). However, what distinguishes AI-driven ITSs is that, as foreshadowed by Pask's SAKI, they also include a learner model: "a representation of the hypothesized knowledge state of the student."[226] In fact, many ITS incorporate a wide range of knowledge about the student—such as their interactions, material that has challenged the

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[220] For example, many ITS set out to address student "learning styles" (Kumar, Amit, Ninni Singh, and Neelu Jyothi Ahuja. (2017). "Learning-styles based adaptive intelligent tutoring systems: Document analysis of articles published between 2001 and 2016." *International Journal of Cognitive Research in Science, Engineering and Education* 5 (2): 83–98. https://doi.org/10.5937/IJCRSEE1702083K This construct that has been widely discredited, e.g., Kirschner, P.A. (2017). "Stop propagating the learning styles myth." *Computers & Education* 106: 166–171. https://doi.org/10.1016/j.compedu.2016.12.006

[221] Bereiter, C. and Scardamalia, M. (1989). "Intentional learning as a goal of instruction." *Knowing, Learning, and Instruction: Essays in Honor of Robert Glaser*, 361–392.

[222] Vygotsky, *Mind in Society*, 86ff.

[223] Rohrer, D., and Taylor, K. (2007). "The shuffling of mathematics problems improves learning." *Instructional Science* 35 (6): 481–98. https://doi.org/10.1007/s11251-007-9015-8

[224] Mayer, R.E. and Moreno, R. (2003). "'Nine ways to reduce cognitive load in multimedia learning." *Educational Psychologist* 38 (1): 43–52.

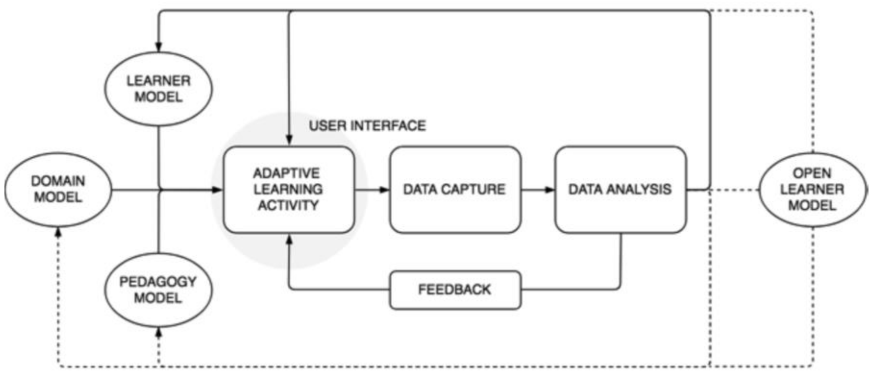
[225] Shute, V.J. (2008). "Focus on formative feedback." *Review of Educational Research* 78 (1): 153–89. https://doi.org/10.3102/0034654307313795

[226] Self, J.A. (1974). "Student models in computer-aided instruction." *International Journal of Man–Machine Studies* 6 (2), 261–276. http://dx.doi.org/10.1016/S0020-7373(74)80005-2

student, their misconceptions, and their emotional states while using the system—all of which can be used to inform what is being taught and how, together with what support needs to be provided and when. In fact, most ITSs go much further. The knowledge stored about the individual student is augmented with knowledge of all the students who have used the system so far, from which the system machine learns in order to predict which pedagogical approach and which domain knowledge is appropriate for any particular student at any specific stage of their learning. It is the learner model that enables ITS to be adaptive, and the machine learning that makes this adaptivity especially powerful.

A Typical ITS Architecture

The following figure shows how the domain, pedagogy, and learner models might be connected in a typical ITS.



A typical ITS architecture, including the pedagogy, domain, learner, and open-learner models.

In this exemplar architecture, the ITS algorithm draws on the domain, pedagogy, and learner models to determine what adaptive learning activity should be presented to the individual student and how it should be adapted to that student's needs and capabilities. For example, in a mathematics ITS, the domain model might contain knowledge about quadratic equations, the pedagogy model might contain knowledge of an effective way to teach quadratic equations, and the learner model might contain knowledge about the student's experience learning about quadratic equations in this ITS (for example, a misconception that they exhibited, or the fact that this topic caused them some anxiety). The learner model will also contain knowledge of all students who have ever used this ITS to learn about quadratic equations.

Drawing all of this together, the ITS algorithm will determine what adaptive learning activity to present to the student in the user interface—in other words, which specific aspect of quadratic equations to deliver (perhaps factorizing or completing the square) and what approach to use to best help the student learn about those aspects of quadratic equations (perhaps some instructional text, an image or video, or an interleaved practice activity), all of which is also dependent on the learner model (the knowledge of the individual's and all students' experience of learning quadratic equations in this ITS).

While the student engages with the adaptive learning activity selected by the system, data capture involves the system capturing thousands of data points representing each individual interaction (what is clicked on the screen and what is typed, and possibly even how rapidly they move the mouse around the screen), together with the student's achievements (which tasks they have answered correctly or partially) and any misconceptions that they have demonstrated. Some advanced ITS also capture other data such as the student's speech, physiological responses, and an inference of their affective (emotional) state.

The next step involves data analysis, in which all of the captured data is automatically examined, possibly using machine learning (or a Bayesian network, an AI technique that is introduced in appendix 2, both to provide the student with individualized formative feedback (to support their learning according to their individual needs) and to update the learner model (to inform the system's decision of which adaptive learning activity to deliver next, and to contribute to the model of all students). The analysis might also, in some circumstances, update the pedagogy model (identifying which approaches have been shown to support student learning most or least effectively, in particular circumstances) and the domain model (perhaps with previously unknown misconceptions that have become apparent from the student interactions).

Over time, this ITS cycle—(a) drawing on the domain, pedagogy and learner models, (b) delivering adaptive learning activities, (c) data capture, (d) data analysis, and (e) updating the models—means that each individual student will experience their own unique personalized learning pathway through the available learning activities. If their interactions suggest that they find factorizing particularly challenging, perhaps they will spend more time engaging with multiple relevant activities; whereas if their interactions suggest otherwise, perhaps they made fewer errors along the way, they will work through fewer activities for this topic and will more quickly move onto another topic deemed to be more appropriate for their particular needs.

Finally, as also shown in the preceding figure, a few ITS also feature a fourth model, known as an open learner model.[227] Open learner models aim to make visible or explicit, for both the students and their teachers to inspect the teaching and learning that has taken place and the decisions that have been taken by the system. The open learner model enables learners to monitor their achievements and personal challenges, supporting their metacognition, and enables teachers to better understand each individual learner's learning (their approach, any misconceptions and their learning trajectories) in the context of the whole class, as well as potentially informing the teacher's professional development.

Evaluating ITS

Over the years there have been countless examples of ITS, many of which have been evaluated in schools or universities. Usually these evaluations have focused on learning gains, comparing one or other ITS with traditional teaching methods, such as whole class or one-to-one teaching by a human teacher, or with CAI systems. In fact, as detailed by du Boulay and colleagues, there have also now been several meta-

[227] Dimitrova, V., Mccalla, G., and Bull, S. (2007). "Preface: Open learner models: Future research directions." Special issue of the *International Journal of Artificial Intelligence in Education, Part 2*. http://psycnet.apa.org/psycinfo/2007-13116-001

reviews[228] (i.e., review papers that aim to draw some general conclusions by combining and analyzing the trends in several individual evaluations). For example, one meta-analysis notes: "Developers of ITSs long ago set out to improve on the success of CAI tutoring and to match the success of human tutoring. Our results suggest that ITS developers have already met both of these goals."[229] However, pooling the outcomes of the several meta-studies suggests that ITSs have not yet quite achieved parity with one-to-one teaching—when combined, the meta-reviews show an average small negative effect size of –0.19.[230] On the other hand, for ITSs that are compared with whole-class teaching, the outcomes of the meta-reviews have been very positive. They show a weighted average effect size of 0.47[231] —in educational intervention research, effect sizes above 0.4 are thought to be "worth having."[232]

As we mentioned at the start of this section, ITS tend to focus on well-defined domains such as mathematics or physics. However, it is also worth noting that over recent years ITS for ill-defined problems (such as legal argumentation, intercultural skills acquisition, and dispute

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228 VanLehn, K. (2011). "The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems." *Educational Psychologist* 46 (4): 197–221. https://doi.org/10.1080/00461520.2011.611369; Ma, W., et al. (2014). "Intelligent tutoring systems and learning outcomes: A meta-analysis." *Journal of Educational Psychology* 106 (4): 901; Nesbit, J.C., et al. (2014) "How effective are intelligent tutoring systems in computer science education?" In *2014 IEEE 14th International Conference On Advanced Learning Technologies*. http://ieeexplore.ieee.org/abstract/document/6901409/; Kulik, J.A. and Fletcher, J.D. (2015). "Effectiveness of intelligent tutoring systems a meta-analytic review." *Review of Educational Research*, https://doi.org/10.3102/0034654315581420; Steenbergen-Hu, S. and Cooper, H. (2013). "A meta-analysis of the effectiveness of intelligent tutoring systems on K–12 students' mathematical learning." http://psycnet.apa.org/journals/edu/105/4/970/; Steenbergen-Hu, S. and Cooper, H. (2014). "A meta-analysis of the effectiveness of intelligent tutoring systems on college students' academic learning." http://psycnet.apa.org/journals/edu/106/2/331/

229 Kulik, J.A., & Fletcher, J.D. (2015). "Effectiveness of intelligent tutoring systems a meta-analytic review." *Review of Educational Research*, 0034654315581420. https://doi.org/10.3102/0034654315581420

230 Although one meta-review did find that ITSs were "just as effective as adult, one-to-one tutoring": VanLehn, "The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems," 214.

231 The effect size measures how far the mean of the experimental group is from the mean of the control group measured in terms of the standard deviation of the control group scores.

232 Hattie, J. (2008). *Visible Learning*. Routledge.

resolution) have also been explored.[233] One reason for the relatively low-levels of interest in ITS for ill-defined domains probably stems from the fact that imprecise problems often require students to apply cognitively complex skills, while the contexts can be uncertain and dynamic, all of which can be challenge to model in traditional ITS. The relative lack of structure also makes it difficult to scaffold effective learning pathways without artificial constraints, to provide appropriate feedback, and to evaluate what learning is actually happening. ITS in ill-defined domains can also require additional pedagogical approaches, such as non-didactic Socratic dialogue, collaborative activities, or exploratory learning (which we look at in more detail later).

As we have noted, because what AIED looks like and can do is still emerging, in this chapter we are going to introduce a wide range of AIED examples. Our list is far from definitive, but it will indicate the broad areas of AIED research, and it will highlight the many possibilities and challenges introduced by the application of AI technologies in classrooms. In this section, we are discussing ITS—so we begin with some prominent current ITS examples, most of which focus on structured domains (such as mathematics): Carnegie Learning's Mathia, Worcester Polytechnic Institute's Assistments, and Knewton's alta.

Mathia

Building on research at Carnegie Mellon University, Mathia[234] (previously known as Cognitive Tutor) delivers AI-driven personalized mathematics instruction for K–12 students. As the students work through carefully structured mathematics tasks, the system acts as a personal coach, monitoring their progress (their successes and misconceptions) and

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233 Lynch C., et al. (2006). "Defining "ill-defined domains"; a literature survey." In (2006), Proceedings of the Workshop on Intelligent Tutoring Systems for Ill-Defined Domains at the 8th International Conference on Intelligent Tutoring Systems. http://people.cs.pitt.edu/~collinl/Papers/Ill-DefinedProceedings.pdf; Woolf, B. (2010). "Social and caring tutors." ITS 2010 keynote address. https://link.springer.com/chapter/10.1007/978-3-642-13388-6_5; Lane, C., et al. (2007). 'Intelligent tutoring for interpersonal and intercultural skill." http://ict.usc.edu/pubs/Intelligent Tutoring for Interpersonal and Intercultural Skills.pdf

234 https://www.carnegielearning.com/products/software-platform/mathia-learning-software

directing them along individualized learning pathways. It also provides automatic feedback that aims to explain not just why the individual student got something wrong but also how they might get it right. Interestingly, Carnegie Learning argues that Mathia is most effective when it is used as part of a blended learning approach (i.e. they acknowledge that, on its own, it is insufficient), which includes the use of both print and digital resources, and involves students learning collaboratively in groups as well as individually.

Assistments

Our second example of a current instructional ITS is Assistments,[235] developed at Worcester Polytechnic Institute, which overall uses a similar approach to Mathia. However, Assistments also aims to address a key issue for ITS, that they by definition leads to students progressing at different rates, meaning that in any one classroom the students can be at increasingly diverging levels of attainment (potentially making the classroom teacher's job more, rather than less, challenging). Accordingly, Assistments is designed to help students catch up in the evenings, working independently at home, so that in the classroom everyone's progress remains roughly aligned. Both Mathia[236] and Assistments[237] have strong, although not definitive,[238] evidence for their effectiveness.

alta

Our third example ITS is Knewton's alta,[239] which is doubly unusual: it is designed for Higher Education students and it focuses on a range of subjects, including mathematics, economics, chemistry, and statistics. Nonetheless, like most ITS, alta aims to function like a 1:1 tutor, with personalized, step-by-step instruction, assessment, feedback, and just-in-

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235 https://www.assistments.org

236 Pane, J.F., et al. (2015). "Continued progress. Promising evidence on personalized learning." https://www.rand.org/content/dam/rand/pubs/research_reports/RR1300/RR1365/RAND_RR1365.pdf

237 Roschelle, J., et al. (2017). *How Big Is That? Reporting the Effect Size and Cost of ASSISTments in the Maine Homework Efficacy Study*. SRI International.

238 Holmes, W., et. al. Technology-enhanced Personalised Learning, 65 & 68.

239 https://www.knewtonalta.com

time remediation while a student engages with an assignment. The alta approach clearly maps onto the typical ITS architecture outlined earlier. For each subject, it has a domain model, which uses open educational resources[240] (OER) and includes tutor-selectable learning objectives, together with a semantic network (or knowledge graph)[241] of relationships between the content and objectives. The domain models also include databases of relevant questions, together with data about the difficulty of those questions (based on how previous students have performed when responding to them). Alta's pedagogy model is based on item response theory[242] (it works at the granularity of individual questions, taking into account both the question's difficulty and their representativeness of the underlying concepts). It also adopts a mastery level approach (students do not move onto new learning objectives until they have achieved mastery of earlier learning objectives). In particular, the model assumes that if a student masters one of two learning objectives that are related according to the domain model's knowledge graph, there is a good chance that they have also mastered the other one. Meanwhile, alta's learner model represents a student's level of mastery in terms of the learning objectives at any given point in time. This is based on the observed history of the individual student's interactions, and of all student interactions, including which questions the students have answered correctly and incorrectly, giving more weight to an individual student's most recent responses.

Some Final Examples

In addition to these three examples of current ITSs, there are many others. Meanwhile, as we have repeatedly commented, new ones seem to appear all the time, such that any list will always be incomplete. With this in mind, we will round out our discussion by briefly mentioning just four

[240] Hylén. J. (2006). "Open educational resources: Opportunities and challenges." *Proceedings of Open Education,* 49–63.

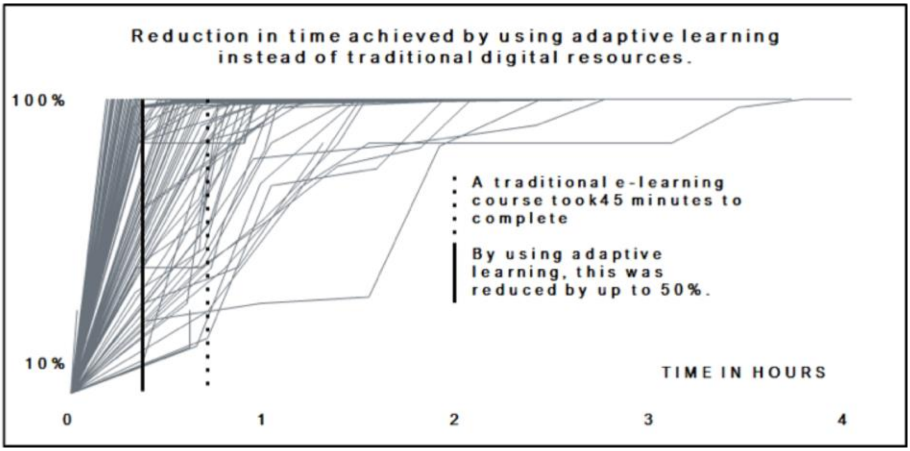
[241] Paulheim, H. (2016). "Knowledge graph refinement: A survey of approaches and evaluation methods.' , *Semantic Web* 8 (3): 489–508. https://doi.org/10.3233/SW-160218

[242] Embretson, S.E. and Reise, S.P. (2013). *Item Response Theory.* Psychology Press.

more, perhaps less well-known, but widely available ITS (chosen because they adopt slightly different approaches): Area9 Lyceum's Rhapsode, Dreambox, Toppr, and Yixue. We could also have chosen ALEKS,[243] Bjyu,[244] Century,[245] CogBooks,[246] iReady,[247] RealizeIt,[248] Smart Sparrow,[249] Summit Learning,[250] or ... the list goes on.

Area9 Lyceum[251] stands out. They develop an organization's existing learning materials into adaptive content that is delivered on their platform. Like all ITS, their approach aims to match the learning content and pathway to the needs and skill level of each individual learner, but the platform also uses an approach they call "continuous self-assessment." This involves learners rating how confident they are in their response to each question and task, which is then used to further adapt the learner's experience (even if they give a correct answer to a question, if they are not confident in that answer, they will be given additional related learning support). The following diagram shows how adaptive learning simultaneously reduces the time spent on learning for the bulk of the students, while allowing the slower ones to achieve mastery at their own pace.

243 https://www.aleks.com
244 https://byjus.com
245 https://www.century.tech
246 https://www.cogbooks.com
247 https://www.curriculumassociates.com/Products/i-Ready
248 http://realizeitlearning.com
249 https://www.smartsparrow.com
250 https://www.summitlearning.org
251 https://area9learning.com



Source: Area9 Lyceum, private communication.

Our second example, Dreambox,[252] aims to provide students with personalized learning pathways, in K–8 mathematics: "the right next lesson, at the right level of difficulty, at the right time." Again adopting a typical ITS approach, their AI-driven technology collects more than 48,000 data points every hour a student engages with the system, which it uses to evaluate the strategies the student employed to solve the problems, to adjust the lesson's level of difficulty, to sequence the lessons and to provide hints. Of the commercial ITS, Dreambox is fairly unusual in encouraging independent evaluations, with a recent study conducted by Harvard University finding that "the evidence for the causal impact of DreamBox on student achievement is encouraging but mixed."[253]

Meanwhile, Toppr[254] is an India-based company that offers personalized learning ITS mobile apps, across a wide range of school ages and subjects (from history to accounting). It uses machine learning to map out a student's strengths and weaknesses, based on their previous behavior, in order to personalize questions and adjust the speed of presentation to make the experience optimal for each individual. This

[252] http://www.dreambox.com

[253] Fullerton, J. (2016). "Dreambox learning achievement growth in the Howard county public school system and rocketship education." Center for Educational Policy Research. https://cepr.harvard.edu/dreambox-learning-achievement-growth

[254] https://www.toppr.com

ITS prediction system is complemented by a novel AI-driven technology that is, they say, designed "to solve doubts." Students can upload an image of a topic about which they are unsure, which a bot checks against a growing database of other uploaded doubts and solutions.

Our final example ITS is Yixue,[255] which styles itself as the first intelligent adaptive education system in China. Again as a typical ITS, Yixue aims to simulate a teacher, providing students with a personalized learning plan and one-to-one tutoring. Drawing on standard textbooks, Yixue have broken each of its various subjects into around 10,000 separate knowledge points, which are used to benchmark an individual student's understanding and capabilities, so that the system can predict which materials and pathway will be most effective.

Dialogue-Based Tutoring Systems

We began our discussion of ITS with Jaime Carbonell's SCHOLAR.[256] However, SCHOLAR is in at least one sense unlike most of the ITS that we have so far explored. Rather than presenting an individualized sequence of instructional material or learning activities (as is typical of ITS), SCHOLAR engaged students in conversations about the topic to be learned. This aspect gave rise to a version of ITS known as dialogue-based tutoring systems (DBTS). However, as with ITS, what constitutes DBTS is fuzzy-edged. Instead, we will again introduce some prominent examples : CIRCSIM, AutoTutor, and Watson Tutor.

CIRCSIM

One of the earliest DBTSs was CIRCSIM,[257] which was developed in the 1980s at the Illinois Institute of Technology in partnership with Rush Medical College. It was designed for first-year medical students, to help them learn about the baroreceptor reflex control of blood pressure. CIRCSIM used one-to-one tutorial dialogues, involving some limited

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[255] http://www.classba.cn

[256] Carbonell, J.R., "AI in CAI." 190–202.

[257] Evens, M. and Michael, J. (2006). *One-on-One Tutoring by Humans and Computers*. Psychology Press.

natural language processing and natural language generation, on the assumption that real understanding of something involves being able to talk articulately about it. It also used a rule-based expert systems approach, implementing conditional rules such as:

— If the student answer is correct, then proceed.
— If the student answer is partially correct, then give acknowledgement and proceed.
— If the student answer is a 'near miss', then introduce a nested method.
— If the student answer is "don't know", then give answer and proceed.[258]

Interestingly, CIRCSIM was not designed to introduce students to the topic. Instead, students were expected to have already acquired the facts and concepts from their readings and lectures. Their dialogue with the system helped the students explore in depth, better understand and consolidate what they had already learned. With this aim, students were asked to solve problems while engaging in an iterative typed dialogue. They would begin with a mandatory, guided virtual experiment. The program then directed the students step-by-step through a sequence of eight procedures, guiding them to predict outcomes based on supplied data, and to develop a simplified model for the homeostatic baroreceptor reflex system. Throughout, the emphasis was on the need for developing a chain of causal reasoning in solving this and similar problems.

AutoTutor

Our second example, AutoTutor,[259] which has been extensively researched for over twenty years, is probably the most influential DBTS. Developed at the University of Memphis, it simulates a tutorial dialogue between human tutors and students as they work step-by-step through online tasks (most often in computer science topics, but also in physics, biology, and critical thinking). The aim is to encourage students to

[258] Ibid, 45.
[259] Graesser, A,C., et al. (2001). "Intelligent tutoring systems with conversational dialogue." *AI Magazine* 22 (4): 39.

develop detailed responses and an in-depth understanding, rather than the short responses and shallow knowledge that can be the outcome of some step-by-step instructional ITS.

AutoTutor uses a statistical technique known as latent semantic analysis (LSA) to compare student-written speech with a multidimensional matrix of concepts drawn from a large corpus of relevant textbooks.[260] This matrix of concepts and a curriculum script (comprising example questions, problems, diagrams, declarative knowledge, and good and bad responses) effectively constitutes AutoTutor's ITS domain model.

Meanwhile, its version of a pedagogy model comprises Socratic tutoring principles (probing with questions rather than providing instruction) and classroom-based tutorial practices (based on analyses of dialogue from more than 100 hours of face-to-face human tutorials). Its adaptive learning activities involve engaging the student in a tutorial dialogue, a developing conversation in which the students are guided towards discovering for themselves a correct solution for the current problem.

An AutoTutor tutorial dialogue typically comprises five steps:[261] (1) AutoTutor (sometimes represented by an online animated character) poses a question or problem, (2) the student attempts to answer, typing their response into the system (or, with some versions, speaking aloud), (3) the tutor determines whether the student understands the target concept, by assessing how closely their contribution matches the concept as expressed in the textbook corpus (the LSA approach means that the

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[260] Graesser, A.C., et al. (2000). "Using latent semantic analysis to evaluate the contributions of students in AutoTutor." *Interactive Learning Environments* 8 (2): 129–47. https://doi.org/10.1076/1049-4820(200008)8:2;1-B;FT129. Latent semantic analysis (LSA), developed by Thomas Landauer (University of Colorado) originally for indexing documents for information retrieval, is "both a computational model of human knowledge representation and a method for extracting semantic similarity of words and passages from text". Peter W. Foltz, Darrell Laham, and Thomas K. Landauer. (1999). "The intelligent essay assessor: Applications to educational technology." *Interactive Multimedia Electronic Journal of Computer-Enhanced Learning* 1 (2). http://www.imej.wfu.edu/articles/1999/2/04/printver.asp

[261] Graesser, A.C. (2011). "Learning, thinking, and emoting with discourse technologies." *American Psychologist* 66 (8): 746–57. https://doi.org/10.1037/a0024974

student does not have to match specific wording but only the underlying concept), (4) if the tutor decides the student has not sufficiently understood the concept, the tutor provides feedback (in the form of corrective statements, questions, prompts, hints or summaries), perhaps to correct a misunderstanding or to encourage the student to extend their answer, and (5) steps two to four are repeated, with the aim of helping the student improve their answer. Finally, AutoTutor's version of a student model comprises the student's contributions to the dialogue, together with the goodness of fit (the closeness of the student's answer to the corpus of texts) of each of those student inputs.[262]

An AutoTutor dialogue[263] might look something like this:

> **AutoTutor** <Main Question>: Suppose a boy is in a free-falling elevator and he holds his keys motionless in front of his him and he lets go. What will happen to the keys? Explain why.
> **Student**: The keys would not move but hover at the start point.
> **AutoTutor** <Pump for information>: I bet you can explain this a little bit more.
> **Student**: The velocity of the keys is the same due to gravity.
> **AutoTutor** <Hint>: What about the acceleration of the objects involved?
> **Student**: What is acceleration again?
> **AutoTutor** <Answer>: Let me try to answer your question. Acceleration is the rate that velocity changes over time, like getting faster or getting slower. Acceleration is a vector quantity, so it needs to have a direction.
> **AutoTutor** <Hint>: Let's try this again. What about the acceleration of the objects involved?
> Student: The acceleration of the objects in the elevator are the same as the acceleration of the elevator which is the earth's gravitational acceleration.

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[262] Wiemer-Hastings, P., et al. (1998). "The foundations and architecture of AutoTutor." *Intelligent Tutoring Systems*. Springer. 334–343. http://link.springer.com/chapter/10.1007/3-540-68716-5_39.

[263] Nye, B.D., Graesser, A.C., and Hu, X. (2014). "AutoTutor and family: A review of 17 years of natural language tutoring." *International Journal of Artificial Intelligence in Education* 24 (4): 434 https://doi.org/10.1007/s40593-014-0029-5

AutoTutor <Short Feedback>: Good job!
AutoTutor <Prompt>: Try this. What direction are the objects going? The objects are falling <the animated character gives a downwards hand gesture to cue the student to express something>?
Student: Downward.
AutoTutor <Short Feedback>: Right.
AutoTutor <Prompt-completion>: The objects are falling downward.

Over its two decades, AutoTutor has been evaluated in multiple studies.[264] In summary, these have shown that it can achieve average learning gain-effect sizes of approximately 0.8, with higher gains for deep learning (understanding concepts) than for shallow learning (knowing facts), suggesting that it is more effective than many non-expert human tutors and might in some situations be as effective (at least in terms of learning gains) as a typical expert tutor.[265]

Watson Tutor

A more recent DBTS is the Watson Tutor[266] being developed collaboratively by the global corporations IBM and Pearson, which at the time of writing is being evaluated before being released as a commercial product (integrated into a Pearson higher education courseware product called REVEL). Watson Tutor is a dialogue-based tutorial system using natural language conversation that guides students through a review session—in other words, like AutoTutor and CIRCSIM, it does not set out to introduce new knowledge but to enable a deeper understanding of existing knowledge.[267] As the students engage with Watson Tutor, it provides supportive content (such as text, images, and videos), tracks

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[264] D'Mello, S. and Graesser, A. (2012). "AutoTutor and sffective AutoTutor: Learning by talking with cognitively and emotionally intelligent computers that talk back." *ACM Transactions on Interactive Intelligent Systems (TiiS)* 2 (4): 23.

[265] VanLehn, "The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems"; Nye, Graesser, and Hu, "AutoTutor and family."

[266] https://www.ibm.com/watson/education

[267] Ventura, M., Chang, M., Foltz, P., Mukhi, N., Yarbro, J., Salverda, A. P., … Afzal, S. (2018). "Preliminary evaluations of a dialogue-based digital tutor." In Carolyn, R. (ed.). *Proceedings of the 19th International Conference.* AIED 2018 London, UK, 480–483.

their progress, and adapts the conversation based upon a classification of the student's responses and an assessment of their subject mastery.

The Watson Tutor draws heavily on the approach developed by the AutoTutor researchers, although its domain model, the formalization of the knowledge and skills to be learned, is derived from a single textbook. It comprises a set of learning objectives and enabling objectives (sub-learning objectives that support a main learning objective), a knowledge graph of the relationships between the learning objectives, main questions and main answers, assertions (knowledge components of the main answers), and hint questions to elicit assertions (typically 600 main and hint questions are derived from the single textbook) and fill in the blank questions (based on the student assertions). All of this is derived from the chosen textbook by means of an automated analysis undertaken by the IBM Watson toolset (the AI as a service mentioned earlier, which includes natural language understanding and classification tools). This approach to the domain model means that it can, at least in theory, straightforwardly be adapted to any academic domain and its textbook (its initial implementation covered developmental psychology, physiological psychology, abnormal psychology, sociology, communication, and government).

The pedagogy model again adopts a Socratic approach, implemented as a dialogue manager that controls when and which responses are delivered to a student. Starting from a learning objective, Watson Tutor begins by asking the student a main question, with the aim of eliciting from the student the main answer. The student's responses are classified by the IBM Watson system, enabling the system to respond with appropriate feedback or a hint question to help the student work towards an ideal answer. For main questions, the classifier matches the student's response to all the knowledge components of the main answer, using a supervised machine learning approach that requires only 35 scored student answers per question. If the student struggles on a main learning objective, the Tutor will move to an enabling objective, repeating the dialogue approach.

The Watson Tutor's learner model includes an estimation of each student's proficiency over the course of the conversation, in terms of both the learning and enabling objectives. This also functions as an open learner model, since the student's estimated proficiencies and developing performance can be inspected at a high level and with detailed granularity, by the individual students and their teachers.

A Watson Tutor dialogue might look something like this:[268]

> **Watson Tutor** <Learning objective main question>: Let's review this topic… Try answering this question: What are some variations in the definition of family?
> **Student**: A family can be defined as people who live together.
> **Watson Tutor** <Feedback on student assertion>: Excellent. Kinship systems consist of the social links and boundaries, defined by biology and social custom, that establish who is related to whom. Let's take it a bit further.
> **Watson Tutor** <Learning objective hint question>: How do social scientists define the family?
> **Student**: Social scientists define the family as a group of related people that reside together.
> **Watson Tutor** <Feedback on student assertion>: That looks partly correct. There's a little more to the answer. Let's work this out together.
> **Watson Tutor** <Fill in the blank hint>: Can you fill in the missing words? Social scientists typically define family as a group of people who live together in a household and share ________ and/or _____ ties.

Exploratory Learning Environments

An alternative to step-by-step instruction by ITS and DBTS step-by-step dialogue is provided by a third type of AIED, known as exploratory learning environments (ELEs). ELEs adopt a constructivist approach. Rather than following a dynamically generated step-by-step sequence, students are encouraged to actively construct their own knowledge by exploring and manipulating elements of the learning environment.

[268] Based closely on Ventura et al., 482.

In fact, exploratory and discovery learning have been around for a long time,[269] but they remain controversial.[270] Critics argue that, because there is no explicit instruction and students are expected to discover domain principles for themselves, it causes cognitive overload and leads to poor learning outcomes. This is where AI comes in, with many recent ELEs including AI-driven automatic guidance and feedback, addressing misconceptions and proposing alternative approaches, to support the student while they explore.

As we have seen, delivering effective AI-driven support requires a learner model. However, building learner models for unstructured environments like ELEs can be challenging: "The unconstrained nature of the interaction and the lack of easily definable correct behaviors make it difficult to know a priori what behaviors are conducive for learning."[271] Nonetheless, student models are usually an important component of ELEs.

Again, we will briefly explore four examples,[272] each of which includes a student model and use different AI-driven approaches to provide the necessary support: Fractions Lab (which delivers automated feedback according to a student's affective state), Betty's Brain (which involves a teachable agent), Crystal Island (which uses a games-based approach), and ECHOES (which is designed to support children on the autism spectrum).

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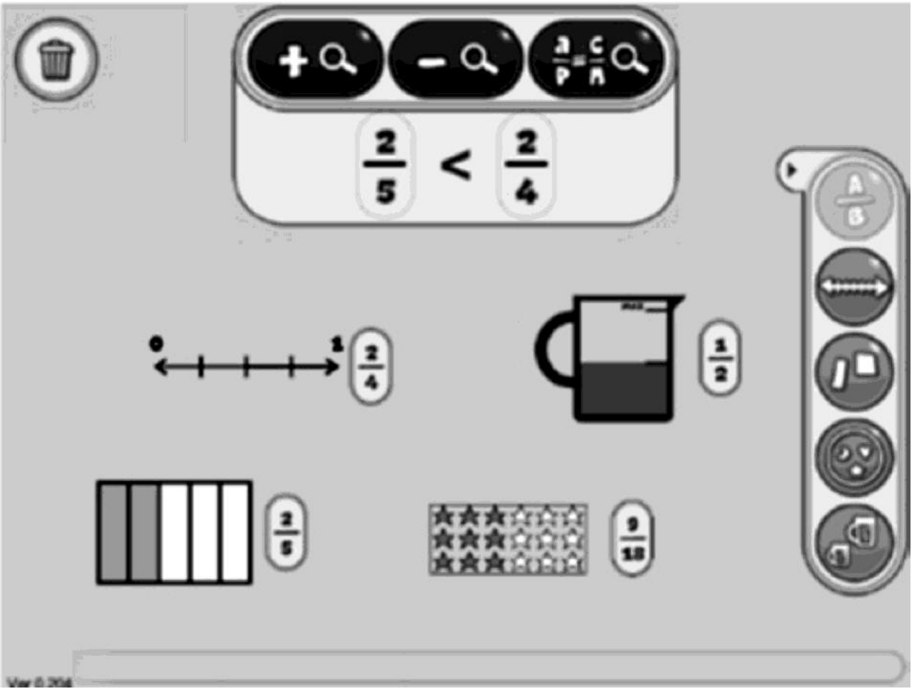
[269] E.g., Bruner, J.S. (1961). "The Act of Discovery." *Harvard Educational Review* 31: 21–32.

[270] Kirschner, P., Sweller, J., and Clark, R.E (2006). "Why minimal guidance during instruction does not work: An analysis of the failure of constructivist, discovery, problem-based, experiential, and inquiry-based teaching." *Educational Psychologist* 41 (2): 75–86.

[271] Fratamico, L., et al. (2017). "Applying a framework for student modeling in exploratory learning environments: Comparing data representation granularity to handle environment complexity." *International Journal of Artificial Intelligence in Education* 27 (2): 321. https://doi.org/10.1007/s40593-016-0131-y

[272] Building on du Boulay, et al. (2018). "What does the research say about how artificial intelligence and big data can close the achievement gap?" In *Enhancing Learning and Teaching with Technology*, Luckin, R. (ed.). Institute of Education Press, 316–27.

Fractions Lab



Fractions Lab, which was developed by an EU-funded research project,[273] is designed to help students develop conceptual knowledge, the underlying principles, of fractions. In this ELE, students can choose and manipulate fraction representations (for example, having chosen a rectangle, jug or number line to represent a particular fraction, they can create the fraction by changing the numerator and denominator), the aim being to solve a given fractions problem (such as "Use the Fractions Lab tools to add together $\frac{2}{3}$ and $\frac{2}{6}$."). To avoid cognitive overload while they address the given task, Fractions Lab uses AI-techniques to provide the students with adaptive support—that is to say, feedback or guidance specific to where they are in their attempted solution (such as "To add the two fractions together, you first need to make them equivalent. How do you need to adjust the denominator?"). However, in addition to providing this context-specific guidance, the feedback also aims to

[273] http://www.italk2learn.eu

enhance the student's affective states that is, to move students from nominally negative affective states (such as frustration or boredom) into nominally positive affective states (which are usually assumed to be more conducive for learning).

This is achieved by means of Bayesian networks trained with data from classroom studies, one of which determines the most appropriate type of formative feedback to be given to the student. For example, if the student is confused, the Bayesian network determines that an affect boost (such as "Well done. You're working really hard!") or specific instructive feedback (such as "Use the comparison box to compare your fractions.") is most effective.

Other feedback provided by the system includes Socratic feedback (such as "What do you need to do now, to complete the fraction?"), reflective prompts (such as "What do you notice about the two fractions?"), affirmation prompts (such as "The way that you worked that out was excellent"), and sequence prompts (such as "Are you sure that you have answered the task fully? Please read the task again").

Fractions Lab's pedagogy and domain models comprise both the overall constructivist ELE approach, and the information used to determine the content of the formative feedback. Meanwhile, the learner model includes data about the student's inferred affective state, their progress with the current task, their interactions with the learning environment (whether a representation has been created, selected or manipulated), the type of feedback they have received, and the specific message, and whether or not the student follows the feedback. While the student interacts with the fractions representations to answer the tasks, the learner model is constantly being updated with information, both about those interactions and with the feedback that has been provided to the student.

As part of a larger project,[274] Fractions Lab was evaluated in schools in Germany and the UK, comparing the effectiveness of Fractions Lab in combination with an ITS. Although the tools were only used for a short time, the outcomes showed that the combination of ELE and ITS achieved a learning gains effect size of 0.7 (compared with the ITS alone), suggesting that AI-supported ELEs can offer a useful approach to learning.

Betty's Brain

An iconic ELE is Betty's Brain,[275] which involves an AI-driven, teachable agent. It was designed to facilitate the learning of scientific conceptual understanding, using river ecosystems as a use-case exemplar. What distinguishes Betty's Brain is that, through their engagement with the system, students are encouraged to teach a fellow student, in fact a virtual agent, called Betty. This approach (which is the foundation of the system's pedagogy model) has been adopted because learning by teaching has been shown to be effective—it is known to help students structure, reflect on and develop a more in-depth understanding of whatever is being learned.[276]

Within an overarching narrative (helping Betty to join a science club), students are supported to teach Betty, then to query Betty to see how much she has understood, and finally to quiz Betty to see how well she does on questions generated automatically by the system, many of which the student may not have considered.

The mechanism used for teaching Betty centers on a concept map editor, which represents what the student has taught Betty. Drawing on a range of provided reading materials and using the available editing tools, the student builds a conceptual map of the river ecosystem (the

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[274] Rummel, N., et al. (2016). "Combining exploratory learning with structured practice to foster conceptual and procedural fractions knowledge." In Looi, C.K., Polman, J., Cress, U., and Reimann, P. *(eds.) Transforming Learning, Empowering Learners: The International Conference of the Learning Sciences* 1: 58–65.

[275] Leelawong, K. and Biswas, G. (2008). "Designing learning by teaching agents: The Betty's Brain system." *International Journal of Artificial Intelligence in Education* 18 (3): 181–208.

[276] Biswas, G., et al. (2005). "Learning by teaching: A new agent paradigm for educational software." *Applied Artificial Intelligence* 19 (3–4): 363–92. https://doi.org/10.1080/08839510590910200

relationships between a river's plants, animals, microorganisms, chemical components, and physical characteristics), attaching nodes (representing particular knowledge components) via edges (representing causal and other links between the various components). In effect, the students build their own semantic network, which forms the core of the system's learner model (i.e. it represents the student's current knowledge and understanding). The learner model also includes a record of the student's interactions with the system. Interestingly, the concept map, because it is visual and open to inspection by the student and the teacher, also functions as an open learner model.

Once Betty has been taught, the student can ask her a question (such as, "If macroinvertebrates increase what happens to bacteria?"). In response, Betty reasons using the concept map to generate an answer (such as, "An increase in macroinvertebrates causes no change in bacteria"). The student can also ask Betty for an explanation, which Betty gives while highlighting the causal paths in the concept map.

The system also uses the concept map, together with the system's domain model, to generate the quiz questions that are administered by Mr. Davis, a virtual teacher. Betty's responses to the quiz questions draw directly from the concept map, while Mr. Davis's feedback also uses the domain model to suggest how the student might edit the concept map in order to help Betty achieve a higher quiz score—in other words, to correct any mistakes made by Betty and to identify any misconceptions. Mr. Davis also makes suggestions at the meta-cognitive level, for example about making better use of the reading materials, in an effort to help the learner develop good meta-learning strategies (study skills).

Betty's Brain has been evaluated in multiple studies,[277] although in its original configuration student outcomes were often split, almost half and half, between those who made very good progress with the system and

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[277] Biswas, G., Segedy, J.R., and Bunchongchit, K. (2016). "From design to implementation to practice a learning by teaching system: Betty's Brain." *International Journal of Artificial Intelligence in Education* 26 (1): 350–364.

those who struggled. The researchers went on to develop a new version, which they used to investigate different learning behavior profiles.[278]

Crystal Island

Crystal Island[279] emerged from research at North Carolina State University. It takes an immersive, first-person, computer-game approach, with students playing the role of a detective investigating a mysterious disease on a remote island. This games-based learning approach[280] functions as Crystal Island's pedagogy model. In solving the mystery, students use and develop their literacy skills while gaining experience of professional scientific inquiry methods (including evidence gathering, hypotheses testing, and data analysis), all of which together constitute the domain model. Meanwhile, the students' developing knowledge, their affective states and their skills, are automatically modeled (in the ELE's learner model) and they receive automated supportive feedback. In addition, throughout the gameplay, they engage with AI-driven autonomous non-player characters (companion agents), which build on AI techniques developed over many years in mainstream computer games.[281]

ECHOES

Our fourth example ELE, ECHOES,[282] again involved a games-based approach, but this time to support young children who are on the autism spectrum. ECHOES was a virtual environment, a magic garden, in which the child interacted with an intelligent child agent called Andy. The child's teacher (not AI) selected one of twelve learning activities, led by

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[278] Jeong, H., et al. (2008). "Using hidden Markov models to characterize student behaviors in learning-by-teaching environments." In *Intelligent Tutoring Systems*, 614–25. https://doi.org/10.1007/978-3-540-69132-7_64

[279] http://projects.intellimedia.ncsu.edu/crystalisland

[280] Holmes, W. (2017). "Digital games-based learning. Time to adoption: Two to three years?" In *Education and New Technologies: Perils and Promises for Learners*. Sheehy, K. and Holliman, A.J. (eds.). Routledge.

[281] Yannakakis, G.N. and Togelius, J. (2018). *Artificial Intelligence and Games.* Springer International Publishing. https://doi.org/10.1007/978-3-319-63519-4

[282] Bernardini, S., Porayska-Pomsta, K., and Smith, T.J. (2014). "ECHOES: An intelligent serious game for fostering social communication in children with autism." *Information Sciences* 264 (April): 41–60. https://doi.org/10.1016/j.ins.2013.10.027

Andy, each of which was designed to enhance the child's capacities for joint attention and to help them develop their social communication skills.

The magic garden was displayed on a large touchscreen monitor, allowing the child and Andy to interact with each other and with objects in the garden. Sometimes, when touched, the garden objects transformed in unusual ways. For example, tapping the petals of a flower could turn it into a floating bubble or a bouncy ball. The system also included an eye-tracking camera, allowing Andy to "know" where the child was looking.

Andy was designed to function as an artificially intelligent social partner who could act both as a peer and as a tutor. Its implementation was based on a well-established AI agent architecture called FAtiMA,[283] which enabled it to be autonomous, proactive, reactive, and socio-emotionally competent. In particular, Andy was designed to be a positive and supportive character. For example, he always greeted the child by name, gave positive feedback when the child participated in an interaction, and tried to re-engage the child if they appeared distracted. Andy also used facial expressions and gestures to indicate his emotional responses. For example, he smiled and gave a thumbs-up when the child initiated an activity.

ECHOES also included a pedagogy model, which monitored the developing interactions between the child and Andy, to help ensure that the learning objectives were achieved, and a user model that aimed to monitor the cognitive and emotional state of the child, so that Andy could give appropriate real-time feedback.

Summary

As we have seen, because ELEs are unstructured and open-ended learning environments that students can explore as they like, there is no clear definition of correct behaviors, which makes it difficult to model the student and to provide the necessary guidance. With this in mind,

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[283] Dias, J., and Paiva, A. (2005). "Feeling and reasoning: A Computational model for emotional characters." In *Progress in Artificial Intelligence*, 127–40. Springer. https://doi.org/10.1007/11595014_13

over several years, Conati and colleagues have developed and researched a multilayered, student-modeling framework,[284] which they implemented in an ELE called CCK, which can potentially be applied in other ELEs. This framework uses multiple, logged student actions to learn which behaviors should trigger remedial guidance, and which lead to what outcomes (such as high- or low-achieving). It involves the use of unsupervised-learning to cluster groups of students who, based on their logged data and learning outcomes, learn similarly. The logged data includes the components used (such as a light bulb), student actions (join), and simulation outcomes (a change in light intensity). The student-clusters model is then used to classify new students, and to trigger real-time, adaptive support based on the logged and thus anticipated behaviors, in order to support students to achieve higher learning outcomes.

Automatic Writing Evaluation

The AIED applications we have looked at so far—the step-by-step instructional and dialogue-based systems, and the exploratory learning environments—all involve students working on computers (sometimes mobile devices),[285] following individualized learning pathways while receiving immediate adaptive support. Another type of AIED, automatic writing evaluation (AWE), uses natural language and semantic processing to provide automatic feedback on student writing submitted to the system.[286]

[284] Kardan, S. and Conati, C. (2015). "Providing adaptive support in an interactive simulation for learning: an experimental evaluation." In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems,* 3671–3680. https://doi.org/10.1145/2702123.2702424

[285] Fujitani, S. and Minemura. K. (2017). "An analysis of expectations for artificial intelligence-supporting software in mobile learning." https://www.researchgate.net/publication/324537420_An_Analysis_of_Expectations_for_Artificial_Intelligence-supporting_Software_in_Mobile_Learninght

[286] According to John Behrens (Pearson), automated essay grading is one area that "machine learning is starting to make progress." Quoted in Johnson, S. (2018). *What Can Machine Learning Really Predict in Education?* https://www.edsurge.com/news/2018-09-26-what-can-machine-learning-really-predict-in-education

Broadly speaking, there are two overlapping AWE approaches, formative (providing support to enable a student to improve their writing before submitting it for assessment)[287] and summative (automatic scoring).[288] However, in line with the long established automated grading of multiple choice and fill-in-the-blank tests, much of the work is directed to scoring over feedback. It has often been driven by the desire to improve the cost, reliability, and generalizability of summative assessments, whether for use in small-scale settings by teachers (for low-stakes classroom assessment) or large-scale settings by testing companies (for large-scale, statewide, or national, high-stakes assessments).

> Efficiency is where the automated readers excel. The e-rater engine can grade 16,000 essays in about 20 seconds, according to ETS. An average teacher might spend an entire weekend grading 150 essays, and that efficiency is what drives more education companies to create automated systems.[289]

This is why automated essay feedback and scoring is probably the best-funded area of AIED research, and why it has spawned a large number of commercial systems.[290] There are so many available AWE systems,[291] with different approaches and limitations, that we will again simply introduce some prominent examples.

PEG

The beginnings of AWE can be traced to the development in 1966 of Project Essay Grade (also known as PEG) by Ellis Page at Duke

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[287] One example being M-Write: https://lsa.umich.edu/sweetland/m-write.html

[288] One example being Gradescope: https://www.gradescope.com

[289] https://www.npr.org/sections/alltechconsidered/2012/04/24/151308789/for-automatic-essay-graders-efficiency-trumps-accuracy?t=1542533112695

[290] Dikli, S. (2006). "An overview of automated scoring of essays." *The Journal of Technology, Learning and Assessment* 5 (1). https://ejournals.bc.edu/ojs/index.php/jtla/article/view/1640. Raczynski, K., and Cohen, A. (2018). "Appraising the scoring performance of automated essay scoring systems—some additional considerations: Which essays? Which human raters? Which scores?" *Applied Measurement In Education* 31 (3): 233–40. https://doi.org/10.1080/08957347.2018.1464449. See also, Hubert's "AI in education—automatic essay scoring." https://medium.com/hubert-ai/ai-in-education-automatic-essay-scoring-6eb38bb2e70

[291] Stevenson, M. and Phakiti, A. (2014). "The effects of computer-generated feedback on the quality of writing." *Assessing Writing* 19: 51–65.

University. The original version of PEG used correlational statistics to compare submitted essays with a training set of up to 400 comparable essays that had already been marked by teachers, an approach that was shown in various studies to achieve predicted scores comparable to the human markers. However, the PEG system was criticized for focusing on indirect measures of writing skill (the surface features of essays such as the number of sentences, use of punctuation and grammar) rather than on the meaning of the sentences, the writing style, or how the writer had developed their arguments (in other words, it was criticized for focusing on the form rather than the content of the essays). For this reason, PEG was incapable of providing meaningful formative feedback, to enable students to improve the academic (rather than the surface) quality of their essay, and instead provided only a summative mark. The effectiveness of the system was also dependent on the selection of the training essays, and the quality of the assessments made by the training set's human markers. More recently, PEG was re-engineered to include computational linguistics, machine learning, and natural language processing techniques. It was also included in the Hewlett Foundation-sponsored Automated Student Assessment Prize competition.[292]

Intelligent Essay Assessor

An alternative early AWE approach, Intelligent Essay Assessor (IEA), used latent semantic analysis (LSA), the statistical technique that we introduced when discussing the dialogue-based tutoring system AutoTutor. LSA enables IEA to infer the meanings of words and sentences, by considering the context in which they occur, and to calculate the semantic relatedness of a target document to the training corpus: "The underlying idea is that the meaning of a passage is very much dependent on its words and changing even only one word can

[292] Shermis, M. D. (2014). "State-of-the-art automated essay scoring: competition, results, and future directions from a United States demonstration." *Assessing Writing* 20 (April): 53–76. https://doi.org/10.1016/j.asw.2013.04.001

result in meaning differences in the passage. On the other hand, two passages with different words might have a very similar meaning."[293]

The IEA calculated similarity scores for essays when compared with a set of training texts, which included a large number of pre-scored student essays, expert model essays, and knowledge source materials (such as textbooks and academic papers). The system determined the essay's mark by averaging the similarity scores. However, the comparison with the key domain-representative texts also allowed the system to provide diagnostic and evaluative formative feedback across six areas: ideas and content, organization, sentence fluency, word choice, conventions, and voice. IEA was also able to detect some plagiarism (i.e., passages replicating text in the knowledge source materials) and collusion (similar passages appearing in more than one essay in a cohort), both of which (if only because of the scale involved) can be difficult for human markers to identify. IEA was also included in the Automated Student Assessment Prize competition.[294]

WriteToLearn

Over recent years, the IEA approach has been further developed by the international education company Pearson and incorporated in their product WriteToLearn.[295] The current system draws on a broad range of AI techniques in order to provide both in-depth formative feedback and summative scoring. Essays are assessed against one or more rubrics, using a supervised machine-learning approach involving a training set of around 300 representative essays that have been scored by humans. The rubrics involve traits such as focus, development of ideas, organization, language and style, voice, sentence correctness, and sentence fluency. The system is also able to detect a variety of errors in the submitted essay, and thus to provide a series of specific prompts in terms of narrative, exposition, description, and persuasion, all scaffolded on the student's writing performance and designed to enable the student to improve their

[293] Dikli, "An overview of automated scoring of essays," 5.

[294] Shermis, M.D. (2014). "State-of-the-art automated essay scoring: Competition, results, and future directions from a United States demonstration." *Assessing Writing* 20: 53–76. https://doi.org/10.1016/j.asw.2013.04.001

[295] https://www.writetolearn.net

next draft. In addition, the system also gives a score to the writing, by assessing it against a rubric designed to represent characteristics of high-quality writing: ideas, organization, conventions, sentence fluency, word choice, and voice. A secondary component in the software can be used to assess and provide feedback based on students' summarizations of given texts, which has been shown to help students build their reading comprehension skills.

WriteToLearn has been evaluated in a number of studies. In one state-wide study,[296] involving more than 20,000 students and 70,000 assignments, the students submitted an average of around four revised drafts (more than is typical in a traditional classroom setting) and improved their overall scores by almost one point out of a maximum of 6 (effect sizes are not given). The improvements were shown to be in both basic writing skills and higher-level traits like ideas and voice.

e-Rater

A third AWE approach, originally known as e-Rater, which was developed by the Educational Testing Service, is widely used (for example, in GMAT tests and, in a more recent version, for Common Core Standards).[297] Like the earlier systems, e-Rater analyses a large set of linguistic features (syntactic variety, topic content, and lexical and syntactic cues) that it automatically extracts from essays using natural language processing techniques. Algorithms then assign values for every feature identified in an essay, which are computed using linear regression and compared to a training set of essays scored by human experts, to predict a final score. ETS claims the psychometric validity of e-Rater scores across a range of subject areas, while accounting for cultural and second-language differences.

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[296] Foltz. P.W. and Rosenstein, M. (2013). "Tracking student learning in a state-wide implementation of automated writing scoring." In *NIPS Workshop on Data Driven Education*.

[297] Kukich, K. (2000). "Beyond automated essay scoring." *IEEE Intelligent Systems*. https://doi.org/10.1109/5254.889104

Revision Assistant

Three, short, final AWE examples are Revision Assistant, OpenEssayist, and AI grading. Perhaps best known for their antiplagiarism software, which automatically checks student writing against billions of internet documents and journal papers, the Turnitin corporation also now offers Revision Assistant. This system is designed to evaluate and provide formative feedback on short student essays (between 200 and 700 words) in a range of genres, which it achieves by using both supervised machine learning (involving training essays that have been scored by at least two human teachers) and unsupervised machine learning (involving a collection of thousands of unscored essays collected from students who have already used the system in classrooms).

The Turnitin analysis works by representing the submitted essays in terms of large numbers of low-level textual features (such as word n-grams and essay length), and it uses multiple methods to compute a prediction. For example, one core analytical technique is to delete a sentence from the submitted essay to determine how that edit affects the predicted score. If the predicted score increases, the system infers that the sentence is strong for the particular trait being evaluated. This allows the system to automatically provide sentence-level formative feedback specific to the rubric in question, drawn from a pool of more than a thousand feedback comments authored by content experts, for each draft that a student submits.

Classroom observations (at the time of writing there have been no published efficacy studies) have suggested that the system generates automated feedback that is both well received by students and aligned with improving scores. Turnitin argues that their automated essay feedback system not only provides more frequent formative feedback to students but also "allows the teacher to step back from the sometimes-adversarial red pen and engage with their class as guides and readers, modeling the interpretation of feedback alongside their students."

OpenEssayist

OpenEssayist,[298] which was developed by The Open University and Oxford University in the UK, takes a somewhat alternative approach, again using natural language processing but focusing more on how the feedback is presented to the students so that it is easily actionable. The system's linguistic analysis engine uses unsupervised algorithms to cluster key words, phrases, and sentences from the student's essay. It then generates several external representations. For example, key words and phrases are presented in a word cloud, which can be explored and organized into groups. It also uses automatically generated animations and interactive exercises to encourage the student to reflect on the content of their essay. This aims to help the student improve their writing, while also promoting higher-order learning processes: self-regulated learning, self-knowledge, and metacognition.

AI Grading

Our final, un-named, example was developed to address the problem of marking essays for thousands of students on the EdX MOOC (massive open online courses) platform.[299] This system again uses an innovative machine-learning algorithm, which was trained with hundreds of teacher-graded essays, and configured with teacher-written rubrics.[300] However, the EdX system warrants only a brief mention because it does not appear to be currently available, and details are difficult to find. However, it is included here for two reasons: because it is likely that the further developments in MOOC approaches to teaching and learning will require some way to assess student contributions at scale, and because it helped catalyze a critical reaction to the whole project of automatic essay scoring. Criticisms have been neatly summarized, and comprehensively

[298] Whitelock, D., et al. (2013). "OpenEssayist: An automated feedback system that supports university students as they write summative essays." http://oro.open.ac.uk/41844/

[299] https://www.edx.org

[300] Reilly, E.D., et al. (2014). "Evaluating the validity and applicability of automated essay scoring in two massive open online courses." *The International Review of Research in Open and Distributed Learning* 15 (5). http://www.irrodl.org/index.php/irrodl/article/view/1857

referenced, on the Professionals Against Machine Scoring Of Student Essays In High-Stakes Assessment website:

> Studies show that by its nature computerized essay rating is: trivial (rating essays only on surface features such as word size, topic vocabulary, and essay length), reductive (handling extended prose written only at a grade-school level), inaccurate (missing much error in student writing and finding much error where it does not exist), undiagnostic (correlating hardly at all with subsequent writing performance), unfair (discriminating against minority groups and second-language writers), and secretive (testing companies block independent research into their products).[301]

Finally, we should pose the diametrically reversed question. What happens when students have access to AI technologies that are capable of automatically writing (generating) high-quality essays (leading inevitably to an arms race for supremacy between automatic writing and automatic assessment?)[302] For now a moot point, but almost certainly not for long.

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[301] http://humanreaders.org/petition/index.php

[302] Much like the ongoing arms race between AI-generated fake news (such as https://www.technologyreview.com/s/610635/fake-news-20-personalized-optimized-and-even-harder-to-stop) and AI tools to identify fake news (such as http://adverifai.com).

What Other AIED is Out There?

As we saw in our discussion of ITS, any survey of applications of AI in education will always be incomplete, because new AIED applications using new AIED techniques are being launched every day. This follows the upsurge in general interest in AI and the many recent advances made possible by faster computer processors, large amounts of educational big data, and new computational approaches. In fact, because education has become a key focus for many AI developers (as we noted at the outset, the market for AIED is predicted to be worth $6 billion by 2024), a quick Google search will identify hundreds of AI products claiming to support students and improve learning outcomes. The EdTech consultancy GettingSmart recently published just such a search with a long list of thirty-two types of commercial "applications that are (or soon will be) making good use of machine learning to support better education."[303]

In fact, as summarized in the following table, most existing AIED applications may be categorized in terms of five complementary dimensions: (i) the type of learners for which the AIED is designed, (ii) the learning domain that it covers, (iii) the learning approaches it facilitates, (iv) the learning support that it provides, and (v) the teaching support that it provides. AI might also be found at an institutional level (outside of learning), both in learning management systems (such as MOOCs) and school-management platforms (to deal with class timetabling, staff scheduling, facilities management, finances, cybersecurity, safety and security, and e-authentication). However, these administrative uses of AI in education are beyond the scope of this book.

One key distinction to note between AIED technologies that are designed to support students directly (student-facing tools, such as the ITS, DBTS, ELE, and Automatic Writing Evaluation systems that we have discussed) and AIED technologies that are designed to support teachers to support students (teacher-facing tools). We will return to this distinction later.

[303] http://www.gettingsmart.com/2018/08/32-ways-ai-is-improving-education

Dimension	Examples
Type of learners	Early years. K–12. Higher education. Informal. Professional. Students who have additional needs.
Learning domain	From maths and physics, to language learning and music, and beyond.
Learning approach	Step-by-step instructional adaptive learning. Dialogue-based adaptive learning. Exploratory learning. Writing analysis.
Learning support	Learning diagnostics. Mentoring. Assessment. Network connectors. Chatbots.
Teaching support	Automatic learner profiles. Smart gradebooks.

Here, however, we will conclude our look at applications of AI in education with six further sets of tools or technologies, some of which build on the AIED approaches that we have already mentioned, while others adopt alternative AI techniques. We begin with what we can only think to call ITS+, then AI-supported language learning, chatbots, augmented and virtual reality, and learning network orchestrators.

ITS+: ALT School, ALP, and Lumilo

By ITS+ we mean approaches that augment or extend standard ITS functionalities, that perhaps expand the reach of an ITS or add another layer. Our first example is is ALT School,[304] a Silicon Valley venture founded by a former Google executive and funded by the Chan Zuckerberg Initiative. What sets ALT School apart from conventional schools is their use of a big data ITS approach to deliver individualized

[304] http://www.altschool.com

learning to students throughout the whole school—in other words, this is in effect a school-wide ITS. Each week, all ALT School students are given an automatically generated individual playlist of activities that are designed to develop student mastery, and while they engage with the activities a vast range of data about their interactions is recorded and analyzed. The results, which include each student's strengths, weaknesses, and progress, are made available to the teachers. Meanwhile, video footage of student activities, captured by classroom wall-mounted cameras, is also analyzed using AI techniques, to provide indicators of student engagement. Interestingly, ALT School appears recently to have pivoted their business model. Perhaps inspired by our next example, they now offer their technologies to other schools rather than focusing on running their own.

Our second ITS+ is ALP (adaptive learning platform), by Kidaptive,[305] which offers an "AIED engine as a service" to the developers of educational technologies that are not themselves enabled with AI—in other words, ALP offers backend ITS functionality for standard edTech. Partner companies connect their EdTech products to ALP, using client- or server-side software development kits (SDKs), which then analyzes their user data in real time. Data streams from a variety of learning contexts can be aggregated to create in-depth psychometric profiles (learner models) of each individual student's interactions, preferences, and achievements. It then uses an item response theory, psychometric framework to determine the student's optimal next challenge, instructional material, or activity, which is then delivered to the student by the partner's EdTech product. ALP also provides personalized insights and recommendations to teachers and parents about the best ways in which they can support individual learners.

[305] http://kidaptive.com

We have left possibly the most intriguing ITS+ for last: Lumilo.[306] So far only a research project, Lumilo uses mixed-reality smart glasses to enable teachers to access a student's real-time ITS data simply by looking at the student. In other words, Lumilo enables teachers to take advantage of ITS-driven adaptive learning and analytics, at the same time that they observe and engage with their classrooms as they would in a world without computers.

The tool emerged from research that suggested teachers using ITS "wanted to be able to instantly see when a student is "stuck" (even if that student is not raising her/his hand), to instantly detect when a student is off-task or otherwise misusing the software, and to be able to see students' step-by-step reasoning, unfolding in real-time."[307] However, while typical ITS might provide much of this information, they are not capable of registering or highlighting the many subtle cues exhibited by students that experienced teachers pick up on and use all the time.

Accordingly, the Lumilo transparent smart glasses superimpose real-time indicators of students' behavioral and learning states on top of the teachers' view of their classroom (in other words it functions as an Augmented Reality system, which we discuss in more detail later). As the teacher looks around the classroom, observing their students' ITS[308] activities, summary information appears, floating above each student's head. Looking at a particular student, and clicking a handheld clicker or making a specific hand-gesture, brings up a live feed of the student's screen or more detailed information (such as the number of errors they have made or the number of hints they have requested). By combining

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[306] Holstein, K., McLaren, B.M., and Aleven, V. (2018). "Student learning benefits of a mixed-reality teacher awareness tool in ai-enhanced classrooms." In *Artificial Intelligence in Education*, ed. Rosé, C. P., et al. https://doi.org/10.1007/978-3-319-93843-1_12

[307] Holstein, K., et al. (2018). "The classroom as a dashboard: Co-designing wearable cognitive augmentation for K-12 teachers." In *Proceedings of the 8th International Conference on Learning Analytics and Knowledge—LAK '18*. https://doi.org/10.1145/3170358.3170377

[308] Lumilo has been researched with an ITS, called *Lynette,* which has been designed to teach linear equations. Lynnette adaptively selects pathways using Bayesian knowledge tracing, and provides step-by-step guidance and feedback. *See* Aleven V., et al. (2016). "Example-tracing tutors: Intelligent tutor development for non-programmers." *International Journal of Artificial Intelligence in Education* 26(1): 224–269.

these two types of data, ITS data and teacher observations, the Lumilo researchers aim to enable teachers to intervene appropriately with their students, as and when they decide.

Language Learning: Babbel and Duolingo

Another application of AI in education, which has recently seen considerable growth, is language learning. However, to digress briefly, potentially the most transformative application of natural language processing in recent times was the 2017 introduction of the Google Pixel Buds,[309] which emerged from the research that we discussed earlier into statistical approaches to natural language processing. The Pixel Buds' algorithms, although far from perfect, are capable of translating between two spoken languages in real time, enabling two speakers who do not share a language to have a proper conversation—finally making real some long-anticipated science fiction gadgets. Remember the universal translator[310] from *Star Trek*, or the Babel fish[311] from *The Hitchhiker's Guide to the Galaxy*?

Nonetheless, currently there remain good reasons for learning another language.[312] Two of the most prominent AI-driven language learning commercial products, although there is little evidence that any are used extensively in formal educational settings, are Babbel and Duolingo (we

[309] https://www.blog.google/products/pixel/pixel-buds

[310] http://www.startrek.com/database_article/universal-translator

[311] http://hitchhikers.wikia.com/wiki/Babel_Fish

[312] Which of course calls into question whether language learning might become as quaint as massive memorization? The CCR will be tracking this issue closely. At present its recommendation is that language acquisition matters for three reasons: First, communication can be superseded by translation technology for conversational applications, though perhaps not for conversations that require fluency. Next is cultural understanding, which may be taught via other mechanisms, and finally, cognitive benefits, which are unclear through research. Will this become as indefensible as memorization after the invention of the alphabet? While this situation unfolds, CCR's recommendation is that, given the sensitive period of language acquisition, one can easily set the foundation for multiple language acquisition through basic exposure to multiple languages. It was suggested that two languages of close linguistic distance could be mastered early (for instance for native English speakers: English at both for the first 2 years + Spanish or French by age 2–3; both Indo-European, but one Germanic and one Latin-based), and that maximum gains would come from a third that is very distant linguistically from a different linguistic family, and script-wise (for example, Mandarin or Arabic) taught by age 7.
The key issue of time can be helped by technology as described herein.

could easily have chosen the similar Memrise,[313] Rosetta Stone,[314] Mondly,[315] or many others).

Our first example is Babbel,[316] which has been using AI-driven speech recognition (along with typical ITS personalization algorithms) to support language learning for about a decade. Their approach involves comparing student-spoken words with samples of speech recorded by native speaking course editors, and providing immediate feedback to help the student improve their pronunciation. There are two main steps: recognizing words and evaluating pronunciation, both of which can be challenging. To recognize words, the system first has to detect when the user starts and stops speaking, which in a typical environment means filtering out the ambient noises (such as other people speaking in the background or an airplane flying overhead). The words are then compared with the database of speech samples, first to recognize the word and then to check its pronunciation, taking into account that different people (male/female, young/old) have quite different voices (they speak at different frequencies and tempos).

With Duolingo,[317] which also uses speech recognition, we will focus on their use of ITS-style personalization. Duolingo's approach draws on two principles that are well established in the learning sciences: the spacing effect[318] (we remember things more effectively if we use spaced practice, short study periods spread out over time, rather than massed practice, or cramming) and the lag effect[319] (we learn even better if the spacing between practices gradually increases).[320] Accordingly, an

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[313] https://www.memrise.com
[314] https://www.rosettastone.co.uk
[315] https://app.mondly.com
[316] https://www.babbel.com
[317] https://www.duolingo.com
[318] Ausubel, D.P., and Youssef, M. (1965). "The effect of spaced repetition on meaningful retention." *The Journal of General Psychology* 73: 147–50. https://doi.org/10.1080/00221309.1965.9711263
[319] Melton, A.W. (1970). "The situation with respect to the spacing of repetitions and memory." *Journal of Verbal Learning and Verbal Behavior* 9 (50): 596–606.
[320] Duolingo is not unique in doing this but they it is notable in having conducted various studies to optimise the approach.

algorithm based on the Leitner Box method,[321] in which flashcards answered incorrectly remain at the front of a containing box to be encountered again after only a short interval, while those answered correctly are sent to the back of the box thus delaying when they will be seen again) predicts the best time to deliver a word to the student for practice. It does so by inferring the probability that the student will correctly recall the word as a function of the lag time since the word was last practiced and the half-life of the word (the strength of the word in the learner's long-term memory). This is based on a student model that incorporates trace data of the learner's previous learning experiences (the number of times a student has seen the word, the number of times it was correctly recalled, and the number of times incorrect). A 2012 independent study found that students using Duolingo improved their Spanish language abilities by the equivalent of one college semester of standard language classes (however, the study did not compare Duolingo with standard language classes or with any similar product, and no effect sizes are given).

Chatbots: Ada and Freudbot

The first computer program that appeared able to converse in natural language, the precursor to AI chatbots, was ELIZA (which we describe in appendix 2). Now, after fifty years of development, chatbots are becoming mainstream,[322] with the launch of digital assistants from tech's Big Five: Amazon (Alexa), Apple (Siri), Facebook (Messenger),[323] Google (Assistant), and Microsoft (Cortana). Nonetheless, progress has not always been straightforward (remember the racist rants tweeted by

[321] Leitner, S. (1995). *So Lernt Man Lernen: Angewandte Lernpsychologie—Ein Weg Zum Erfolg*. Herder.

[322] E.g., Dale, R. (2016). "The return of the chatbots." *Natural Language Engineering* 22 (5): 811–817, and "Everything you ever wanted to know about chatbots (but were afraid to ask)." https://www.jisc.ac.uk/blog/everything-you-ever-wanted-to-know-about-chatbots-but-were-afraid-to-ask-08-oct-2018

[323] https://messenger.fb.com

Microsoft's chatbot Tay?),[324] and no chatbot has yet convincingly passed the Turing Test (if a human cannot decide whether a computer is human or a computer, the computer is said to have passed the Turing Test).[325] Having said that, recently the Google Duplex chatbot was presented making a restaurant reservation and booking a hairdresser appointment (however, the demonstration was clearly carefully orchestrated and more than a little controversial).[326] Nonetheless, today, one chatbots-as-a-service company alone[327] claims that more than 300,000 bots have been created using its toolsets, and this is just one of many such platforms.[328]

In general, chatbots are designed to respond automatically to messages (SMS texts, website chats, social messaging posts, and voice), using rules and keywords to select from pre-programmed scripted responses (as with ELIZA and most current simple bots), or adaptive machine learning algorithms to generate unique responses (as with the more sophisticated bots such as Siri, Duplex, and Tay). Chatbots are quickly becoming ubiquitous, for everything from booking a flight,[329] to ordering food,[330] as a doctor,[331] or a financial adviser,[332] in recruitment,[333]

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[324] Wolf, M.J., Miller, K., and Grodzinsky, F.S. (2017). "Why we should have seen that coming: Comments on Microsoft's tay 'experiment,' and wider implications." *SIGCAS Comput. Soc.* 47 (3) 54–64. https://doi.org/10.1145/3144592.3144598.

[325] The Turing Test, or more correctly the Imitation Game, was devised by Alan Turing (who is regarded by many as the father of both modern computing and artificial intelligence), to determine whether we might consider a computer intelligent: "I believe that in about fifty years' time it will be possible to program computers … to make them play the imitation game so well that an average interrogator will not have more that 70 percent chance of making the right identification after five minutes of questioning." Turing, A. (1950). "Computing machinery and intelligence." *Mind* 59 (236): 433–460.

[326] See both https://www.extremetech.com/computing/269030-did-google-duplexs-ai-demonstration-just-pass-the-turing-test and https://www.extremetech.com/computing/269497-did-google-fake-its-google-duplex-ai-demo

[327] https://home.pandorabots.com

[328] https://www.techworld.com/picture-gallery/apps-wearables/platforms-for-developers-build-chatbots-3639106

[329] https://bb.klm.com/en

[330] https://www.tacobell.com/Tacobot

[331] https://www.your.md

[332] https://www.rbs.com/rbs/news/2016/03/rbs-installs-advanced-human-ai-to-help-staff-answer-customer-que.html

[333] https://hiremya.com

and accounting,[334] to help with shopping,[335] as a personal companion,[336] and to support young people who are suffering from anxiety.[337]

Chatbots are also increasingly being used in educational contexts for a variety of purposes. For example, students making initial enquiries about courses may find themselves conversing with a bot whose job it is to direct them to the information that they want.[338] In some configurations,[339] they can also provide ongoing student support and guidance, in academic services, accommodation, facilities, examinations, IT, health and more.[340] And in some situations, they can also be used to directly support learning—indeed, the DBTS that we met earlier (including AutoTutor and Watson Tutor), may be considered special cases of educational chatbots). For example, chatbots might provide feedback to support student reflection and self-efficacy,[341] while already some language learning apps use chatbots for embarrassment-free speaking practice in simulated real-life situations.[342]

However this is not to suggest that chatbots are an educational silver bullet. For example, a student's "willingness to communicate in a foreign language... seems to decline rapidly over time as students lose interest in chatbots as language partners compared to human learning partners. This

[334] https://www.sage.com/en-gb/products/pegg

[335] https://bots.kik.com/#/vspink

[336] https://www.pandorabots.com/mitsuku

[337] Fitzpatrick, K.K., Darcy, A., and Vierhile, M. (2017). "Delivering cognitive behavior therapy to young adults with symptoms of depression and anxiety using a fully automated conversational agent (woebot): A randomized controlled trial." *JMIR Mental Health* 4. https://doi.org/10.2196/mental.7785

[338] https://www.virtualspirits.com/chatbot-for-university.aspx

[339] https://www.slu.edu/alexa/index.php

[340] E.g., Deakin University uses IBM Watson to run a student services support chatbot: http://www.deakin.edu.au/about-deakin/media-releases/articles/ibm-watson-helps-deakin-drive-the-digital-frontier, while the Open University of Hong Kong launched The i-Counseling System. https://library.educause.edu/resources/2012/5/case-study-9-the-open-university-of-hong-kong-the-icounseling-system

[341] Lundqvist, K.O., Pursey, G., and Williams, S. (2013). "Design and implementation of conversational agents for harvesting feedback in elearning systems." In *European Conference on Technology Enhanced Learning*, 617–618.

[342] http://bots.duolingo.com

could happen because of a simple novelty effect or simply the weaker value of chatbots compared to human assistants."[343]

Typical education chatbots (in addition to the DBTS discussed earlier) are Ada and Freudbot. Ada[344] has been developed by a UK community college, using IBM's Watson Conversation platform. In short, Ada demonstrates how education chatbots have been implemented using limited resources and AI-as-a-service technologies. Available on multiple devices (desktop, mobile, and kiosk), and named after the computer pioneer Ada Lovelace, Ada is able to respond to a spectrum of student enquiries, delivering personalized and contextualized responses that draw on data such as the student's courses, their progress, their goals and their individual targets. Ada is already able to respond to questions about the library, student services, finance, accommodation, transport, careers, and examinations—and it learns more with every interaction. For example, a student might ask about their lessons that morning, or where tomorrow's exam is happening, or what mark they achieved in a recent assignment. Meanwhile, a teacher can ask for a list of professional development workshops they have recently attended, or about a specific student's academic performance.

An earlier chatbot (and in effect a primitive DBTS) called Freudbot[345] engaged students in a conversation about an educational topic (rather than being designed to provide students with information about their institution and studies, as in the case of Ada). It took on the role and persona of the psychoanalyst Sigmund Freud, chatting in the first person with introductory psychology students about his theories and life. Freudbot was developed before the availability of easily accessed machine learning techniques, and so used rules and recognized keywords to select from pre-programmed scripted responses, drawing on a

[343] Winkler, R. and Soellner, M. (2018). "Unleashing the potential of chatbots in education: A state-of-the-art analysis." *Academy of Management Proceedings* (1): 1–17. https://doi.org/10.5465/AMBPP.2018.15903abstract

[344] http://www.aftabhussain.com/ada.html

[345] Heller, B., et al. (2005). "Freudbot: An investigation of chatbot technology in distance education." In *EdMedia: World Conference on Educational Media and Technology,* 3913–3918. https://pdfs.semanticscholar.org/ba80/d43699062892440f7e9adb6aea8e3ca1ddfe.pdf

university resource comprising explanations of Freudian terms and concepts together with an open-source biography. And when a student's question or response was outside its rule-base, Freudbot would default to a backstop strategy, such as asking for clarification or suggesting a new topic for discussion, always with the aim of leading the user back to the core discussion of Freudian topics.

Augmented and Virtual Reality

Virtual reality (VR) and augmented reality (AR) are two innovations that many have been trying to apply in educational contexts[346] (for example, Google has developed for educational contexts more than a 1000 VR and AR Expeditions).[347] VR provides an immersion experience that shuts out the physical world, enabling users who are wearing appropriate VR goggles to be transported into a vast range of real world or imagined environments, such as the International Space Station, an operating theatre,[348] or Hogwarts castle.[349] AR, on the other hand, as we saw earlier with Lumilo, overlays computer-generated images on top of the user's view of the real world (much like a fighter pilot's heads up display),[350] when seen through a smartphone or other similar device—the aim being to enhance or mediate the user's view of reality. For example, when a smartphone's camera is pointed at a mountain range, the names of the mountains and their elevations might be superimposed,[351] while pointing at a particular QR code might reveal a 3D human heart that can be explored in detail,[352] and in a particular street location a Pokémon character might be found waiting to be caught.[353] Although not traditionally thought of as AI technologies, we have mentioned VR and

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[346] E.g., http://www.classvr.com
[347] https://edu.google.com/expeditions
[348] http://ossovr.com
[349] https://www.pottermore.com/news/new-expanded-fantastic-beasts-and-where-to-find-them-vr-experience-announced
[350] https://www.youtube.com/watch?v=Ay6g66FbkmQ
[351] https://www.peakfinder.org
[352] https://medmovie.com/augmented-reality-heart
[353] https://www.pokemongo.com/en-gb

AR here because both are frequently combined with AI machine learning, image recognition and natural language processing, with the aim of further enhancing the user experience.[354]

While the thought of thirty students all wearing goggles and immersed in another world might strike fear in the heart of a classroom teacher, and while "VR does not intrinsically make every experience better in terms of motivation and learning,"[355] used judiciously, both VR and AR do have potential to become useful tools in the educator's toolbox. To give a few brief examples: VR has been used effectively to give breast cancer patients an anxiety-relieving virtual experience of the radiotherapy process, tailored to each individual patient,[356] VR simulations have been used extensively to provide training for neurosurgical residents on a variety of neurosurgical procedures,[357] and to enable students to interact directly with historical characters,[358] while a VR classroom has been used to provide trainee teachers with an "absorbing, realistic and interactive virtual classroom, allowing them to engage in realistic interactions with virtual students."[359] Researchers have also proposed the use of VR to enhance student experiences in immersive simulations such as EcoMUVE,[360] an immersive multi-user virtual environment and associated inquiry-based curriculum developed at Harvard University. EcoMUVE was designed to enable school students to learn about

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[354] E.g., https://www.apple.com/uk/ios/augmented-reality, https://www.samsung.com/global/galaxy/galaxy-s9/augmented-reality and https://ametroslearning.com

[355] Dede, C., et al. (2017). "Virtual reality as an immersive medium for authentic simulations." https://doi.org/10.1007/978-981-10-5490-7_8

[356] Jimenez, Y.A., et al. (2018). "Patient education using virtual reality increases knowledge and positive experience for breast cancer patients undergoing radiation therapy." *Supportive Care in Cancer* 26 (8): 2879–88. https://doi.org/10.1007/s00520-018-4114-4

[357] McGuire, L.S. and Alaraj, A. (2018). "Competency assessment in virtual reality-based simulation in neurosurgical training." In *Comprehensive Healthcare Simulation: Neurosurgery*. Springer. 153–157.

[358] Baierle, I.L.F., Gluz ,J.C. (2018) "Programming intelligent embodied pedagogical agents to teach the beginnings of industrial revolution." In Nkambou, R., Azevedo, R., Vassileva, J. (eds.) *Intelligent Tutoring Systems. Lecture Notes in Computer Science* 10858. Springer. https://doi.org/10.1007/978-3-319-91464-0_1

[359] Stavroulia, K.E., et al. (2018). "Designing a virtual environment for teacher training: Enhancing presence and empathy." In *Proceedings of Computer Graphics International 2018 on CGI 2018*. ACM Press. https://doi.org/10.1145/3208159.3208177

[360] http://ecolearn.gse.harvard.edu

ecosystems by playing the role of a scientist, exploring and collecting data in a virtual ecosystem in order to answer research questions. Although a VR interface might make some tasks more difficult, the researchers suggest that it has the potential to make the simulation more realistic by increasing the students' feeling of being present in the simulated environment, which in turn is likely to enhance transfer of the learning from the virtual to the real world.[361]

AR, on the other hand, has been used to enable students to explore and manipulate three-dimensional models of organic molecules in order to enhance their understanding of chemistry,[362] to help primary school students learn about history,[363] and in an AR-enabled digital games-based learning environment to support students' reading comprehension.[364] These few examples only touch the surface of the research that has investigated VR and AR in education.[365]

Learning Network Orchestrators: Third Space Learning and Smart Learning Partner

Learning network orchestrators (LNO),[366] are tools or approaches that enable and support networks of people engaged in learning (students and their peers, students and their teachers, or students and people from industry). LNOs typically match participants based on their availability, the subject domain, and the participants' varied expertise, and can

361 See Dede et al. (2017), in which they discuss in depth the potential and limitations of VR for simulated environments, and suggest some useful principles for effective implementation.

362 Behmke, D., et al. (2018) "Augmented reality chemistry: Transforming 2-D molecular representations into interactive 3-D structures." *Proceedings of the Interdisciplinary STEM Teaching and Learning Conference* 2(1). https://doi.org/10.20429/stem.2018.020103

363 Efstathiou, I., Kyza, E.A., and Georgiou, Y. (2018). "An inquiry-based augmented reality mobile learning approach to fostering primary school students' historical reasoning in non-formal settings." *Interactive Learning Environments* 26 (1): 22–41. https://doi.org/10.1080/10494820.2016.1276076

364 Tobar-Muñoz, H., Baldiris, S. and Fabregat, R. (2017) "Augmented reality game-based learning: Enriching students' experience during reading comprehension activities." *Journal of Educational Computing Research* 55 (7). http://journals.sagepub.com/doi/10.1177/0735633116689789

365 Radu, J. (2014) "Augmented reality in education: A meta-review and cross-media analysis." *Personal and Ubiquitous Computing* 18 (6): 1533–1543.

366 E.g., Nepris (https://www.nepris.com) and Educurious (https://educurious.org), which both support schools to connect with experts from around the world, to bring an industry perspective into the classroom. Possibilities include interactive question and answer sessions, virtual field trips, and project mentorships.

facilitate coordination and cooperation between them: "participants can interact with one another, share their learning experiences, build relationships, share advice, give reviews, collaborate, co-create and more." [367] AI techniques are slowly being introduced to LNO products, to automate much of this orchestration, and opening up network possibilities previously unachievable.

For example, in a novel approach, Third Space Learning connects UK primary school children who are at risk of failure in mathematics with mathematics tutors in India and Sri Lanka. The system supports individual tutoring, with tutors and students communicating with each other by means of a secure online virtual classroom that has two-way audio and a shared interactive whiteboard. AI is being introduced to automatically monitor every session, thousands of hours of teaching and learning every week, which generates huge quantities of data. Algorithms then aim to guide the tutor with real-time feedback, ensuring that teaching broadly follows an outline script that adopts well-supported learning sciences principles, identifying where students have misconceptions not picked up by the tutor (by comparing individual and overall student models), and empowering the tutors to constantly improve their teaching skills.

The Smart Learning Partner,[368] on the other hand, uses much simpler AI technologies to put students more in control of their own learning. It is the result of a collaboration between Beijing Normal University's Advanced Innovation Center for Future Education and Tongzhou district of Beijing, in China. A key component of the Smart Learning Partner system is an AI-driven platform that enables students to connect with a human tutor via their mobile phones. The platform uses AI somewhat like a dating app—except it matches students and tutors according to student queries and tutor areas of expertise, together with the tutor's availability and ratings given to them by other students whom they have already tutored. The student uses the app to search for a tutor,

[367] Holmes, W., et al. *Technology-Enhanced Personalised Learning.*

[368] http://slp.bnu.edu.cn (Note: Only accessible to students and faculty who have an account.)

to ask what they want to know about any school topic, and they then receive twenty minutes of one-to-one online tuition (sharing audio and screens only).

What Else is Possible?

Much of the AIED that we have discussed so far involves the application of AI techniques to mainstream learning approaches, and tends to reflect (or automate) existing educational assumptions and practices. In addition, although we have seen some notable exceptions, much AIED has been designed (whether intentionally or not) to supplant teachers or to reduce them to a functional role,[369] and not to assist them to teach more effectively. This approach, while potentially useful in contexts where teachers are few and far between, clearly undervalues teachers' unique skills and experiences, as well as learners' needs for social learning and guidance. However, instead of just automating the teaching of students sat at computers, conceivably AI might help open up teaching and learning possibilities that are otherwise difficult to achieve, that challenge existing pedagogies, or that help teachers to be more effective. Here we will speculate on some possibilities, some of which have been foreshadowed by the AIED tools we have already discussed, while others are both novel and complex to achieve, and all of which raise interesting social questions. We begin with AI to support collaborative learning, then AI-driven student forum monitoring, AI to support continuous assessment, AI learning companions for students, and AI teaching assistants for teachers, before concluding with AIED as a research tool to further the learning sciences (i.e. in order to help us better understand learning).[370]

Collaborative Learning

Collaborative learning, where students work together to solve problems, is well known to be able to lead to better learning outcomes, but effective

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[369] Worryingly, one of the developers we have mentioned has suggested that the sophistication of their AIED means that teachers only need to play an auxiliary role, working like fast-food chefs ("KFC-like") to strictly regulated scripts.

[370] One intriguing use of AI in education that we will not consider in detail, because its efficacy has not yet been demonstrated, but that should still be acknowledged is the automatic generation of quiz questions (https://mt.clevere.st and https://learningtools.donjohnston.com/product/quizbot).

collaboration between learners can be difficult to achieve.[371] AIED offers various possibilities. To begin with, an AIED tool could automatically suggest groups of students best suited for particular collaborative tasks, drawing on and making intelligent connections between individual student models (each of which comprises knowledge about the student's previous learning experiences and achievements, what the student is learning in other classrooms, their personalities, and more).[372] Having elicited the teachers' requirements, the tool might also suggest groups of mixed or similar-ability students, or groups designed to give particular students opportunities to take on leadership roles, or groups that avoid personality or temperament clashes, and so on, all the while enabling the teacher to quickly and easily override any of the tool's suggestions (which the AI will learn from, for next time). An AIED tool might also take on the role of expert facilitator or moderator, monitoring student collaborative activities, recognizing when students are having trouble understanding shared concepts, and then providing targeted support. Alternatively, the AIED might involve a virtual agent that actively contributes to the group discussions (acting as a virtual peer or a teachable agent), or that makes dynamic connections (either with discussions being held by other groups in the same classroom, or with relevant materials drawn from the semantic web). In fact, some research into AI to support collaborative learning has been undertaken,[373] but there are many technical issues to overcome before it becomes possible in real classrooms.

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[371] Luckin, R., et al. (2017). *Solved! Making the Case for Collaborative Problem-Solving.* Nesta. https://www.nesta.org.uk/report/solved-making-the-case-for-collaborative-problem-solving/

[372] The Universitat Politècnica de València have been researching just such a system: Alberola, J.M., del Val, E., Sanchez-Anguix, V., Palomares, A., and Teruel, M.D. (2016). "An artificial intelligence tool for heterogeneous team formation in the classroom." *Knowledge-Based Systems* 101: 1–14. https://doi.org/10.1016/j.knosys.2016.02.010

[373] E.g., Diziol, D., et al. (2010). "Using intelligent tutor technology to implement adaptive support for student collaboration." *Educational Psychology Review* 22 (1): 89–102. https://doi.org/10.1007/s10648-009-9116-9 and Spikol, D., et al. (2016). "Exploring the interplay between human and machine annotated multimodal learning analytics in hands-on stem activities." In *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge*. 522–523.

Student Forum Monitoring

Increasingly, students of all ages are participating in online education, which usually involves the use of discussion forums. Students might post to forums in response to given tasks or to engage in collaborative learning opportunities, or they might want to contact their tutors to clarify course requirements or to ask about course materials. Accordingly, especially when there are large cohorts of students (as can be typical of some distance universities and MOOCs), these online forums can generate massive numbers of forum posts, all of which must be monitored, moderated, and addressed. However, as the number of forum posts increases, this becomes at best an inefficient use of a tutor's time (dealing with repetitive and minor practical issues) and at worst an increasingly impossible task. It also makes it difficult for students to keep up to date with other student posts that might connect to their interests.

AIED might help in a number of ways (again, some research has already been conducted in this area)[374]—in particular by helping the teachers/tutors to be better able to support their students. First, an AIED tool might triage the forum posts, identifying those that can be dealt with automatically (perhaps practical questions around course dates, such as "When do I need to submit…?"), and those that require a response from a human tutor (such as those discussing more in-depth core subject issues). The simple posts, the ones that the AIED is capable of handling, would receive immediate automatic responses, relieving the human tutors of much repetitive work while enabling the students to move on quickly to more substantive work. Other posts would automatically be referred up to a human tutor, to ensure that students receive high quality, appropriate responses whatever the nature of their posting.

Taking this a step further, the more demanding posts (of which there still might be many) would be further analyzed, the aim being to identify

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[374] Goel, A.K., and Joyner, D.A. (2017). "Using AI to teach AI: Lessons from an online AI class." *AI Magazine* 38(2): 48. https://doi.org/10.1609/aimag.v38i2.2732

and aggregate similar posts or posts that raise overlapping issues (in a course with a thousand students, it is unlikely that there will be a thousand unique responses to a single course activity, but rather a much smaller number of closely related posts). A human tutor would then write a response to the much smaller number of aggregated posts, which in turn would be issued to all of the original posters. Although this is unlikely to be as good as replying to each individual student, it would clearly be better than the students receiving no responses at all—which, in a large online course, can all too often be the case. Another approach that might also help in student forums is for the AIED to interpret and make dynamic connections between posts, informing tutors when particular issues have been raised (e.g., known and unknown misconceptions), for them to address, or informing students about other posts that they might find interesting.

Finally, the AIED might also use sentiment analysis AI techniques to identify posts that reveal negative or non-productive student emotional states (perhaps a student is overly challenged, or likely to drop out of the course, or possibly suffering from mental health issues), posts that are unacceptable (perhaps because they include racist, misogynist or gratuitously aggressive comments), or posts that suggest topic drift (the tendency for forum posts to drift from the original intent). Any such posts (which, because of the overall number of posts, can be easy for humans to miss) would be referred up to a human tutor, so that the tutor can respond quickly, appropriately and effectively (perhaps by calling the student by phone, rather than depending on a digital intervention). Together, these various techniques might also enable tutors to be kept well informed of student opinions, collective worries, or recurrent themes that emerge from the forums.

Continuous Assessment

Psychologists and educators know that it is wrong to make decisions based upon a single test score and that decisions should reflect a balanced, complete understanding of each child. Numbers and scores can be very misleading if we don't consider the whole picture, something that means using both a qualitative and quantitative approach.[375]

Although there is little evidence for their validity, reliability or accuracy, high-stakes examinations are core to educational systems around the world.[376] Perhaps this is because that is how it has always been, perhaps because they efficiently rank students, perhaps because no practical, cost effective at scale, alternative has ever been devised, or perhaps because those who run the systems are typically those who were most successful at exams (and do not emotionally resonate with the need for change). Whatever the reason, with high-stakes examinations in place, schools and universities all too often end up teaching to the test, prioritizing routine cognitive skills and knowledge acquisition over in-depth understanding and authentic application. In other words, the examinations, rather than the needs of students or wider society, determine what is taught and learned. Meanwhile, ironically, AI technologies are automating exactly the type of knowledge that examinations mostly assess: "There's lots of elements of human intelligence that cannot be automated but the bit that we've tended to value, that relates to academic exam success, is one of the bits that we've managed to automate."[377] In any case, stop-and-test examinations (standardized, unseen tests that are at set points in the learning schedule, thus potentially interrupting the learning) are not able to rigorously evaluate a student's understanding of all that has been learned—at best they can only provide a snapshot of fragments of what has been studied over the duration of a course. Last, but not least, students of all ages can sometimes suffer from serious exam anxiety, which can easily negatively impact on the student's success in a typical three-hour end of course examination (further clouding their accuracy and trustworthiness).

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[375] Gunzelmann, B.G. (2005). "Toxic testing: It's time to reflect upon our current testing practices." *Educational Horizons* 83 (3): 214.

[376] https://curriculumredesign.org/wp-content/uploads/Evolving-Assessments-for-the-21st-Century-Report-Feb-15-Final-by-CCR-ARC.pdf

[377] Rose Luckin quoted in https://www.jisc.ac.uk/news/the-ai-revolution-is-here-17-aug-2018

Nonetheless, most AIED research in this area has been unambitious. It has focused on improving existing examination systems (developing AI-driven techniques to authenticate the identity of students taking exams online),[378] rather than challenging the underlying principles. However, as we have seen, typical ITS and other AIED tools already and constantly monitor student progress to provide targeted feedback and to assess whether the student has achieved mastery of the topic in question. Similar information could be captured by AIED tools designed to support collaborative learning, while intelligent essay assessment tools can also make inferences about a student's understanding. All of this information and more might be collated throughout a student's time in formal educational settings (the learning sciences have long understood the value of students engaging with constructive assessment activities), together with information about the student's engagement with non-formal learning (such as learning a musical instrument, or a craft or other skills) and informal learning (such as language learning or enculturation by means of learning from experience or active participation), to help create a picture of the whole learner. In other words, the AI-driven assessment would happen in the background, all of the time—making it next to impossible for students to cheat or subvert the system's intention (as can be the case when wealthier students employ personal tutors),[379] or take the test as many times as necessary until they achieve a good-enough score.

This more detailed and nuanced information about an individual student might then be represented (and perhaps visualized in dynamic graphics) in an AI-driven e-portfolio,[380] an intelligent personal resumé (in fact, an extended open student model). This e-portfolio could perhaps be

[378] For example, http://tesla-project.eu

[379] Luckin, R. (2017). "Towards artificial intelligence-based assessment systems." *Nature Human Behaviour* 1. https://doi.org/10.1038/s41562-016-0028

[380] Per one of the authors' US patent numbers 9,262,640 and 9,582,567, which also protect privacy and security.

underwritten and authenticated by blockchain technologies[381] as used by virtual currencies such as Bitcoin (essentially open, distributed ledgers, hosted simultaneously by millions of computers across the internet and linked using cryptography, that can share data in a verifiable, incorruptible, and accessible way). In this way, students would have a robust, accredited, in-depth record of all their learning experiences and achievements, far more detailed and useful than a collection of certificates. Parts or all of this smart resumé they might share when applying for admission to another course or for a new job, while retaining full control of their academic persona and data. From a learner's perspective, an additional benefit is that continuous assessment can act as a moving average, a fluid-like shock absorber that evens out the blips of bad days and disadvantageous personal situations (it simply does not sense that a young person's academic outcomes and future life can be determined by difficulties at home that coincide with the day of an important exam).

In short, although the constant monitoring of student behaviors and achievements raises significant and far-reaching ethical questions that must first be properly investigated and addressed, it is conceivable that stop-and-test examinations could soon be entirely removed from our educational systems and relegated to a more primitive past.

AI Learning Companions

The smart resumés that we have just proposed could also play a role in a much larger AIED possibility: AI-driven lifelong students' learning companions.[382] As we have seen, the desire for every student to have their own personalized tutor is what first inspired the development of ITS, but what about taking this to its logical conclusion? AI has the potential to provide every student with their very own personalized learning companion, operating sometimes as a learning partner, other

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[381] Sharples, M. and Domingue, J. (2016). "The blockchain and kudos: A distributed system for educational record, reputation and reward." In *European Conference on Technology Enhanced Learning.* Springer. 490–496.

[382] The University of Southern California have been researching just such an application over many years: http://ict.usc.edu/prototypes/personal-assistant-for-life-long-learning-pal3

times as a guide through the mass of available learning opportunities, and sometimes as an instructor, all the time recording the student's interests and progress in their blockchain-protected, smart resumé. The arrival and rapid developments of Siri, Cortana, Google Home and Alexa, suggest that this possibility is tantalizingly close.[383] In many countries, smartphones with extraordinary processing power and always-on internet access are more than common. It would not necessarily be a big technical step to leverage these capabilities, to create an AI-driven smartphone learning companion that could accompany and support individual learners throughout their studies, from kindergarten to old age.

Such a learning companion brings many possibilities. Once the student has decided on a particular topic of interest, it might provide some instructional activities, monitor the student's progress, remind them when a task needs to be completed, and offer targeted feedback and guidance—all on their speech-driven smartphone (and available on all their other devices). In other words, it might function as what we have called an ITS+.

But a learning companion would also operate at a higher and more strategic level. Building on the student's individual interests and life goals, it could also help them decide what to learn, as well as where and how to do the learning (the companion might identify and connect with the learning opportunities that are available, both formal and informal, both on and off-line). It could then also guide the student along overarching long-term individualized learning pathways designed to help the student address their emerging personal life-goals, connecting their learning interests and achievements, while reminding them of and encouraging them to reflect on and perhaps develop their long-term learning aims. The learning companion[384] might suggest learning opportunities that focus on some so-called 21st Century Skills,[385] and social-emotional

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[383] https://www.theatlantic.com/magazine/archive/2018/11/alexa-how-will-you-change-us/570844/

[384] World Economic Forum. (2015). New Vision for Education: Unlocking the Potential of Technology. World Economic Forum.

[385] Trilling, B. and Fadel, C. (2012). *21st Century Skills: Learning for Life in Our Times*. John Wiley & Sons.

learning.[386] It could also potentially connect learners, in the same classroom or from opposite sides of the world, depending on their shared interests and goals, helping them develop and work together in projects that prioritize both individual and collective achievements (and, in turn, helping to promote other critical skills in collaboration, teamwork, and intercultural awareness).

AI Teaching Assistant

As we have noted several times, most AIED technologies are designed with the aim of relieving teachers of the grunt work of teaching (most often by automating time-consuming activities such as the marking of classroom or homework assignments). However, despite these best of intentions, many AIED technologies in effect take over teaching (they deliver personalized and adapted learning activities better than teachers), or at least they reduce teachers to a functional role (perhaps their job is to work to strictly regulated scripts, or to ensure that the technology is ready for the student to use). Nonetheless, as we and colleagues have written previously: Crucially we do not see a future in which AIED replaces teachers. What we do see is a future in which the role of the teacher continues to evolve and is eventually transformed; one where their time is used more effectively and efficiently, and where their expertise is better deployed, leveraged, and augmented.[387]

This might be more of an emotional plea than a coherent argument—but it assumes that teaching involves more than delivering knowledge, and that it is a fundamentally social process. From this perspective, a key role for AI is supporting teachers to teach and support students.

One way in which this might be achieved is by augmenting teachers' expertise and skills with an AI teaching assistant, to complement and work with the students' AI learning companion, that goes far beyond the useful but by comparison somewhat primitive teacher dashboards

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[386] Fadel, C., Bialik, M., and Trilling, B. (2015). *Four-Dimensional Education: The Competencies Learners Need to Succeed.* Center for Curriculum Redesign.
[387] Luckin. R., et al. *Intelligence Unleashed*, 11.

featured in so much education technology. This would be a key way that AIED can support teachers to support students. Just such a possibility has been explored in the short narrative "A.I. is the New T.A in the Classroom,"[388] which describes a possible classroom of the future in which the teacher is supported by a dedicated and personalized AI teaching assistant (AI TA).

Many of the ideas we have suggested could play a role in this possible scenario (such as automatically setting up collaborative groupings of students, replacing stop-and-test examinations with AI-supported continuous assessment, and managing peer-marking and undertaking some automated marking). The AI TA could also automatically provide teaching and professional development resources (texts, images, videos, augmented-reality animations, links, network connections) that the teacher might choose to call upon to support their teaching. It could also monitor the students' performance as they engage in their classroom activities, continuously updating their learner models, making connections with the domain models of topics being taught, and tracking progress over time. All of this information (together with data about each student from additional sources: assessments from other classes, informal learning achievements, and relevant medical or family information) could be readily available to the teacher, whenever the AI TA computes it might be useful or whenever the teacher calls for it. In this possible future, what and how to teach the students, and how best to support them, would remain the responsibility and prerogative of the teacher. The AI TA's role would simply be to make the teacher's job easier and more effective.

AIED as a Research Tool to Further the Learning Sciences

As has probably been noticed, each of AIED's possible future uses are firmly rooted in existing AIED research and approaches. This is no less true of our final example, the use of AIED as a research tool to further

[388] Luckin, R., and Holmes, W. (2017). "A.I. is the new T.A. in the classroom." *How We Get To Next*. https://howwegettonext.com/a-i-is-the-new-t-a-in-the-classroom-dedbe5b99e9e

the learning sciences. Implementing an educational practice in any technology means that the practice has to be both better understood and then systemized. As a consequence, the technology acts much like a virtual spotlight, highlighting issues that have existed for years but that have been hidden or overlooked (for example, around the most effective approaches to teaching). This is particularly true of the introduction of AI to education, which is beginning to throw an extraordinarily bright spotlight onto many learning sciences issues. However, while there have been notable developments in this area of AIED research, mostly it has been at a relatively theoretical level, such that their potential and implications remain somewhat unclear.

In fact, AIED as a learning sciences research tool is often linked to a pair of other independent but overlapping academic fields that use statistical techniques drawn from big data research:[389] learning analytics and educational data mining.[390] While learning analytics involves "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs;"[391] educational data mining[392] "is concerned with gathering and analyzing data so as to understand, support and improve students' learning."[393] One example, that avoids this distinction, and that has been shown to be effective, is

[389] Mayer-Schonberger, V. and Cukier, K. (2013). *Big Data: A Revolution That Will Transform How We Live, Work and Think*. John Murray.

[390] Readers who would like to learn more about the similarities and differences between learning analytics and educational data mining might be interested to read Benedict du Boulay and others, "What does the research say about how artificial intelligence and big data can close the achievement gap?" in Luckin, R. (ed.) (2018). *Enhancing Learning and Teaching with Technology*. Institute of Education Press, 316–27; or Siemens, G., and Baker, R.S.J.d.. (2012). "Learning analytics and educational data mining: Towards communication and collaboration." In *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge*, 252–254. http://dl.acm.org/citation.cfm?id=2330661

[391] Siemens, G. (2011). "1st International conference on learning analytics and knowledge 2011: Connecting the technical, pedagogical, and social dimensions of learning analytics. https://tekri.athabascau.ca/analytics/about

[392] In a distinction reminiscent of Monty Python's *Life of Brian*: "BRIAN: Are you the Judean People's Front? REG: F**k off! BRIAN: What? REG: Judean People's Front. We're the People's Front of Judea! Judean People's Front. Cawk." http://montypython.50webs.com/scripts/Life_of_Brian/8.htm

[393] du Boulay, et al., "What does the research say about how artificial intelligence and big data can close the achievement gap?" 270.

The Open University's OU Analyse[394] tool, which draws on data from across the university (such as student access of online learning materials, submission of assessments, and outcomes) to identify students who might be at risk of dropping out from their studies—to enable tutors and student-support staff to provide appropriate pro-active remedial support. In fact, with the fields continually informing and cross-fertilizing each other, the distinctions between learning analytics, educational data mining, and AIED as a learning sciences research tool are becoming increasingly blurry. Often, it simply comes down to the communities who are involved in the research and the terminology that they use. Here, as we are writing about AIED, we will continue to use AIED terminology.

One prominent example of AIED as a learning sciences research tool has recently been published by the Medical Research Council Cognition and Brain Sciences Unit at the University of Cambridge.[395] The traditional grouping of students with learning difficulties in broad categories such as ADHD, dyslexia, and autism has long been known to be insufficiently helpful, when educators try to improve learning outcomes for individuals. For this reason, the Cambridge researchers are investigating the use of machine learning to categorize struggling students at a more granular level (based on measures of listening skills, spatial reasoning, problem solving, vocabulary, and memory). By analyzing data from more than 500 children, the machine learning revealed four clusters of learning difficulties (which had not previously been so clearly delineated): difficulties with working memory skills, difficulties with processing sounds in words, broad cognitive difficulties in many areas, and typical cognitive test results for the student's age. The researchers found that diagnosing struggling learners in terms of these four clusters was both

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[394] See Herodotou, C., et al. (2017). "Predictive modelling for addressing students' attrition in higher education: The case of OU analyse." http://oro.open.ac.uk/49470/ and https://analyse.kmi.open.ac.uk

[395] See Astle, D.E., Bathelt, J. and Holmes, J. (2018). Remapping the cognitive and neural profiles of children who struggle at school." *Developmental Science*. https://doi.org/10.1111/desc.12747 and, for a short summary, https://www.opencolleges.edu.au/informed/learning-strategies/artificial-intelligence-identifies-students-struggle-school

more accurate and more useful, helping educators address individual learning difficulties, than the traditional diagnostic labels.

We will conclude our brief discussion of AIED as a learning sciences research tool with one final example, one that is in the early stages but has important potential: the use of machine learning to improve learning design. Learning design refers to a range of methodologies "for enabling teachers/designers to make more informed decisions in how they go about designing learning activities and interventions."[396] These methods are intended to inform decisions about pedagogy (teaching and learning) and about ways to support student learning experiences, and can also be used to provide core data for learning analytics or educational data mining. Most approaches in use in universities[397] draw on teachers' professional knowledge of teaching and learning (knowledge that is often tacit and thus has had to be elicited from them, which is a non-trivial task and can lead to fuzziness and inconsistencies). Instead, the approach currently being researched at the Open University involves machine learning from thousands of existing module activities to identify categories of activities at a highly granular level. Once these learning design activity categories are identified, and have been robustly authenticated, it should then be possible to correlate the actual learning designs of course modules with student outcomes, to help us better understand how students learn. In turn, this might inform teachers and learning designers about which learning designs (depending on, for example, domain, specific subject, duration and level of study) are most effective in practice.

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[396] Conole, G. (2012). *Designing for Learning in an Open World* (v. 4). Springer Science & Business Media. https://books.google.co.uk/books?hl=en&lr=&id=gjHNlbc1BMYC&oi=fnd&pg=PR5&dq=Designing+for+learning+in+an+open+world+&ots=SwmKc5sSR3&sig=9RUsYFxOKFtZkfxj85WsLkJGcKc

[397] E.g., Cross, S., et al. (2012). "OULDI-JISC project evaluation report: The impact of new curriulum design tools and approaches on institutional process and design cultures." http://oro.open.ac.uk/34140/; Laurillard, D., et al. (2013). "A constructionist learning environment for teachers to model learning designs." *Journal of Computer Assisted Learning* 29 (1): 15–30; Dalziel, J. (ed.), *Learning Design*. Routledge.

AI in Education—A Tentative Summary

In the previous sections we have discussed a wide variety of existing and potential AIED technologies. One way to access this variety is to consider the technologies in terms of whether they are mainly student teaching (they take a mainly instructionist approach), or student supporting (they take a mainly constructivist approach), or teacher supporting (they mainly help teachers do what they already do but more quickly or with less effort). A summary representation of this is shown in the following table. A cursory examination of this table will reveal that the categorization provides only a high-level overview, while many of the AIED approaches overlap, and most of the technologies could easily appear in another place in the table. It is also likely that over time different AIED technologies will merge into multi-capable systems, perhaps incorporating sequenced (ITS), Socratic (DBTS), and self-directed (ELE) learning in one technology.[398]

[398] Early examples of this include Holmes, W. (2013). "Level up! A design-based investigation of a prototype digital game for children who are low-attaining in mathematics." (Unpublished PhD thesis, University of Oxford) and Rummel, N., et al. (2016). "Transforming learning, empowering learners." *The International Conference of the Learning Sciences* 1.

	Student Teaching (mainly instructionist)	Student Supporting (mainly constructivist)	Teacher Supporting
AIED Applications	• ITS • DBTS • Language learning apps	• ELEs • Automatic writing evaluation (formative) • Learning network orchestrators • Language learning apps • AI Collaborative learning • AI Continuous assessment • AI Learning companions	• ITS+ • Automatic writing evaluation (summative) • Student forum monitoring • AI Teaching Assistants • AI as a research tool to further the learning sciences
AIED Technologies and Approaches	• Chatbots • AR and VR • Natural Language Processing • Adaptivity		

Student teaching, student supporting, and teacher supporting AIED.

This summary is given more flesh in the following table, Characteristics of AIED Technologies.

Type of AIED	**Characteristics**	**Determined by**	**Target**
Intelligent Tutoring Systems	• Step-by-step sequence of instruction and tasks. • Individualized pathways. • System-determined content and pathways. • Students working with computers (or mobile devices). • Individualized feedback. • Real-time adaptivity.	System	For students
Dialogue-based Tutoring Systems	• Step-by-step dialogue-based instruction and tasks. • Individualized conversations. • System-determined content and pathways. • Students working with computers (or mobile devices). • Individualized feedback. • Real-time adaptivity.	System	For students
Exploratory Learning Environments	• Exploratory tasks. • Individualized pathways. • System-determined content and pathways, with student choice within tasks. • Students working with computers (or mobile devices). • Individualized feedback. • Real-time adaptivity.	System and learner	For students
Automatic Feedback and Scoring of Essays	• Essays (and other assignments) uploaded and analyzed by the system. • Some provide individualized formative feedback (to help students improve their writing), some only summative assessment (to score/grade the essay).	System	For students (formative) For teachers (summative
ITS+	• Depends on the ITS+. • Whole-school wraparound ITS. • Student data visible to teacher; superimposed	n/a	For students and teachers

	above each student via augmented-reality glasses. • Back-end ITS functionality (AIED as a service) for other providers of EdTech products.		
Language Learning Apps	• Step-by-step sequence of instruction and tasks. • System-determined content and pathways. • Students working with computers (or mobile devices). • Individualized feedback.	System	For students
Chatbots	• Mostly providing information.	Student (i.e., responds to student questions)	For students
Augmented and Virtual Reality	• Mostly providing access to otherwise unavailable environments.	Mixed	For students
Learning Network Orchestrators	• Mostly providing access to learning opportunities.	Mixed (i.e., sometimes responds to student requests)	For students
Collaborative Learning	• Facilitating the organization of collaborative learning. • Facilitating collaborative learning.	System	For students
Student Forum Monitoring	• Providing automatic feedback to forum posts, perhaps making connections between posts and sentiment analysis.	n/a	For students, and for teachers
Continuous Assessment	• Assessing student competencies on an ongoing basis (e.g., during talk), rather than using tests or exams.	System	For students
AI Learning Companions	• Potentially, lifelong learning companions for students.	Student and system	For students
AI Teaching Assistants	• Potentially, AI assistants for teachers.	Teacher and system	For teachers

Finally, we might compare all of the AIED technologies with the SAMR model discussed in the context section of this book. This highlights how most of the near and medium-term advantages of AIED are in the augmentation and modification of present-day activities, while the long term might see a substantial Holy Grail benefit in redefinition.

	EdTech at Large (using the SAMR model)	AIED in Particular
Redefinition	Technology allows for the creation of new tasks, previously inconceivable.	• AI removing the need for stop-and-test examinations (i.e. by providing continuous highly adaptive assessments).
Modification	Technology allows for significant task redesign.	• AR and VR learning experiences • AI Learning Companions • AI Teaching Assistants • AI as a Learning Sciences research tool.
Augmentation	Technology acts as a direct tool substitute, with functional improvement.	• ITS • DBTS • Exploratory Learning Environments • Automatic Writing Evaluation • ITS+ • Language Learning • Chatbots • Collaborative Learning support • Student forum monitoring
Substitution	Technology acts as a direct tool substitute, no functional change.	Not applicable (as of this writing)

AIED and the SAMR model.

The Social Consequences of AI in Education

As we have seen, the application of AI in educational contexts is growing rapidly. In this book, we have explored the various AI techniques being used, the applications that have been in development for almost fifty years, and the futuristic possibilities that are becoming ever more likely (whatever our personal values).

Clearly, AIED has achieved some notable successes, while the conceivable applications are at the least intriguing. However, AIED's potential impact on students, teachers and wider society is yet to be fully worked out. This is true of issues as broad as accuracy, choice, predictions, privacy, teachers' jobs, and what we should be teaching school and university students.[399] But it is especially true for AIED's emerging ethical questions: "Around the world, virtually no research has been undertaken, no guidelines have been provided, no policies have been developed, and no regulations have been enacted to address the specific ethical issues raised by the use of artificial intelligence in education."[400]

In any case, one wonders why, if AIED is so effective, has it not yet been widely adopted by schools, universities and training companies? In fact, it is not yet even clear whether the AI technologies being imported into education are actually up to the task. For many years, non-AI technologies in educational settings have been critiqued. The question is whether AIED is destined to become the latest computer technology to be oversold yet underused in classrooms.[401, 402] We also need to consider

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[399] E.g., "Machine learning: universities ready students for AI revolution," https://www-timeshighereducation-com.libezproxy.open.ac.uk/news/broader-four-year-degrees-offered-in-response-to-ai-revolution and "The most important skills for the 4th industrial revolution? Try ethics and philosophy."
https://www.edsurge.com/news/2018-10-06-the-most-important-skills-for-the-4th-industrial-revolution-try-ethics-and-philosophy

[400] Holmes, W., et al. (2018). "Ethics in AIED: Who cares?"In *Artificial Intelligence in Education* (ed. Rosé, C.P., et al.). 19th International Conference Proceedings, Part II. https://doi.org/10.1007/978-3-319-93846-2

[401] Cuban, L. (2001). *Oversold and Underused: Computers in the Classroom*. Harvard University Press.

[402] "Pretty much all edtech sucks. And machine learning is not going to improve edtech."—Al Essa, McGraw-Hill Education; and "I don't see a child sitting in front of an Alexa and being taught, because there is a whole other set of cues they need to learn. I don't see machine learning reaching that point."—Janel Grant. Both

what might happen, what might be the impact on individual learners, if ineffective AI techniques (or biased data sets) are used in classrooms (for example, what might happen if the face recognition technology that achieved 95% false positives for the UK's Metropolitan Police[403] was used in classroom monitoring)? Meanwhile, there are few examples of cumulative or replicable AIED research: the field is developing so rapidly while AIED data sets and algorithms tend to be (jealously?) guarded. There is also little available robust evidence of the efficacy at scale of the rapidly increasing numbers of AIED tools. Even those, such as Mathia and Assistments, that do have some evidence, have typically been compared with business as usual rather than with another technology that has at least some level of comparability.[404] The purported effectiveness of many other tools may be due to their novelty in classrooms,[405] rather than anything to do with the AI employed—we simply do not have the evidence to say one way or another.

The Implications of AIED Technologies for Classrooms

We began our AIED journey with intelligent tutoring systems, which as we saw are the most common of AIED applications, and which we will now use to scaffold and highlight some social consequences of AI applied to education that deserve more detailed attention. It has long been recognized that AI by design amplifies hidden features of its initial data and effectively reinforces its underlying assumptions. In particular, if the algorithms "are trained on data which contains human bias then of course the algorithms will learn it, but furthermore they are likely to amplify it. This is a huge problem, especially if people assume that

quoted in Johnson, S. (2018). "What can machine learning really predict in education?" *EdSurge*. https://www.edsurge.com/news/2018-09-26-what-can-machine-learning-really-predict-in-education

[403] *The Independent*, May 2018. https://ind.pn/2InMfGf

[404] Holmes, W., et al. *Technology-Enhanced Personalised Learning*, 65 and 68.

[405] Schomaker, J. and Meeter, M. (2015). "Short- and long-lasting consequences of novelty, deviance and surprise on brain and cognition." *Neuroscience & Biobehavioral Reviews*. https://doi.org/10.1016/j.neubiorev.2015.05.002

algorithms are impartial."[406] In this respect, both rule-based and machine learning ITSs are no different. Their very design, their implementation of step-by-step instructionist methods focused on a knowledge curriculum while ignoring contextual and social factors, amplifies existing yet contested assumptions about effective approaches to teaching, and even to what it means to learn.[407]

ITSs also embody a usually unacknowledged paradox, the dependence of personalized approaches to learning on identifying what is collective or average.

> [ITS] recommend lessons to users based on how other learners on the system have performed. These systems "learn" each student by presuming them to be similar to others.... We herald an intervention as a success if [an efficacy study shows that] it works on average, discarding the nuances of why it may work for some students more than others, and to what degree. [In summary], the individual struggle of the individual learner is easily lost in the noise.[408]

In other words, focusing on the average to determine an appropriate intervention is inevitably limiting: if a robust study shows that one approach is more effective on average compared with a second approach, the second approach is likely to be fully rejected, despite the fact that it might be more effective for particular individuals or groups.

ITSs by design also can reduce student agency. Although constrained by the curriculum (as decided by local or national policy-makers), it is generally the ITS (its algorithms and student models) and, at a higher level, the ITS designers, that determine what should be learned, in what order and how; while the student is given little choice but to follow the

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[406] Douglas, L. (2017). "AI is not just learning our biases; it is amplifying them." *Medium.* https://medium.com/@laurahelendouglas/ai-is-not-just-learning-our-biases-it-is-amplifying-them-4d0dee75931d

[407] Instructionism "is based on cognitive learning theories that center on teaching as education performed by a teacher. In the view of instructionism, instruction has to be improved in order to achieve better learning results." Seel, N.M., ed. (2012) *Encyclopedia of the Sciences of Learning*. Springer.

[408] Mubeen, J. (2018). "When 'personalised learning' forgets to be 'personalised.'" *Medium.* https://medium.com/@fjmubeen/when-personalised-learning-forgets-to-be-personalised-48c3558e7425

ITS-determined individual pathway (it also in some sense makes the teacher somewhat redundant—it is the system, not the teacher, that decides what is best for a student to learn). For example, most ITS begin with the basics, before guiding the individual student through tasks that take them step-by-step towards mastery targets, minimizing failure along the way. However intuitively appealing, the assumptions embodied in this instructionist approach[409] also ignore the value of other approaches researched in the learning sciences (such as collaborative learning, guided discovery learning, blended learning, and productive failure).[410]

ITSs also raise issues centered on the selection of data, raising complex issues centered on trust.[411] For example, it has been argued that there is no such thing as raw data:[412] data used in any analysis has been pre-selected (it is not possible to include all data generated by a system in its computations), and these choices are inevitably subject to conscious or unconscious, explicit or implicit, selection biases.[413] Similarly, the algorithms chosen or developed raise additional issues, such as those centered on the accuracy and implications of their predictions (if the computation is incorrect, are students being guided away from their best interests, and how do we ensure that mistakes err on the side of failing in the least harmful way?), the increasing focus on inferring and responding to the students' affective states (are a student's innermost feelings not private anymore?)[414] and the usual focus on teaching the type of knowledge that is the easiest to automate and thus potentially the least useful in the long-term for students.[415]

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409 Gagné, *Conditions of Learning and Theory of Instruction*.

410 Dean Jr., D. and Kuhn D. (2007). "Direct instruction vs. discovery: The long view." *Science Education* 91. https://doi.org/10.1002/sce.20194

411 E.g., https://www.theatlantic.com/magazine/archive/2018/11/alexa-how-will-you-change-us/570844/

412 Gitelman, L., et al. (2013). *"Raw Data" Is an Oxymoron*. MIT Press.

413 "Data is easily gotten, but it has a lot of bias in it." John Behrens (Pearson), quoted in Johnson, *What Can Machine Learning Really Predict in Education?* https://www.edsurge.com/news/2018-09-26-what-can-machine-learning-really-predict-in-education

414 "Tech firms want to detect your emotions and expressions, but people don't like it." https://theconversation.com/tech-firms-want-to-detect-your-emotions-and-expressions-but-people-dont-like-it-80153

415 Rose Luckin quoted in https://www.jisc.ac.uk/news/the-ai-revolution-is-here-17-aug-2018

In any case, as we discussed earlier, the efficacy of ITSs in real educational settings remains to be confirmed (although many have been shown to be broadly effective when compared against usual classroom teaching).[416] Indeed, one ITS, Summit Learning,[417] which was developed by engineers from Facebook and is being used in around 400 schools, has been the focus of student protests and boycotts.

> Unfortunately we didn't have a good experience using the program, which requires hours of classroom time sitting in front of computers... The assignments are boring, and it's too easy to pass and even cheat on the assessments. Students feel as if they are not learning anything and that the program isn't preparing them for the Regents exams they need to pass to graduate. Most importantly, the entire program eliminates much of the human interaction, teacher support, and discussion and debate with our peers that we need in order to improve our critical thinking. Unlike the claims made in your promotional materials, we students find that we are learning very little to nothing. It's severely damaged our education, and that's why we walked out in protest.[418]

Finally, ITSs typically set themselves up as doing at least some of the job of teachers, increasingly more effectively than teachers, thus questioning the role of teachers in future classrooms.[419] As we have seen, the ambition of many researchers is to relieve teachers of the burdens of teaching (such as monitoring progress and marking assignments), enabling them to focus on the human aspects of teaching (such as social engagement). In fact, "AI cannot create, conceptualize, or manage complex strategic planning; cannot accomplish complex work that requires precise hand-eye coordination; cannot deal with unknown and

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[416] du Boulay, B. "Artificial intelligence as an effective classroom assistant." *IEEE Intelligent Systems* 31. https://doi.org/10.1109/MIS.2016.93

[417] https://www.summitlearning.org

[418] The Chan Zuckerberg Initiative funded the Summit Learning project and disputes these claims. https://www.washingtonpost.com/education/2018/11/17/students-protest-zuckerberg-backed-digital-learning-program-ask-him-what-gives-you-this-right/?noredirect=on&utm_term=.27d5e322ac1c

[419] At least one ITS company appeared to pivot from attempting to sell their product into schools, because teachers were unsure why they should use a technology that did their job instead of them.

unstructured spaces, especially ones that it hasn't observed; and cannot, unlike humans, feel or interact with empathy and compassion… tasks that can only be done by a human teacher. As such, there will still be a great need for human educators in the future."[420] But, on the other hand, if we (students, educators, and parents) do not critically engage, perhaps AIED might lead to fast-food chef, script-driven classroom managers[421] rather than teachers, while the AI deals with all of the cognitive demands of teaching (a dystopian scenario that is only some short steps away from removing humans from teaching entirely).

Naturally, there are many examples of ITSs that challenge at least some of these issues (such as Mathia, whose developers recommend it is delivered in a blended context). We have also looked at alternative approaches, such as DBTSs (that prioritize a Socratic, albeit step-by-step, approach rather than an instructionist approach to learning) and AI-driven ELEs (that prioritize a guided-discovery approach to learning). And we have considered alternative ways in which AI is being or might be used in innovative ways, that have the potential to step outside dominant educational practices: for example, relatively simple AI that enables students to connect to their choice of human tutors (to get support on what they want to learn), and complex AI that provides a lifetime learning companion dedicated to their needs. Yet even these approaches depend on huge amounts of personal data and efficient algorithms, raising privacy and ethical issues that have yet to be fully considered.

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[420] https://www.linkedin.com/pulse/10-jobs-safe-ai-world-kai-fu-lee. Also see, "Intelligent machines will replace teachers within 10 years, leading public school head teacher predicts." https://www.independent.co.uk/news/education/education-news/intelligent-machines-replace-teachers-classroom-10-years-ai-robots-sir-anthony-sheldon-wellington-a7939931.html; "Could artificial intelligence replace our teachers?" https://www.educationworld.com/could-artificial-intelligence-replace-our-teachers; and "Why artificial intelligence will never replace teachers," https://www.thetechedvocate.org/artificial-intelligence-will-never-replace-teachers

[421] As we mentioned earlier, one ITS developer has suggested that the sophistication of their AIED means that teachers only need to play an auxiliary role, working like fast-food chefs ("KFC-like") to strictly regulated scripts.

The Ethics of AIED

Indeed, the ethics of AI applied in education, although left to last in this book, requires urgent attention. For example, one school

> has installed facial recognition technology to monitor how attentive students are in class. Every movement of pupils ... is watched by three cameras positioned above the blackboard.... Some students are already changing their behaviour due to the increased monitoring.... "I don't dare be distracted after the cameras were installed in the classrooms. It's like a pair of mystery eyes are constantly watching me." The system works by identifying different facial expressions from the students, and that information is then fed into a computer which assesses if they are enjoying lessons or if their minds are wandering.... The computer will pick up seven different emotions, including neutral, happy, sad, disappointed, angry, scared and surprised. If it concludes that the student is distracted with other thoughts during the class, it will send a notification to the teacher to take action."[422]

This example of AI being used to maximize student attention is from China. However, before we dismiss it as a culturally-specific phenomenon, we should remember that ALT Schools[180] also uses AI-driven classroom cameras to monitor student behavior (while in the UK, "tens of thousands of pupils aged as young as five are at risk of being spied on through their webcams..., often without students or their parents ever knowing").[423] This is not to say that the use of AI to analyze classroom video feeds is by definition unethical. For example, researchers at the University of Pittsburgh are using AI and classroom videos to help better understand how the quality of classroom talk, the liveliness of

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[422] https://www.telegraph.co.uk/news/2018/05/17/chinese-school-uses-facial-recognition-monitor-student-attention/

[423] https://https://www.telegraph.co.uk/technology/2018/12/15/children-young-5-risk-spied-webcams-using-school-software

discussion, and the level of student engagement contributes to effective learning, to inform better approaches to teaching.[424]

On the other hand, there are examples of AI companies[425] collecting huge amounts of student interaction data, in order to use machine-learning techniques to "search for patterns." The aim, naturally, is to "improve student learning by teaching the software to pinpoint when children are feeling happy, bored, or engaged."[426] Nonetheless, this approach is controversial, with such data collection being characterized as "borderline mental-health assessments..., [that] encourage a view of children as potential patients in need of treatment."[427]

The reality is that, while the range of AI techniques and technologies researched in classrooms and discussed at conferences are extensive and growing, the ethical consequences are rarely fully considered (at least, there is very little published work considering the ethics). In fact, most AIED research, development, and deployment has taken place in what is essentially a moral vacuum (for example, what happens if a child is unknowingly subjected to a biased set of algorithms that impact negatively and incorrectly on their school progress?). In particular, AIED researchers are working without any fully worked out moral groundings.

In fact, as we have seen, AIED techniques raise an indeterminate number of self-evident but as yet unanswered ethical questions. To begin with, as with mainstream AI, concerns exist about the large volumes of data collected to support AIED—albeit data that is collected with the best of intentions (such as the recording of student competencies,

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[424] Kelly, S., Olney, A.M., Donnelly, P., Nystrand, M., and D'Mello. S.K. (2018). "Automatically measuring question authenticity in real-world classrooms." *Educational Researcher* 47. https://doi.org/10.3102/0013189X18785613

[425] E.g., https://www.algebranation.com

[426] "How (and why) ed-tech companies are tracking students' feelings." https://mobile.edweek.org/c.jsp?cid=25919761&bcid=25919761&rssid=25919751&item=http%3A%2F%2Fapi.edweek.org%2Fv1%2Few%2Findex.html%3Fuuid=C08929D8-6E6F-11E8-BE8B-7F0EB4743667

[427] Jane Robbins, American Principles Project Foundation, quoted in preceding note, "How (and why) ed-tech companies are tracking students' feelings."

emotions, strategies, misconceptions, and screen usage,[428] to better help students learn). Who owns and who is able to access this data, what are the privacy concerns, how should the data be analyzed, interpreted, and shared, and who should be considered responsible if something goes wrong? In a parallel domain, healthcare, the use of personal data can be contentious and is frequently challenged[429] —but this has yet to happen noticeably in education.

However, while data raises major ethical concerns for the field of AIED, AIED ethics cannot be reduced to questions about data. Other major ethical concerns include the potential for bias[430] (conscious or unconscious) incorporated into AI algorithms (i.e., how the data is analyzed)[431] and into AIED models (what aspects of a domain are assumed worth learning, what approaches to pedagogy are assumed to be most effective, and what student information is assumed to be the most pertinent?). On the other hand, if a computer's decisions are indistinguishable from that of a human, or at least from a panel of human experts (because humans are well known to sometimes disagree, for example when marking essays),[432] perhaps those decisions should be

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[428] "FaceMetrics lands $2 million to gamify kids' screen time and track immersion with AI." https://venturebeat.com/2018/06/13/facemetrics-lands-2-million-to-gamify-kids-screen-time-and-track-immersion-with-ai

[429] For example, https://www.bbc.co.uk/news/technology-46206677: "A controversial health app developed by artificial intelligence firm DeepMind will be taken over by Google …" Lawyer and privacy expert Julia Powles [said]: "DeepMind repeatedly, unconditionally promised to 'never connect people's intimate, identifiable health data to Google.' Now it's announced... exactly that. This isn't transparency, it's trust demolition."

[430] "[A]s algorithms play an increasingly widespread role in society, automating—or at least influencing — decisions that impact whether someone gets a job or how someone perceives her identity, some researchers and product developers are raising alarms that data-powered products are not nearly as neutral as scientific rhetoric leads us to believe." Kathryn Hume, integrate.ai, quoted in "AI needs debate about potential bias," by Carole Piovesan, https://www.lawtimesnews.com/article/ai-needs-debate-about-potential-bias-15180. Also see, The Fairness Toolkit, https://unbias.wp.horizon.ac.uk/fairness-toolkit

[431] A recent survey by The Pew Research Center found that "the public is frequently skeptical of [algorithms] when used in various real-life situations. … [with] 58% of Americans feel[ing] that computer programs will always reflect some level of human bias." http://www.pewinternet.org/2018/11/16/public-attitudes-toward-computer-algorithms/

[432] To give an anecdotal example, a Masters thesis written by one of the authors at a prestigious university was marked as a distinction by one professor and a fail by another.

accepted.[433] Nonetheless, each decision that goes into constructing these algorithms and models might impact negatively on the human rights of individual students (in terms of gender, age, race, socio-economic status, income inequality, and so on)—at present we just do not know whether or not they will.

But these particular AI ethical concerns, centered on data and bias, are the "known unknowns," and are the subject of much research and discussion in mainstream AI research.[434] What about the "unknown unknowns," those ethical issues raised by the application of AI in education that have yet to be even identified?

AIED ethical questions include (there are many more):

- What are the criteria for ethically acceptable AIED?
- How does the transient nature of student goals, interests and emotions impact on the ethics of AIED?
- What are the AIED ethical obligations of private organizations (developers of AIED products) and public authorities (schools and universities involved in AIED research)?
- How might schools, students, and teachers opt out from, or challenge, how they are represented in large datasets?

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[433] From another perspective, the UCLA law professor Eugene Volokh argues that "a computer should be accepted if a panel of humans thinks the opinions it writes are on par with or better than those written by a human judge…" (https://www.axios.com/artificial-intelligence-judges-0ca9d45f-f7d3-43cd-bf03-8bf2486cff36.html)

[434] E.g., Ada Lovelace Institute (https://www.adalovelaceinstitute.org), AI Ethics Initiative (https://aiethicsinitiative.org), AI Ethics Lab (http://www.aiethicslab.com), AI Now (https://ainowinstitute.org), DeepMind Ethics and Society (https://deepmind.com/applied/deepmind-ethics-society), and the Oxford Internet Institute (https://www.oii.ox.ac.uk/blog/can-we-teach-morality-to-machines-three-perspectives-on-ethics-for-artificial-intelligence). Also see Winfield, Alan F. T., and Jirotka, M. (2018). "Ethical governance is essential to building trust in robotics and artificial intelligence systems." *Phil. Trans. R. Soc. A* 376. https://doi.org/10.1098/rsta.2018.0085 And see "Top 9 ethical issues in artificial intelligence." https://www.weforum.org/agenda/2016/10/top-10-ethical-issues-in-artificial-intelligence "Establishing an AI code of ethics will be harder than people think." https://www.technologyreview.com/s/612318/establishing-an-ai-code-of-ethics-will-be-harder-than-people-think, and Willson, M. (2018). "Raising the ideal child? Algorithms, quantification and prediction." *Media, Culture & Society*, 5. https://doi.org/10.1177/0163443718798901

- What are the ethical implications of not being able to easily interrogate how AIED deep decisions (using multi-level neural networks) are made?

Strategies are also needed for ameliorating risk, since AI algorithms are vulnerable to hacking and manipulation (as the Facebook–Cambridge Analytica data scandal showed was more than possible): "It's impossible to have personal privacy and control at scale, so it is critical that the uses to which data will be put are ethical – and that the ethical guidelines are clearly understood."[435] Where AIED interventions target behavioral change (such as by nudging individuals towards a particular behavior or course of action), the entire sequence of AIED-enhanced pedagogical activity also needs to be ethically warranted. Finally, it is important to recognize another perspective on AIED ethical questions: in each instance, the ethical cost of inaction and failure to innovate must be balanced against the potential for AIED innovation to result in real benefits for learners, educators, and educational institutions.

In short, the ethics of AIED is complicated.

As is likely already clear, the authors of this book are excited by what AI has to offer teaching and learning ... but we are also very cautious. We have seen an extraordinary range of AIED approaches (from Mathia, AutoTutor and Betty's Brain, to the Ada chatbot, OpenEssayist, and Lumilo, and more) and some amazing future AIED possibilities (from the end of exams, to lifelong learning companions, and AI teaching assistants). However, we have also identified a range of critical issues that need to be addressed before AI becomes an acceptable integral part of everyday learning.

Most important, the ethics of AIED need to be fully worked out—a non-trivial task that requires the involvement of a wide range of stakeholders (from students to philosophers, teachers to policymakers, and parents to developers). We (teachers, policymakers, and learning

[435] Tarran, B. (2018). "What can we learn from the Facebook–Cambridge Analytica scandal?" *Significance* 15 (3): 4–5.

scientists) need to understand the key issues raised by the collection of data (such as the choice of what data to collect and what data to ignore, the ownership of data, and data privacy). We also need to understand the computational approaches being applied (what decisions are being made, what biases are creeping in, and how do we ensure that decisions are 'correct and transparent?).[436] This much is self-evident, which is why so many initiatives to both determine and govern the ethics of AI have been established around the world.

However, we also need to have a thorough understanding of the ethics of education, of teaching and learning (the ethics of particular approaches, curriculum choices, focusing on averages, the allocation of available funds, and much more besides), another non-trivial task. For without that, how will we know what might happen when these three areas (data, computation, and education) collide?

This returns us to our introduction, and is hopefully our main takeaway. Whether we welcome it or not, AI is increasingly being used widely across education and learning contexts. We can either leave it to others—the computer scientists, AI engineers[437] and big tech companies—to decide how artificial intelligence in education unfolds, or we can engage in productive dialogue. It is up to each of us to decide whether we acquiesce, take what we are given, or whether we adopt a critical stance, to help ensure that the introduction of AI into education reaches its potential and has positive outcomes for all.

[436] See, Miller, T. (2019). "Explanation in artificial intelligence: Insights from the social sciences." *Artificial Intelligence* 267. https://doi.org/10.1016/j.artint.2018.07.007

[437] "You and AI–,achine learning, bias and implications for inequality." https://royalsociety.org/science-events-and-lectures/2018/07/you-and-ai-equality

Appendix 1

Connections Between Topics and Concepts

When designing a curriculum, it is important to make sure all content serves to highlight the (Threshold) Concepts of the relevant knowledge areas, across levels. Table X shows the relationship between sample Chemistry Topics and relevant Chemistry Core Ideas.

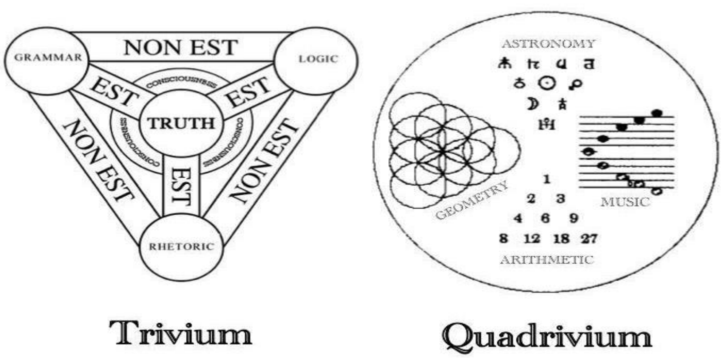
Sample Topics (Chapter Headings)	Relationship to Core ideas
Periodic Trends	**Atomic/Molecular Structure and Properties:** Trends that repeat across rows and down columns arise from the atomic structure.
	Electrostatic and Bonding Interactions: Electrostatic interactions (that give rise to effective nuclear charge) between subatomic particles explain most periodic trends.
	Energy: Quantum: Patterns in ionization energies arise from the quantized nature of the energy levels. Shielding by core electrons determines the effective nuclear charge experienced by valence electrons and results from the relationship between the quantized energy levels in atoms and the associated shell structure.
	Change and Stability in Chemical Systems: Balance between attractive and repulsive forces determines the size of atoms.
Solutions	**Atomic/Molecular Structure and Properties:** Solubility of a substance depends upon the molecular level structure of both solute and solvent.
	Electrostatic and Bonding Interactions: Interactions between solvent and solute partly determine the solubility.
	Energy: Macroscopic: Temperature changes that take place when a substance dissolves depend on the energy required to overcome interactions and energy released when new interactions are formed.
	Change and Stability in Chemical Systems: Solubility of a substance depends on the total entropy change when a substance dissolves.
Phases and Phase Changes	**Atomic/Molecular Structure and Properties:** Melting/boiling point of a substance depends on its molecular-level structure.
	Electrostatic and Bonding Interactions: Types and strengths of interactions at the molecular level influence melting/boiling points.
	Energy: Macroscopic: Energy changes associated with phase changes are determined by the types and strengths of interactions.
	Change and Stability in Chemical Systems: Phase change temperatures depend upon the energy transfer between system and surroundings and the corresponding entropy changes.
Kinetics	**Atomic/Molecular Structure and Properties:** Rates of chemical reactions depend on the structures of the reacting species and the probability of the reactants being properly oriented in a collision. The mechanism for the reaction also depends on the molecular structure.
	Electrostatic and Bonding Interactions: Rates of chemical reactions depend on the strengths of the interactions between the reacting species and the strengths of the bonds within them.
	Energy: Molecular and Macroscopic: Rates of chemical reactions depend on the activation energy (which in turn depends on the structure and interactions) and on the kinetic energy of the colliding reactant molecules.
	Change and Stability in Chemical Systems: Kinetics is the study of how and why chemical change occurs. Competing rates of forward and reverse reactions control the extent of a reaction and when balanced equilibrium is reached.
Thermochemistry	**Atomic/Molecular Structure and Properties:** Some bonds and interactions are broken and new ones formed in a chemical reaction.
	Electrostatic and Bonding Interactions: Types and strengths of bonds and interactions depend on the structure and polarity of the molecules involved. The strength of the interactions can be predicted from electrostatic considerations.
	Energy: Molecular and Macroscopic: Energy change in a chemical reaction is a balance between the energy required to break bonds and interactions, and the energy released when new bonds and interactions are formed.
	Change and Stability in Chemical Systems: Whether a chemical reaction occurs or not depends on the total entropy change, which can be determined from a consideration of enthalpy and entropy changes of the system.

Topics and their alignment to concepts.
Source: Cooper, Posey, and Underwood

In the table above, it may seem that some of the Core Ideas are themselves potential Subjects, in that they are good ways of organizing content. This is a consequence of examining knowledge at such a fine-grained scale; Topics can be a mix of Concepts and Content. However, this provides an important criterion for extracting from the curriculum elements that are dense in content but not in concept.

For example, one can imagine the Krebs cycle as a Topic in Cellular & Molecular Biology, but, although it clearly is relevant to other concepts, it is *itself* not a useful concept. Contrasting that with the Topic of Succession in Ecology, it becomes evident that although Succession may be a chapter title in a textbook, it is also itself an important concept of a type of dynamic that happens in ecosystems over time (likely a Threshold Concept of Ecology). Perhaps, then, the Krebs cycle should not be memorized for its own sake, and instead only be studied to the degree that it serves other concepts, whereas Succession may be a fruitful stand-alone Topic of Ecology.

Evolution of Content



The classical Greek education frameworks

The most influential of early Western formulations of the curriculum were the Trivium and Quadrivium—a medieval revival of classical Greek education theories that defined the seven liberal arts for university education: grammar, logic, rhetoric, astronomy, geometry, arithmetic, and music.

Changes have occurred very slowly, with some subjects becoming optional (astronomy, ethics, Latin, etc.), or taught at tertiary education level (rhetoric, oratory as "communications"). Knowledge discipline standards in secondary education in the United States were first established in 1893 by the Committee of Ten, led by Charles Eliot, the president of Harvard University and sponsored by the National Education Association. He convened ten committees of education experts, led mostly by college presidents and deans, and charged them with defining the standardized curriculum requirements for all public secondary schools.

Table III of the Report of the Committee of Ten

1st Secondary School Year.	
Latin	5 p.
English Literature, 2 p. / " Composition, 2 p.	4 p.
German [or French]	5 p.
Algebra	4 p.
History of Italy, Spain, and France	3 p.
Applied Geography (European political — continental and oceanic flora and fauna)	4 p.
	25 p.

2nd Secondary School Year.	
Latin	4 p.
Greek	5 p.
English Literature, 2 p. / " Composition, 2 p.	4 p.
German, continued	4 p.
French, begun	5 p.
Algebra,* 2 p. / Geometry, 2 p.	4 p.
Botany or Zoölogy	4 p.
English History to 1688	3 p.
	33 p.

* Option of book-keeping and commercial arithmetic.

3rd Secondary School Year.	
Latin	4 p.
Greek	4 p.
English Literature, 2 p. / " Composition, 1 p. / Rhetoric, 1 p.	4 p.
German	4 p.
French	4 p.
Algebra,* 2 p. / Geometry, 2 p.	4 p.
Physics	4 p.
History, English and American	3 p.
Astronomy, 3 p. 1st ½ yr. / Meteorology, 3 p. 2nd ½ yr.	3 p.
	34 p.

* Option of book-keeping and commercial arithmetic.

4th Secondary School Year.	
Latin	4 p.
Greek	4 p.
English Literature, 2 p. / " Composition, 1 p. / " Grammar, 1 p.	4 p.
German	4 p.
French	4 p.
Trigonometry, / Higher Algebra,	2 p.
Chemistry	4 p.
History (intensive) and Civil Government	3 p.
Geology or Physiography, 4 p. 1st ½ yr. / Anatomy, Physiology, and Hygiene, 4 p. 2nd ½ yr.	4 p.
	33 p.

FIG. 2. The Range of Offerings for a High School As Set Forth by the Committee of Ten in Table III, p. 41, of the Report. [Table III represented the total program as derived from recommendations of the conferences, with some adjustment of periods per week. From it the programs of individual pupils could be derived. Eliot apparently preferred this to the set courses of study identified by the committee in Table IV.]

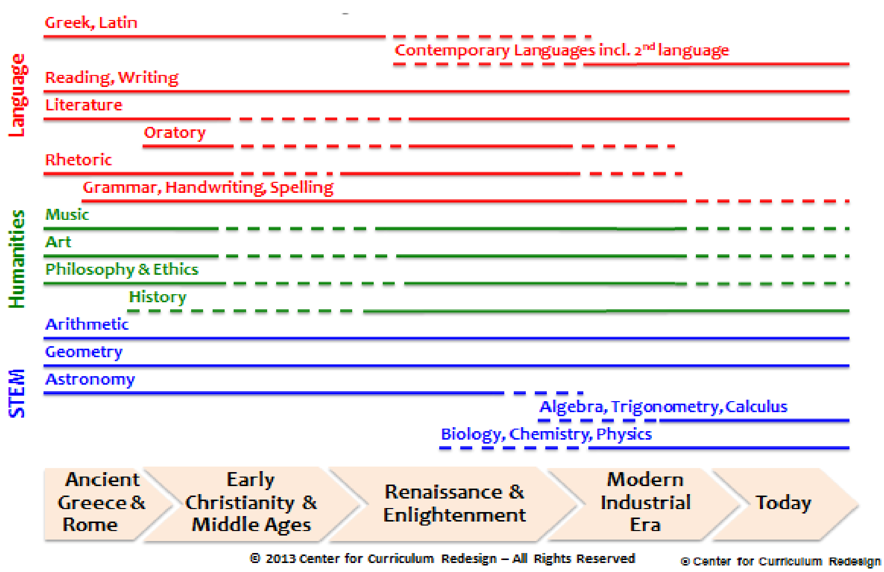
The Report of the Committee of Ten

To various degrees, these early education discipline standards (minus the Greek, Latin, and other specific language requirements) are still reflected in secondary school graduation requirements in many education systems today.

Thus the traditional disciplines taught in most education systems around the world are:

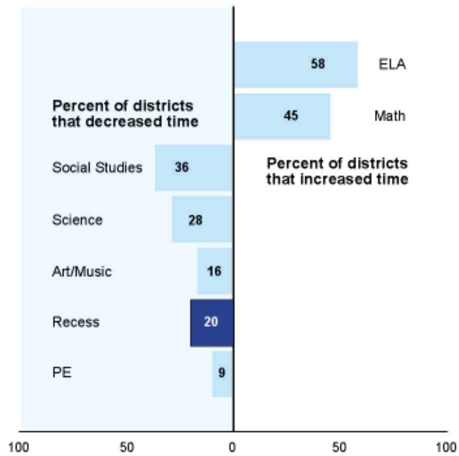
- Languages (domestic)
- Mathematics (arithmetic, geometry, algebra)
- Science (biology, chemistry, physics)
- Languages (foreign)
- Social studies (history, geography, civics, economics, etc.)
- Arts (performing & visual)
- Wellness (often physical education in particular)

Within the disciplines, the pattern is similar; areas of knowledge are added on when they became common enough, but nothing has been majorly redesigned. In math for example, the curriculum reflects the monumental contribution of Leonardo de Pisa (Fibonacci) who wrote the book Liber Abbaci in 1202 to help merchants transition from using Roman numerals to using the ten digits of the Hindu-Arabic system, and to learn things like ratio and proportion, rate, linear equations, etc.



The evolution of content over time. *Source*: CCR

It has become clear that what was relevant for 13th century merchants is not relevant to 21st century students. Progress in human endeavors has increased exponentially, and although Trigonometry and Calculus were added to the curriculum, more modern subjects, such as Robotics and Entrepreneurship, do not fit into the current over-crowded system. Furthermore, standardized assessments are placing pressure in particular on language and mathematics, thereby further narrowing the scope of school subjects. In the image below, Social Studies, Science, Recess, Art/Music, and PE have by and large been squeezed out to make room for ELA and Math in the United States.



Percentage of districts in the US with change in allotted time per discipline since 2001 *Source: Center for Public Education*

Cross-Cutting Themes

Environmental Literacy

As discussed earlier, humankind is fast approaching or may have surpassed a number of our planet's ecological limits, and to avoid future major environmental crises or ecological disasters, every citizen must have a basic understanding of the fundamentals of environmental science and the impacts of our societies on the long-term sustainability of humankind.

The Partnership for 21st Century Skills defines the components of environmental literacy as the abilities to:

Demonstrate knowledge and understanding of the environment and the circumstances and conditions affecting it, particularly as they relates to air, climate, land, food, energy, water and ecosystems.

- Demonstrate knowledge and understanding of society's impact on the natural world (e.g., population growth, population development, resource consumption rate, etc.)
- Investigate and analyze environmental issues, and make accurate conclusions about effective solutions.
- Take individual and collective action towards addressing environmental challenges (e.g., participating in global actions, designing solutions that inspire action on environmental issues).

Global Literacy

Our global community continues to grow more interconnected, and it is no longer enough to learn from the perspective of only one country. To be educated for the twenty-first century, every student now needs to learn each subject from a variety of cultural perspectives from around the world. This means for example that world history includes histories from countries all over the world, math class discusses relevant Eastern (Arab, Indian, and Chinese) mathematicians, not just Western ones, and students are prompted to critically examine their cultural biases and perspectives, and develop understanding and acceptance of other viewpoints. Throughout the curriculum, students should learn to see individual issues within the context of their global socio-cultural significance, gain an international awareness, and a deep appreciation of cultural diversity.

Civic Literacy

Humans and education systems exist within societies, and the main ways to interact most directly with society is through law and policy. It is important that students feel connected to their society and feel that it's possible to effect change. In the coming years, there are going to be many issues that will need to be discussed publicly and decided at the societal scale, and civic literacy will therefore become increasingly relevant. To make sure that what is learned is school can be transferred to those conversations when necessary, it will be helpful to explicitly highlight the ways that law and policy connect with course content, and the kinds of questions facing society in the near future that need to be considered from an informed perspective. According to the Partnership for 21st Century Skills, civic literacy is:

- Participating effectively in civic life through knowing how to stay informed and understanding governmental processes.
- Exercising the rights and obligations of citizenship at local, state, national and global levels.
- Understanding the local and global implications of civic decisions.

They also recommend several resources to learn more about civic literacy

Information Literacy

According to Eric Schmidt, CEO of Google, every two days we create as much information as was created from the dawn of civilization to 2003. The amount of scientific papers grows by seven to nine percent every year (compounded), which equates to a doubling of scientific output roughly every ten years.,

While it is true that many people know how to search for information on the Internet, it is not clear that they have grasped the more nuanced reasoning skills necessary to critically evaluate and synthesize what they find, especially when we consider the daunting amount of information they must process.

Twenty-First Century Information Literacy Tools (TILT), a program of The People's Science, has identified six core skills and sensibilities for interacting with and applying information in real-world contexts. These objectives outline the essential capacities that must be developed in order to responsibly curate, evaluate, and transform an abundance of information into usable knowledge.

TILT identifies the following core capacities of 21st century information literacy:

- Maintain a dynamic disposition by accepting the progressive nature of information and remaining open to new evidence.
- Consider the role of socio-cultural lenses in the interpretation of information and the proliferation of new ideas.
- Cultivate comfort with competing evidence by acknowledging informed debate as a critical, nuanced step towards replication, refinement, and eventual consensus.
- Evaluate source credibility for common access points in the information dissemination cycle.
- Develop an informed orientation to ensure clarity of how specific evidence is situated in the broader landscape of relevant knowledge.

With information output growing at an unprecedented rate, information literacy skills are increasingly important for all students throughout all subject areas.

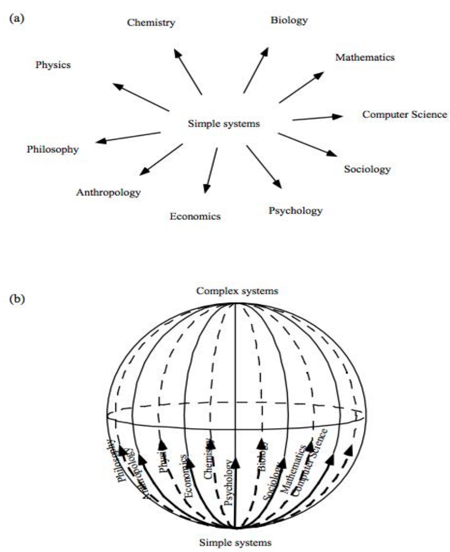
Digital Literacy

As discussed above, technological savvy is becoming increasingly important. As tools and technologies continue to develop, students must learn to use a variety of new technologies. The majority of jobs are going to require upskilling, as we begin to integrate technological innovations across the majority of possible careers. It is important that students learn to be comfortable with existing technological tools, such as searching on the internet, word processing, spreadsheets, and social media applications, and that they feel comfortable learning new technologies.

All these themes offer educators and students alike a way to make learning more relevant, grounded in the real world, motivating, and action-oriented. They also provide a foundation for interdisciplinary thinking, as they are lenses that educators can mix and match to content areas and competencies.

Systems Thinking

Scientific disciplines as well as social systems are converging on the ideas of complex systems (see the following figure). This requires a paradigm shift from the mechanistic and reductionist model of twentieth century Western culture, toward a more balanced approach. Analysis continues to serve a critical purpose by isolating parameters, thereby allowing for their deep treatment and understanding, but it must be integrated with a holistic perspective through synthesis, such that each part can be considered as a whole, each whole as a part of a larger system, and the relationships between all of them explored.



Systems Thinking as it relates to disciplines
Source: Bar-Yam, Y. *Dynamics of Complex Systems*

According to educational theorist and cognitive scientist Derek Cabrera, students should be encouraged to consider distinctions, systems, relationships, and perspectives (DSRP).

- Distinctions: Develop increasingly sophisticated characterizations of ideas and objects.

- Systems: Deconstruct ideas and re-constructing new integrated concepts with a variety of part/whole interactions.
- Relationships: See connections between things.
- Perspectives: See things from different points of view.

By considering the common properties of complex systems, learners can apply this approach to view more traditional disciplines from a modern, systems perspective.

Design Thinking

As we have seen, the twenty-first century challenges we now face are demanding a major rethinking and redesigning of many of our societal institutions from education, to agriculture and energy use, to product design and manufacturing, to economics and government. Almost every product and service needs to be redesigned in light of our increased use of information and communications technologies, global connectivity, energy and material ecological sustainability, longer lifespans, and increased well-being. Beyond products and services, a design thinking mindset is needed in the ways we approach our challenges.

One way of crisply conceptualizing the design process is through four main principles:

- The human rule: All design activity is ultimately social in nature.
- The ambiguity rule: Design thinkers must preserve ambiguity.
- The redesign rule: All design is redesign (mistakes are a natural part of the process of iterative improvement).
- The tangibility rule: Making ideas tangible facilitates communication.

Computational Literacy

In discussions about how to best prepare students for the 21st century, it is common to focus on the increasingly ubiquitous role of technology, and thus the need for students to learn computer science skills. But experts have agreed that rather than any particular programming language or paradigm, what is most important is internalizing the types of thinking that is involved in mastery of Computer Science. According to the Royal Society, "Computational thinking is the process of recognizing aspects of computation in the world that surrounds us, and applying tools and techniques from Computer Science to understand and reason about both natural and artificial systems and processes." In a recent review article, the following elements were defined as central to CT:

- Abstractions and pattern generalizations (including models and simulations).
- Systematic processing of information.
- Symbol systems and representations.
- Algorithmic notions of flow of control.
- Structured problem decomposition (modularizing).
- Iterative, recursive, and parallel thinking.
- Conditional logic.
- Efficiency and performance constraints.
- Debugging and systematic error detection.

Appendix 2

What is AI?

In the preceding text, we gave a brief introduction to AI (sufficient to ground our discussion of the application of AI in education (AIED)). Here, we build on that primer, to give more details for readers who are interested.

With this in mind, where better to start than with some definitions, to provide some context for what follows. According to the Oxford English Dictionary, artificial intelligence is

> The capacity of computers or other machines to exhibit or simulate intelligent behavior.
>
> —*The Oxford English Dictionary*[438]

This definition confirms that artificial refers to computers or other machines, but it still begs the question what is meant by intelligent behavior, or indeed by intelligence. In fact, what is understood by intelligence and whether machines can be intelligent have long been controversial (for a seminal discussion, see the *Chinese Room Argument*, by the philosopher John Searle).[439] For Alan Turing (who is regarded by many as the father of both modern computing and artificial intelligence), we might consider a computer intelligent if it passes what he called the *imitation game* (and is now mostly known as the *Turing test*), in which a computer hidden from view imitates a human by responding to a series of conversational questions.

> I believe that in about fifty years' time it will be possible to program computers… to make them play the imitation game so well that an average interrogator will not have more than 70 percent chance of making the right identification after five minutes of questioning.
>
> —Alan Turing[440]

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[438] OED. (2018). "artificial intelligence, n." *OED Online*. http://www.oed.com/view/Entry/271625

[439] John R. Searle. (1980). "Minds, brains, and programs." *Behavioral and Brain Sciences* 3 (3): 417–424.

[440] A. M Turing. (1950). "Computing machinery and intelligence." *Mind* 59 (236): 433–460.

Introducing humans (the interrogator) to the discussion also suggests an alternative approach, comparing artificial with human intelligence:

> AI is the science of making machines do things that would require intelligence if done by men.—Marvin Minsky[441]

Updated, this informs another dictionary's expanded explanation. Artificial intelligence is

> [A] discipline concerned with the building of computer programs that perform tasks requiring intelligence when done by humans. Examples of tasks tackled within AI are: game playing, automated reasoning, machine learning, natural-language understanding, planning, speech understanding, and theorem proving.
>
> —*A Dictionary of Computer Science*[442]

On reflection, and inevitably, there are probably as many definitions of artificial intelligence as there are books on the subject (and there are a good many, mostly technical, books). However, Russell and Norvig's work—for many, the key AI textbook[443]—observes that most definitions of artificial intelligence fit into a matrix of four distinct approaches, depending on whether they prioritize thinking or behaving, and whether they take a human-like or rational perspective (as illustrated in the following table): (i) AI that aims to *think like a human*, by automating human cognitive abilities such as decision making and problem solving (as occurs in many AIED individualized tutoring systems (ITS)); (ii) AI that aims to *act like a human*, by automating human non-reflective abilities such as image and voice recognition (as is used in AIED DBTS and automatic essay feedback); (iii) AI that aims to *think rationally*, by means of computational models of perception and reasoning (as might be necessary in an AI teaching assistant); and (iv) AI that aims to *act*

[441] Marvin Minsky (1968) quoted by Blay Whitby in (1996) *Reflections on Artificial Intelligence*. Intellect Books, 20.
[442] "artificial intelligence." In (2016). *A Dictionary of Computer Science*. Butterfield, A. and Ngondi, G.E. Oxford University Press. http://www.oxfordreference.com/view/10.1093/acref/9780199688975.001.0001/acref-9780199688975-e-204.
[443] Russell and Norvig, *Artificial Intelligence*.

rationally, by means of intelligent agents (as is used in many AIED simulations).

	Human-like	**Rational**
Thinking	Thinking like a human. *Automating human cognitive abilities (e.g., decision making and problem solving).*	Thinking rationally. *Computational models of perception and reasoning.*
Acting	Acting like a human. *Automating human non-reflective abilities (e.g., image and voice recognition).*	Acting rationally. *Designing intelligent agents (artifacts with intelligent behaviors).*

Approaches to artificial intelligence.
Source: CCR based on Russell and Norvig, *Artificial Intelligence*, p. 2.

Returning to the use of the word artificial in artificial intelligence and Searle's argument that a computer program can never be capable of independent thinking, perhaps we should stop altogether using the phrase artificial intelligence (intelligence exhibited by something that is not human), thus avoiding the hermeneutic controversy. Indeed, this effectively is argued by many writers, not least by Doug Engelbart[444] and Vint Cerf[445] (two leading pioneers of modern computing) who refer instead to what they call *augmented intelligence*[446] (what others have called *intelligence augmentation*[447] or *intelligence amplification*[448]). This phrasing dodges Searle's objections by retaining the human brain as the source of intelligence, and by positioning the computer and its programs as a sophisticated tool (or complex of tools) with which us humans might

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444 Engelbart, D. C. (1962). "Augmenting human intellect: A conceptual framework." Prepared for the Air Force Office of Scientific Research. Stanford Research Institute. https://www.dougengelbart.org/pubs/augment-3906.html

445 Cerf, V.G. "Augmented Intelligence." *IEEE Internet Computing* 17. https://doi.org/10.1109/MIC.2013.90

446 Pasquinelli, M. (2014). "Augmented intelligence, critical keywords for the digital humanities." http://cdckeywords.leuphana.com/augmented_intelligence

447 https://www.weforum.org/agenda/2017/01/forget-ai-real-revolution-ia

448 Ashby, W.R. (1956). *An Introduction to Cybernetics*. Chapman & Hall Ltd.

enhance or augment our intellectual capabilities. In this approach, computers are employed to do what humans find more difficult (such as finding patterns in huge amounts of data). In fact, some have argued that it is the combination of humans with AI, what others have called *centaurs* (half-human and half-AI)[449], that has the greatest potential, better than either humans or AI alone.

Nonetheless, the debate contrasting augmented and artificial will inevitably run and run, with artificial intelligence winning at least on popular usage even if augmented intelligence is more accurate or useful. This is why, in most of the main text and hereafter, we take the ultimate pragmatic approach and refer almost exclusively to AI, leaving the reader to decide for themselves what the A in AI represents.

A Short History of AI

AI's foundational event is widely considered to be a workshop held at Dartmouth College, a US Ivy League research university, in 1956.[450] It was where what is thought to be the first AI program, the Logic Theorist, was presented and discussed. The Dartmouth workshop involved John McCarthy (who is usually credited with convincing his colleagues to name the new field artificial intelligence), together with others including Marvin Minsky, Allen Newell, and Herbert Simon, all of whom would go on to become leading AI researchers.

Over the following decades, AI developed in fits and starts with periods of rapid progress interspaced with periods, known as *AI winters*, where confidence and funding all but evaporated. In its early years, AI research was centered on just a few labs, in particular, the Massachusetts Institute of Technology, Carnegie Mellon University, and Stanford University, but the scope of AI research quickly mushroomed. Here, to illustrate the breadth of early AI research, we will look briefly at four

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[449] Case, N. (2018). "How to become a centaur." *Journal of Design and Science*. https://doi.org/10.21428/61b2215c

[450] Crevier, D. (1993). *AI: The Tumultuous History of the Search for Artificial Intelligence*. Basic Books.

areas: rule-based systems, computers that play games, computer vision, and natural language processing.

Rule-Based and Expert Systems

Rule-based inference systems were, in fact, both an early focus and a long-lasting AI success. Especially memorable from the early days, a rule-based approach was implemented in ELIZA,[451] which, among other applications, was programmed to impersonate a psychotherapist. ELIZA is self-evidently the original precursor of AIED dialogue-based tutoring systems (DBTS) such as *AutoTutor*. A brief extract of a typical ELIZA conversation, which was typed on a computer terminal, went like this:

> "My boyfriend made me come here."
> ELIZA: "Your boyfriend made you come here."
> "He says I'm depressed most of the time."
> ELIZA: "I'm sorry to hear that you are depressed."

In this way, ELIZA appeared somewhat responsive, perceptive and thus intelligent. However, it was only using rules, such as me–you sentence transformations ("My boyfriend" became "Your boyfriend"), inserting leading phrases ("I'm sorry to hear that"), and later returning to earlier randomly selected sentences as if it were making a novel logical connection. ELIZA is also notable for being one of the first AI tools to have been commercialized, despite it not having any psychological benefits.[452]

Over time, rule-based systems developed into what became known as *expert systems*, "computer program[s] that reason using knowledge to solve complex problems,"[453] with one early example being MYCIN which was designed to diagnose some infectious blood diseases[454] (many early AIED ITS are essentially expert systems). Like other expert systems, MYCIN

[451] Weizenbaum, J. (1966). "ELIZA—a computer program for the study of natural language communication between man and machine." *Communications of the ACM* 9 (1): 36–45.

[452] Weizenbaum, J. (1976). *Computer Power and Human Reason: From Judgment to Calculation*. Freeman.

[453] Feigenbaum, E.A. (1992). "Expert systems: Principles and practice." In *The Encyclopedia of Computer Science and Engineering*.

[454] Shortliffe, E.H., et al. (1975). "Computer-based consultations in clinical therapeutics: Explanation and rule acquisition capabilities of the MYCIN system." *Computers and Biomedical Research* 8 (4): 303–320.

used a sequence of IF... THEN... and other conditional rules, in this case to infer a diagnosis from the result of blood tests and bacterial cultures. A simplified extract illustrates the process of logical inference.

IF	the bacterial culture is positive
AND	the entry is the gastrointestinal tract
AND	the abdomen is the locus of infection
OR	the pelvis is the locus of infection
THEN	Enterobacteriaceae.

Although expert systems typically contain many hundreds of IF... THEN... conditional rules, it is usually possible to follow the instantiated logic that leads to the outcomes—in other words, the system's rules and decisions can be inspected. However, as the interactions between rules can quickly multiply, expert systems can also sometimes be challenging to understand and debug. Nonetheless, expert systems are relatively inexpensive to develop, are resilient to errors, and can be relatively flexible (if a new condition needs to be accounted for, a new rule can usually be added without compromising the existing syntax). For all these reasons, rule-based systems were quickly embraced by industry, although their use was usually limited to specialist applications (for example, encouraged by the fact that their only expert locomotive engineer was nearing retirement, General Electric developed an expert system that was capable of diagnosing 80% of electric locomotive repair problems).[455]

In fact, developing expert systems for specialist applications highlighted a key problem, known as knowledge acquisition. How could the expert-system designers, who were not usually experts in the domain being represented, identify the knowledge that they needed to codify? In turn, this led to developments in both knowledge elicitation (methods for extracting knowledge from domain experts in a way that could logically be instantiated) and knowledge engineering (methods for instantiating the elicited knowledge in the expert systems' conditional rules).[456] With these

[455] Crevier, *AI*, 198.

[456] Cooke, N.J. (1994). "Varieties of knowledge elicitation techniques." *International Journal of Human-Computer Studies* 41 (6): 801–849.

various methods now mature, expert systems are used in various contexts (such as manufacturing, agriculture, engineering, tax assessments, and loan-eligibility calculations), particularly in situations where human experts are mostly unavailable (due to location or cost). More recently, expert systems have been enhanced with new AI techniques, a development to which we will return later.

Each of the other examples of early AI research that we will now discuss (playing games, computer vision, and natural language processing) saw early rapid advances. On the other hand, each is a good example of the "naïveté of early AI efforts"[457]—the fact that early AI researchers and their funders anticipated greater advances than were actually realized.

Computers Playing Games

Some early AI researchers were interested in developing systems capable of playing games such as chess, backgammon, and checkers, because such games comprise only a few basic elements and are rule-bound yet have non-trivial solutions. Various approaches were investigated. One tactic involved trial-and-error search methods, in which the tree-like problem space of possible moves is searched to identify the optimal pathway to success (which in chess was always challenging because of the exponential number of possible moves at any one time). Another approach used evaluation methods, which more closely replicated how humans play, and involved defining criteria to evaluate the goodness of available moves and to choose the move with the best chance of success. Some systems also introduced statistical techniques to weight the choice of moves according to the outcomes of a large number of previous games, while others used pruning (removing obvious dead-ends) or heuristics (rules of thumb) to make problem-space searching more efficient. Many of these systems eventually were capable, thanks mainly to the ability of computers to quickly compute massive amounts of numerical data, of beating advanced human players, although it was not until 1997 that IBM's chess playing Deep Blue managed to beat the

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[457] Crevier, *AI*, 89.

reigning world chess champion, Boris Kasparov. It was not until twenty years later that Google's DeepMind, using a very different AI, beat the world champion Go player, Lee Sedol. Nonetheless, many of the techniques pioneered by the early game researchers are still in use today—especially in the various gaming apps played by millions on their smartphones and tablets..

Computer Vision

To develop computer vision, the ability of computers to recognize objects (to see) in the real world, the early researchers recognized that they needed to drastically simplify the problem. Rather than try to interpret the complexity of the sights that humans see (such as randomly shaped objects, textures, perspective, millions of colors, movement), they started with a highly simplified model: blocks micro worlds. The world was comprised of stationery geometric objects such as pyramids, cubes, and rectangular blocks. Various early attempts worked by first trying to identify corners, edges, and block faces, although many of these efforts failed. One key problem was that the systems did not understand occlusion (when one object partly hides another), an issue that was eventually solved by including various knowledge rules within the system (such as a line has two ends, and an arch has two non-touching upright blocks supporting a third block). Nonetheless, although many significant advances were made, overall progress in computer vision was slow.

Natural Language Processing

Early natural language processing research efforts were in machine translation, which had been funded since the early 1950s by the US government with the aim of automatically translating Cold-War Russian documents. However, the work was unsuccessful: the infamous retranslation (English to Russian to English) of "the spirit is willing but the flesh is weak" as "the vodka is good but the meat is rotten" illustrates the difficulties they were unable to address.[458] Funding was soon

[458] Russell and Norvig, *Artificial Intelligence*, 21.

withdrawn. A much-simplified method was taken by SHRDLU,[459] which adopted the approach of the blocks micro worlds, and their more modest ambitions, although SHRDLU's blocks micro world existed only inside the computer's memory. With SHRDLU, a person could engage in a simple, typed dialogue with the system, instructing a simulated robot arm to interact with (pick up and move) simulated block objects, by using commands expressed in everyday language (pick up the big red block). Like all early approaches to natural language processing, SHRDLU depended on the direct hand coding of conditional rules, an approach that—it was soon realized—could not cope with the full variation of natural languages. Although most languages have a stable underlying structure, all languages have innumerable surface differences and multiple ambiguities; such that, almost as soon as a language rule is encoded, an exception is identified, and another rule becomes necessary, in a seemingly endless cycle.

The First AI Winter

While all of these advances were promising, they all failed to live up to the researchers' and funders' hopes and expectations. Much of the early funding had come from the Defense Advanced Research Projects Agency (DARPA), which had given millions of dollars for AI research with almost no strings attached. However, following a report from the British Science Research Council[460] that suggested most AI research was unlikely in the near future to produce anything useful, and the lack of AI technologies that might be applied usefully to DARPA's work, the money was withdrawn—leading inevitably to the first AI winter, in which AI research slowed to a snail's pace.

The purpose of this brief look at the beginnings of AI research was to illustrate its ambitions, breadth, successes, and challenges, all of which had implications for the application of AI in education. In this appendix,

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[459] Winograd, T. (1980). "What does it mean to understand language?" *Cognitive Science* 4 (3): 209–241.

[460] Lighthill, J. (1973). "Lighthill report: Artificial intelligence: A paper symposium." Science Research Council. http://www.math.snu.ac.kr/~hichoi/infomath/Articles/Lighthill Report.pdf

we will now leap forward to the most recent decade,[461] in which, thanks to three key developments—the advent of faster computer processors, the availability of large amounts of big data, and advances in computational approaches—AI has entered a period of renaissance.

AI Today

As we noted at the beginning of this appendix, AI has become an often hidden but integral, pervasive, and inescapable part of our daily lives. In fact, paradoxically, the more it is integrated into our lives, the less we tend to think of it as AI.

> A lot of cutting edge AI has filtered into general applications, often without being called AI because once something becomes useful enough and common enough it's not labeled AI anymore.[462]

Instead, AI is often known as an advanced computer program (such as email spam filtering),[463] a personal ant (such as Cortana),[464] a recommendation system (such as in Netflix),[465] or perhaps a language-learning app (such as Duolingo).[466] Having said that, recent voice-activated smart speakers, such as Google Home[467] and Amazon Echo,[468] have made AI more visible in our living rooms.

In fact, many recent developments in AI, due mainly to the three key developments noted earlier (faster computer processors, large amounts of big data, and new computational approaches), have been both groundbreaking and in many ways transformative. In fact, this appendix

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[461] Readers wishing to learn more about the history of AI might enjoy Daniel Crevier's *AI: The Tumultuous History of the Search for Artificial Intelligence*, or the first chapter of Russell and Norvig's comprehensive *Artificial Intelligence*.

[462] http://edition.cnn.com/2006/TECH/science/07/24/ai.bostrom/index.html (Professor Nick Bostrom, director of the Future of Humanity Institute, University of Oxford).

[463] E.g., https://www.mailwasher.net which uses Bayesian techniques to learn which emails are spam and which are not.

[464] https://www.microsoft.com/en-us/cortana

[465] https://help.netflix.com/en/node/9898

[466] https://www.duolingo.com

[467] https://store.google.com/gb/product/google_home

[468] https://www.amazon.com/b/?ie=UTF8&node=9818047011

is already necessarily out of date, with new AI techniques, tools, and products being launched all the time.

AI techniques such as machine learning (supervised, unsupervised, and reinforcement learning), neural networks (including deep learning), and evolutionary algorithms have all been used in applications as diverse as autonomous vehicles, online shopping, auto-journalism, online dating, image manipulation,[469] stocks and shares dealing, and legal and financial services. We will look in some detail at these core AI techniques. But first, to give a context, let us consider some recent AI applications.

Face Recognition

Automatic face recognition is one area that has quite recently made qualitative leaps forward while simultaneously becoming almost invisible. It is the technology used in smartphone cameras to ensure that faces are always in sharp focus and at e-passport gates to identify travelers before allowing them to enter a country. Earlier, we described the beginnings of computer vision, and the need to simplify the problem by focusing on blocks micro worlds. Following that work, there was slow progress, but near-human-level computer vision remained far out of reach; at least until 2012, when Google applied a quite different computational approach. Rather than trying to program computer vision, Google researchers presented a brain-inspired AI neural network, made up of 16,000 computer processors, with 10 million randomly selected video thumbnails from YouTube.[470] By using deep-learning techniques, and despite not being told how to recognize anything in particular, this machine learning system soon learned how to detect human faces in photographs. Two years later, Facebook introduced a nine-layer deep AI neural network, involving more than 120 million parameters, to identify (not just detect) faces in timeline photographs.[471] It was trained on a

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[469] https://www.bbc.co.uk/news/av/technology-45361794/how-artificial-intelligence-can-edit-your-pictures

[470] https://www.nytimes.com/2012/06/26/technology/in-a-big-network-of-computers-evidence-of-machine-learning.html?_r=1

[471] Facebook introduced a nine-layer deep AI neural network, involving more than 120 million parameters, to identify (not just detect) faces in timeline photographs. It was trained on a dataset of four million images.

dataset of four million images of faces that had previously been labeled by humans (the Facebook users, who had been happily labeling their friends in uploaded photographs over several years), and was able to achieve accuracy in excess of 97 percent, which almost matches human-level performance. However, although impressive, these examples also highlight a key difference between AI and human intelligence: a human doesn't need to see ten, or even four, million faces before it can easily recognize a family member, a friend, or a celebrity (one of the ways in which humans still currently out-perform AI, although continual advances suggest this will not always be the case).

Autonomous Vehicles

Another area that has seen much AI development in recent years is autonomous vehicles, with neural networks being used to enable cars, trucks, and taxis to drive without human intervention. The avowed aim of the developers is to drastically reduce the number of road accidents, injuries, and fatalities on our roads, and to manage traffic jams out of existence. Autonomous vehicles depend on a complex rig of cameras, sensors, and communication systems, together with massive computing power, to enable them to see, hear, feel, think, and make decisions like a good human driver. As the vehicle drives along, its sensors detect the road's edges and markings, road signs and traffic lights, other vehicles including bicycles, other potential obstacles, and pedestrians (including those who run across the road without looking). Simultaneously, a neural network-driven intelligent agent controls the car's steering, acceleration, and braking. In fact, despite all the necessary AI, the success of autonomous vehicles (which are not likely to be widely available any time soon) still depends on humans—the thousands of people, the wizards behind the curtain,[472] whose job it is to manually label individual frames from thousands of hours of video footage captured by cars driving around the cities. In other words, the autonomous vehicle is an area of

[472] https://www.ft.com/content/36933cfc-620c-11e7-91a7-502f7ee26895 and https://www.bbc.co.uk/news/technology-46055595

AI research that still, and probably will for some time yet, depend on humans.

Auto-Journalism

A probably less well-known use of AI is in journalism. News organizations around the world are developing AI technologies to support their news gathering and news reporting. For example, AI agents continually monitor global news outlets and use semantic analysis to automatically extract key information, which is made available to journalists. to write their stories.[473] There are even some AI technologies that go one step further and automatically write the stories themselves.[474] They take the curated information, match it to a template, and create a story that can be published across multiple platforms. The output might be formulaic, but this approach has been very successful at writing accurate teasers that direct readers to the in-depth writing of the human journalists.[475] Other uses of AI in journalism include moderating forum comments (using sentiment analysis to automatically detect aggressive or otherwise inappropriate postings) ,[476] data visualizations (in which the AI automatically determines the best way to display a particular set of data),[477] chatbots designed to respond to user questions,[478] and detecting fake news.[479] But as well as detecting fake news, AI is also being used to create fake news[480] (if it can write real stories, it can write fake stories) and fake media (using an AI technology known as Deepfakes one can superimpose celebrity faces hyper-realistically on to actors in porn videos).[481] "Think also of the potential abuse, by individuals or state

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[473] E.g., http://bbcnewslabs.co.uk/projects/juicer

[474] E.g., https://narrativescience.com/Products/Our-Products/Quill

[475] E.g., https://www.washingtonpost.com/pr/wp/2016/08/05/the-washington-post-experiments-with-automated-storytelling-to-help-power-2016-rio-olympics-coverage/?utm_term=.e22f1adbfd5d

[476] E.g., https://www.perspectiveapi.com

[477] E.g., https://www.graphiq.com

[478] E.g., https://www.theguardian.com/help/insideguardian/2016/nov/07/introducing-the-guardian-chatbot

[479] E.g., http://adverifai.com

[480] E.g., https://www.technologyreview.com/s/610635/fake-news-20-personalized-optimized-and-even-harder-to-stop

[481] https://www.unilad.co.uk/featured/the-real-reason-pornhub-has-banned-deepfakes

actors bent on spreading misinformation. Deepfakes could put words and expressions on to the face and mouth of a politician and influence elections."[482]

With AI being applied in increasing numbers of contexts, too many to cover fully in this appendix, we will conclude with three brief examples: legal services, weather forecasting, and medical diagnosis.

AI Legal Services

AI e-Discovery tools are being used to help lawyers process the huge amounts of documentation that need to be reviewed as potential evidence in civil or criminal legal cases, which can be a tedious and time-consuming task.[483] One approach involves a machine-learning analysis of a sample of documents that have been reviewed and labeled by an expert. The outcomes enable the AI to then identify which of the remaining documents need to be prioritized for in-depth review. Similarly, AI tools have been developed to research relevant case law and statutes, to perform legal due diligence in mergers and acquisitions, and to undertake contract review as well as contract writing.

AI Weather Forecasting

In weather forecasting, machine learning has been shown to be more accurate at predicting weather than traditional simulation-based forecasting.[484] Meteorologists have long tracked weather data that they enter into complex knowledge-based simulations to make forecasts. However, AI forecasting mines vast amounts of historical and immediate weather data, billions of data records from more than 1,000 weather satellites and 250,000 weather stations worldwide, with one company claiming to use more than 100 terabytes of data every day.[485] These AI weather-forecasting systems use neural networks and deep learning to

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[482] https://www.ft.com/content/8e63b372-8f19-11e8-b639-7680cedcc421

[483] https://talkingtech.cliffordchance.com/en/emerging-technologies/artificial-intelligence/ai-and-the-future-for-legal-services.html

[484] McGovern, A., et al. (2017). "Using artificial intelligence to improve real-time decision-making for high-impact weather." *Bulletin of the American Meteorological Society* 98. https://doi.org/10.1175/BAMS-D-16-0123.1

[485] http://www.theweathercompany.com/DeepThunder

identify data patterns (rather than to feed into simulations) in order to make data-based predictions about future weather conditions.[486]

AI Medical Diagnosis

Our final brief example is the use of AI in medical diagnoses. For example, AI techniques are being used by radiologists to more quickly identify anomalies in medical images while making fewer mistakes.[487] One system looks for irregularities in X-ray images and, depending on what it finds, assigns it a priority. If it finds nodules on an image of a pair of lungs, it assigns a high-priority status and sends it to a pulmonary radiologist for further checks. Another system looks at retinal scans to detect diabetic eye disease, and has shown itself to be slightly more accurate than human ophthalmologists.[488] Another recent innovation is online AI-driven general medical diagnoses,[489] based on individuals entering descriptions of their symptoms and answering expert system-like questions, to enable the AI to come up with a diagnosis—although it still is unclear whether this type of diagnosis is as accurate as that of a real doctor (only time will tell).

AI Techniques

While it is relatively straightforward to understand *what* the applications of AI outlined in the previous section are doing, understanding *how* they are doing it can require some highly technical knowledge—exacerbated by the fact that any one AI application might draw on several different AI techniques. This is one reason why many people involved in AI have advanced degrees in mathematics or physics, although that is changing too. AI is increasingly being offered as a service: for example, Amazon's Machine Learning on AWS,[490] Google's TensorFlow,[491] IBM's Watson,[492]

[486] https://www.techemergence.com/ai-for-weather-forecasting
[487] Hosny, A., et al. (2018). "Artificial intelligence in radiology." *Nature Reviews Cancer* 18. https://doi.org/10.1038/s41568-018-0016-5
[488] https://ai.googleblog.com/2016/11/deep-learning-for-detection-of-diabetic.html, and https://www.google.co.uk/about/stories/seeingpotential
[489] https://www.babylonhealth.com
[490] https://aws.amazon.com/machine-learning

and Microsoft's Azure,[493] Nonetheless, because some AI techniques have already been repeatedly mentioned, and because they play important roles in AIED and so will be mentioned again, some key and closely interlinked AI techniques and terminologies will next be introduced.[494]

Before moving onto our discussion of key AI techniques and terminology, we will first deal with two matters frequently raised whenever AI is the topic of conversation: so-called *artificial general intelligence* and the *singularity*.

Artificial General Intelligence and the Singularity

All the examples of AI mentioned so far are domain-specific or narrow. That is to say, the domain in which they operate is tightly constrained and very limited, and the AI, despite its sophistication, cannot be directly applied to any other domain. For example, the AI used to win at Go is incapable of playing a game of chess, the AI used to predict the weather is incapable of predicting movements in the stock market, and the AI used to drive a car is incapable of diagnosing a tumor. These applications of AI are all examples of what is sometimes referred to as *artificial narrow intelligence*, in contrast to so-called *artificial general intelligence*—AI that, like human intelligence, can be used in any circumstances. Artificial general intelligence has been defined as "AI systems that possess a reasonable degree of self-understanding and autonomous self-control, and have the ability to solve a variety of complex problems in a variety of contexts, and to learn to solve new problems that they didn't know about at the time of their creation."[495] However, with some notable exceptions[496] artificial general intelligence is rarely the focus of AI research and, contrary to some suggestions in the media, does not yet exist. In fact, its

[491] https://www.tensorflow.org

[492] https://www.ibm.com/watson

[493] https://azure.microsoft.com

[494] Readers wishing to learn more about AI techniques might be interested in Russell and Norvig, *Artificial Intelligence*; and Domingos, P. (2017). *The Master Algorithm: How the Quest for the Ultimate Learning Machine Will Remake Our World.* Penguin.

[495] Goertzel, B. and Pennachin, C. (eds.). (2007). *Artificial General Intelligence, Cognitive Technologies*. Springer.

[496] E.g., https://opencog.org

complexity and the challenges that it brings should not be underestimated, such that artificial general intelligence is unlikely to exist in any meaningful sense for many years yet.

The singularity is usually understood as the time in the future when AI is projected to be more intelligent than humans (interestingly, the word is taken from mathematics, where it refers to a property that cannot be described exactly because the equations no longer make sense). Already, algorithms are being developed that are capable of redesigning and improving themselves.[497] This, it is argued will soon lead to a spiral of rapidly increasing AI intelligence, "an intellectual runaway... faster than any technical revolution seen so far,"[498] until we arrive at AI super-intelligence,[499] AI that can conceive of ideas that no human being has ever imagined. This will be the singularity, the "end of the human era"[91] (which, fortunately, is not necessarily the same as the end of the human race).

Unsurprisingly, while some welcome the singularity, believing that the super-intelligent AI will innovate advanced technologies that will help address the world's problems, others worry that it will not share our human goals and values, and that it will inevitably escape our control and possibly move against us.[500] In other words, for some, artificial general intelligence is necessarily a Pandora's box (once open it can never be closed) with unknown and potentially catastrophic (the end of life as we know it) consequences. Nonetheless, just as artificial general intelligence remains an ambition, and despite recent rapid developments in AI more generally, the singularity is also unlikely to occur for many years yet. Even for the leading advocates of artificial general intelligence, the singularity

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497 Kurzweil, R. (2006). *The Singularity Is Near: When Humans Transcend Biology*. Duckworth.

498 Vinge, V. (1993). "Vernor Vinge on the singularity." Presented at VISION-21 Symposium Sponsored by NASA Lewis Research Center and the Ohio Aerospace Institute."

499 Bostrom, N. (2016). *Superintelligence: Paths, Dangers, Strategies*. Oxford University Press.

500 E.g., Hawking. S., et al. (2014). "Transcendence looks at the implications of artificial intelligence—but are we taking AI seriously enough?" *The Independent*. http://www.independent.co.uk/news/science/stephen-hawking-transcendence-looks-at-the-implications-of-artificial-intelligence--but-are-we-taking-ai-seriously-enough-9313474.html

appears to be due to arrive at some ever-receding future date, usually thirty or more years from the time that they are writing.[501]

AI Techniques and Terminology

Algorithms

> *A process or set of rules to be followed in calculations or other problem-solving operations, especially by a computer.*
>
> —The Oxford English Dictionary[502]

As we mentioned briefly in the main text, algorithms are at the core of AI, such that the history of AI might be thought of as the history of the development of increasingly sophisticated and increasingly efficient (or elegant) algorithms. As we have seen, probably the most famous algorithm of recent times is PageRank, developed in 1996 by the founders of Google while they were students at Stanford University (and apparently named after Larry Page rather than web pages). It ranks the relative importance of a website, by counting the number of external links to the website's pages, to determine where the website appears in a Google search.

In fact, all computer programs are algorithms. They comprise hundreds if not thousands of lines of code, representing sets of mathematical instructions that the computer follows in order to solve problems—compute a numerical calculation, grammar-check an essay, process an image, or explain patterns that we see in nature.[503] All that makes AI algorithms distinct from other computer programs is that they involve some specific approaches and, as we have noted, they are applied to areas we might think of as essentially human—such as visual perception, speech recognition, decision-making, and learning.

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[501] Müller, V.C. and Bostrom, N. (2016). "Future progress in artificial intelligence: A survey of expert opinion." In *Fundamental Issues of Artificial Intelligence*. Springer, 553–570. http://link.springer.com/chapter/10.1007/978-3-319-26485-1_33

[502] https://en.oxforddictionaries.com/definition/algorithm

[503] Turing, A. (1952). "The chemical basis of morphogenesis." *Philosophical Transactions of the Royal Society* 237 (641): 37–72.

In the following figure, we show a brief extract from an AI classifier algorithm (complete algorithms can run to thousands of lines), which itself calls a second algorithm called KNeighborsClassifier.

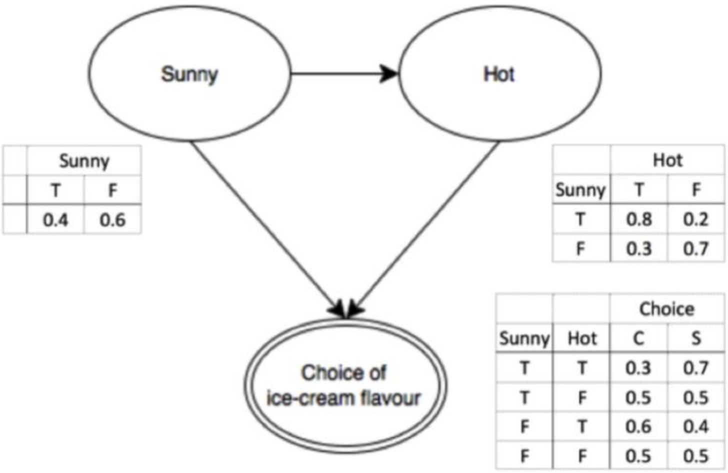
```
>>> # Split iris data in train and test data
>>> # A random permutation, to split the data randomly
>>> np.random.seed(0)
>>> indices = np.random.permutation(len(iris_X))
>>> iris_X_train = iris_X[indices[:-10]]
>>> iris_y_train = iris_y[indices[:-10]]
>>> iris_X_test  = iris_X[indices[-10:]]
>>> iris_y_test  = iris_y[indices[-10:]]
>>> # Create and fit a nearest-neighbor classifier
>>> from sklearn.neighbors import KNeighborsClassifier
>>> knn = KNeighborsClassifier()
>>> knn.fit(iris_X_train, iris_y_train)
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
        metric_params=None, n_jobs=1, n_neighbors=5, p=2,
        weights='uniform')
>>> knn.predict(iris_X_test)
array([1, 2, 1, 0, 0, 0, 2, 1, 2, 0])
>>> iris_y_test
array([1, 1, 1, 0, 0, 0, 2, 1, 2, 0])
```

A brief extract from an AI algorithm that in turn calls
a k-nearest neighbor algorithm.

Bayesian Networks

Bayesian networks are a type of graphical model employed by some AI applications. They represent the probability by which specified aspects of the world are related (their dependencies), and enable computational tasks such as prediction and diagnostics. A Bayes network graph (Bayes net) comprises various lines (known as edges) that connect nodes, with the nodes representing variables and the edges representing interdependencies between those variables, as seen in the following figure. In a typical Bayes net, an edge from one node to another suggests that the first node causes the second, with a specific dependency probability.

To give a very simple example, an AI system might be required to predict (calculate the probability of) the flavor of ice cream that a customer might buy depending on the weather and temperature of the day. Using a Bayes net approach, the nodes represent whether it is sunny, whether it is hot, and choices of ice cream flavor made by previous customers (all of which together constitute the known data) and what ice-cream flavor will be chosen today (an uncertain outcome) The Bayes net computation begins with probabilities given in each node that have been derived from training data (comprising records of weather, temperature and previous customers' choice of ice-cream flavors) to derive the probabilities of various outcomes (the ice-cream flavors that will be chosen by customers in a combination of weather and temperature circumstances).



	Sunny	
	T	F
	0.4	0.6

	Hot	
Sunny	T	F
T	0.8	0.2
F	0.3	0.7

		Choice	
Sunny	Hot	C	S
T	T	0.3	0.7
T	F	0.5	0.5
F	T	0.6	0.4
F	F	0.5	0.5

A simple Bayes net with conditional tables, predicting the ratio of chocolate and strawberry ice cream that will be sold, based on the weather, temperature, and sales of ice cream on previous days.

The type of calculation that a Bayes net prediction involves, based on our ice-cream prediction, looks something like this (which is simplified and shown just to acknowledge their complexity):

$$(S = T) = \frac{P(S = T, C = T)}{(S = T)}$$

This reads as: the probability of a chocolate ice cream being bought if it is sunny equals the probability of it being sunny, and a chocolate ice cream being bought divided by the probability of it being sunny! Fortunately, while it is important for AI engineers (but not so important for us) to understand exactly how this equation works, so they might decide the most appropriate approach in the particular circumstances—

this is the type of computation that is provided by the *AI as a service* platforms mentioned earlier.

In fact, typical AI Bayesian networks might comprise tens (or hundreds) of variables (nodes) with intricate interdependencies (edges), making the equations and their solutions increasingly complex. However, the Bayesian computational approach makes it possible to infer precise probabilities in uncertain environments in order to inform predictions that have practical uses (to continue with the example, to help the ice-cream seller decide how much of each ice-cream flavor to make). In fact, the Bayesian network approach is common in many expert systems, and has been used for applications as wide ranging as house price modeling, petrochemical exploration, tumor classification, victim identification ... the list is endless.

Statistical Approaches to Natural Language Processing

The ultimate goal of natural language processing (NLP) is to understand and generate written and spoken language as well as humans do (which chatbots like Siri, Cortana, and Echo demonstrate appears now to be increasingly possible). As we have noted, early linguistic-based NLP attempts were unsuccessful because of the huge variability in natural languages, which (if only because of the scale of the problem) proved impossible to encode effectively in conditional rules. Starting in the 1980s, NLP researchers began to adopt an alternative approach, using statistical models. As with Bayesian nets, the NLP statistical models quickly become complex. Here, we will only introduce some examples of the multiple approaches taken in NLP.

Statistical NLP begins with inferring properties of linguistic components from large corpuses of text (drawn from, for example, the *Encyclopaedia Britannica*, the *New York Times*, the *Congressional Record*). Each of the five basic types of linguistic components (phonology, morphology, syntax, semantics, and pragmatics) needs to be addressed. One NLP statistical technique is known as density estimation. The likelihood of a sentence being recognized correctly is evaluated based on its occurrence in the text corpus (and the context in which it appears). For example, "give peas a chance" is less likely to occur in the corpus than the similar sounding "give peace a chance," so (assuming that the context is international politics) "peace" is more likely to be the correct interpretation (on the other hand, if the context is young children's dinner time ...).

Inevitably, many sentences (especially longer sentences) do not actually appear in the corpuses of text. In these cases, the outcome can be refined using a second statistical model, such as one that assigns a probability to a sentence by computing the probability of each word in that sentence. The process goes like this: count the number of times "give peace a chance" appears in the corpus, count the number of times "give peace a" appears in the corpus, divide these two numbers to compute the probability of "chance," repeat for all the words in the sentence, and finally multiply the probability of each word to get the probability of the complete sentence! Other NLP statistical approaches involve segmenting words into prefixes, suffixes, and roots (un + friend + ly), identifying parts of speech (noun, verb, and adjective), creating a profile for each word based on how often it appears next to another word (for example, "happy child" is more likely than "triangular child"), and identifying semantically similar nouns (for example, "boy" is more similar to "woman" than it is to "car").

Using these statistical techniques, NLP is designed for a range of applications, such as text summarization, information retrieval, question answering, and machine translation, and has the ultimate aim of dynamic human-to-computer conversation! We have already mentioned digital companion chatbots such as Siri, Google Home, Cortana and Echo; while one of the leading examples of machine translation is Google Translate, which has the capability to instantly translate speech and typed text (and photographs of typed text!) between more than a hundred languages. What is also particularly interesting about Google's approach is that the translations constantly improve over time: the more that it is used, the better that it gets.[504] In other words, statistical NLP is also an example of machine learning, to which we turn next.

Machine Learning

> *Programming computers to learn from experience should eventually eliminate the need for much ... detailed programming effort.*[505]
>
> —A. L. Samuel

As we saw earlier, when we introduced rule-based and expert systems, much AI (like much standard computer programming) involves writing in advance the steps that the computer will take to complete a task, the rules that will be followed exactly. Machine learning, on the other hand, is about getting computers to act without being given every step in advance. Instead of the algorithms being *programmed* exactly what to do, broadly speaking they have the ability to *learn* what to do. This is not to suggest that machine learning does not require large amounts of programming, because it does. But rather that, instead of direct commands leading to direct outputs, machine learning involves large amounts of input data to predict novel outcomes.

Machine-learning algorithms analyze the data to identify patterns and build a model, which is then used to predict future values. By identifying patterns in photographs of named people, it predicts who is shown in other photographs; by identifying patterns in medical symptoms, it predicts a specific diagnosis; and by identifying patterns in a student's interactions in an ITS, it predicts learning pathways that are most likely to lead to success. In other words, machine learning may be considered a three-step process—(i) analyze data, (ii) build a model, (iii) undertake an action—that is continuously iterated. The outcomes of the action

[504] While most translation approaches require corpora of already translated matching texts, Facebook AI researchers have been exploring a method that only requires un-matched texts (i.e., different texts) in the two languages. https://www.forbes.com/sites/samshead/2018/08/31/facebook-develops-new-ai-technique-for-language-translation/ - 7b435f802f71

[505] Samuel, A.L. (1959). "Some Studies in Machine Learning Using the Game of Checkers." *IBM Journal of Research and Development* 3 (3): 210–229.

generate new data, which in turn amends the model, which in turn causes a new action. It is in this sense that the machine is learning.

Many of the applications that we have looked at (including natural language processing, self-driving cars, and digital companions, as well as the Google DeepMind AlphaGo program that beat the world's number one player of Go)[506] have all been made possible thanks to machine learning. In fact, machine learning is so widespread today that, for some commentators when they speak of AI they mean machine learning and vice versa—whereas machine learning is more properly a sub-field of AI. What is true, however, is that the renaissance and exponential growth of AI over the last decade has come about because of significant advances in machine learning (based on faster computer processors, the availability of large amounts of big data, and new computational approaches).[507] With that in mind, we will now move on to consider in more detail the specific machine learning approaches that we introduced in the main text, beginning with the three overarching categories: supervised, unsupervised, and reinforcement learning.

Supervised Learning

> *In supervised learning the agent observes some example input–output pairs and learns a function that maps from input to output.*[508]
>
> —Russell and Norvig

Most practical machine learning involves supervised learning. The AI is first provided large amounts of data for which the output is already known—in other words, data that has already been labeled. For example, the AI might be given many thousands of photographs of streets in which the numerous visible objects (bicycles, road signs, pedestrians) have already been identified and labeled by humans, or many thousands of snippets of speech that have been transcribed by humans, or many

[506] https://www.theguardian.com/technology/2016/mar/15/googles-alphago-seals-4-1-victory-over-grandmaster-lee-sedol

[507] Interestingly, the origins of machine learning can be traced back to at least 1959, with the publication of "Some Studies in Machine Learning Using the Game of Checkers" cited earlier.

[508] Russell and Norvig, *Artificial Intelligence*, 708.

thousands of examples of symptoms with their diagnoses already determined by human doctors. The supervised-learning algorithm aims to identify the function that links the data to the labels, from which it builds a model that can be applied to new similar data. This is, broadly speaking, the approach used by Facebook to identify people in photographs we mentioned earlier, which used millions of photographs submitted and labeled by Facebook users to identify and label automatically the same people in new photographs. Returning to our other examples, a model built from the patterns detected in the labeled photographs of the streets can be used by autonomous vehicles to identify obstacles that they have to negotiate; a model built from the patterns detected in the labeled audio snippets can be used to automatically identify words in other recordings; while a model built from the patterns detected in the symptoms and diseases can be used to automatically diagnose patients who present similar symptoms.

There are, in fact, two types of supervised learning, *classification* (when the output is a category, such as obstacle/not obstacle) and *regression* (when the output is a continuous variable, such as time or weight). There are also many supervised learning algorithms, with possibly the best known being k-nearest neighbors, linear regression, random forest, and support vector machines (the algorithms are named here so that, if you come across them again, they will be recognized for what they are).

To give just one simplified example, we will look briefly at k-nearest neighbors. Imagine that you have some data that has been labeled with two categories (obstacle, not-obstacle). If this data is plotted in a scatterplot, each category of data points will be clustered together (in the scatterplot there will be one cluster of data points for obstacle and one cluster of data points for not-obstacle). If a new data point (representing a new object) is then plotted on the scatterplot, the k-nearest neighbor algorithm will decide to which cluster it belongs (in other words it will predict whether the new object is an obstacle or a not-obstacle), depending on the closest existing data points (the nearest neighbors). If the AI engineer decides to use a *k* of 5 (and there are many factors to take into account), the algorithm will check the 5 nearest neighbors to make its decision.

Unsupervised Learning[509]

> *In unsupervised learning the agent learns patterns in the input even though no explicit feedback is supplied.*[510]
>
> —Russell and Norvig

In unsupervised learning, the AI is provided with even larger amounts of data, but this time data that has not been categorized or classified, that is to say data that is not labeled. By analyzing this unlabeled data, unsupervised learning algorithms aim to uncover hidden patterns in the underlying structure of the data, clusters of data that can be used to classify new data (this is broadly the approach, mentioned earlier, used by Google to detect faces in photographs). Example applications of unsupervised learning include dividing online shoppers into groups, so that they might be served tightly targeted advertisements; identifying different letters and numbers from examples of handwriting; and distinguishing between legitimate and fraudulent financial transactions.

There are, again, two types of unsupervised learning, *clustering* (for example, grouping handwritten letters by their characteristic shapes) and *association* (for example, identifying that people who watch one type of comedy also tend to watch a particular type of action movie). And, again, there are many unsupervised learning algorithms, the most common including k-means clustering, hierarchical clustering, principal component analysis, and singular value decomposition.

To give just one simplified example, k-means clustering automatically clusters the data into *k clusters* (if *k* is 3, the algorithm will cluster the data into 3 clusters; *p*, *d* and *b* handwritten letters). The algorithm involves several steps: (i) a potential center point for each cluster (known as a *centroid*) is selected randomly; (ii) the algorithm assigns each data point to

[509] A comprehensive list of the algorithms available on one of the leading AI as a service platforms, Microsoft Azure, is available at http://download.microsoft.com/download/A/6/1/A613E11E-8F9C-424A-B99D-65344785C288/microsoft-machine-learning-algorithm-cheat-sheet-v6.pdf

[510] Russell and Norvig, *Artificial Intelligence*, 708.

a centroid by calculating which is closest (which initially will result in some very uneven clusters); (iii) it calculates the mean of the distances between each data point and its centroid; (iv) it repositions the centroid to the position indicated by that mean; and (v) it reassigns the data points to centroids as before (which will result in some data points staying in the same cluster and others being reassigned to one of the other clusters). Steps (ii) to (v) are then repeated until no data points change clusters (which results in the most even clusters possible).

Reinforcement Learning

> *In reinforcement learning the agent learns from a series of reinforcements—rewards or punishments.*
>
> —Russel and Norvig[511]

In some senses, reinforcement learning is the most powerful of the machine learning categories. In both supervised and unsupervised learning, the model derived from the data although potentially powerful is fixed, and if the data changes the analysis has to be undertaken again (in other words, the algorithm is run once more). However, reinforcement learning involves continuously improving the model based on feedback—in other words, this is machine learning in the sense that the learning is ongoing. The AI is provided with some initial data from which it derives its model, which is evaluated, assessed as correct or incorrect, and rewarded or punished accordingly (to use a computer game metaphor, its score is increased or reduced). The AI uses this positive or negative reinforcement to update its model and then it tries again, thus developing iteratively (learning and evolving) over time. For example, if an autonomous car avoids a collision, the model that enabled it to do so is rewarded (reinforced), enhancing its ability to avoid collisions in the future; if a medical diagnosis leads to a patient's health improving, the model is again reinforced, enabling the system to diagnose accurately future patients; and if Google AlphaGo makes a mistake that leads to it losing a game, its model is punished, improving its chances of not making the same mistake again. Finally, once again, there are many examples of reinforcement-learning algorithms, including Q-Learning,

[511] Russell and Norvig, *Artificial Intelligence*, 708.

State-Action-Reward-State-Action, and Deep Q Network—all of which, however, are too complex to describe simply.

Category	Characteristics	Aim	Example Algorithms
Supervised Learning	Learns from labeled data.	Automatically label new data.	k-nearest neighbors linear regression random forest support vector machines
Unsupervised Learning	Learns from unlabeled data.	Automatically identify patterns (clusters) in the data.	k-means clustering hierarchical clustering principal component analysis singular value decomposition
Reinforcement Learning	Continually learns by rewards and punishments.	Continually improve the outputs of the model.	Q-Learning State-Action-Reward-State-Action Deep Q Network

The three overarching machine learning categories: supervised, unsupervised, and reinforcement learning.

Artificial Neural Networks

An artificial neural network is an AI algorithm based on the structure and functions of biological neural networks (such as animal brains), that might be applied in advanced supervised, unsupervised, or reinforcement learning. Our brains are made up of billions of individual neurons, each of which is connected (at synapses between axons and dendrites) to as many as a thousand other neurons, giving trillions of connections. Memory is thought to emerge from complex combinations of these connections across the brain, while learning is thought to involve the strengthening of those connections (a process known as Hebbian learning, often summarized as *cells that fire together, wire together*).[512]

Although artificial neural networks have been trained to do some incredible things (such as driving a car without human intervention, or identifying faces in moving crowds of people, or beating the world's best Go players), they remain primitive in comparison to higher-order animal brains. Unlike, for example, the human brain's billions of neurons, they

[512] Löwel, S. and Singer, W. (1992). "Selection of intrinsic horizontal connections in the visual cortex by correlated neuronal activity." *Science* 255 (5041): 209–12.

usually involve only a few thousand neurons (in some exceptional cases, a few million); and, again unlike human brains, the neurons in artificial neural networks are arranged in logical layers, with each neuron in one layer being connected only to each neuron in the layers immediately before and after, as shown in the following figure. For these reasons, it is probably better to think of artificial neural networks as being inspired by biological neural networks, rather than being direct implementations (although, who knows what might be developed over the next few years?).

As illustrated in the following figure, artificial neural networks each comprise three types of layers: an input layer (that takes stimuli from the environment, in the form of millions of data points, perhaps pixels from images), at least one, but often many more, hidden, intermediary layers (that together undertake the computation), and an output layer (that delivers the result). As mentioned, all the artificial neurons in one layer are connected to each artificial neuron in the layers immediately before and after. In fact, each of these connections has a weighting. It is the sum of the weights received by one artificial neuron, whether that weight crosses some predefined threshold, that determines the weight of that artificial neuron's outgoing connections (whether it is excited or inhibited, again in a process inspired by synapses in animal brains). During the machine learning process, it is these weightings that are adjusted in a process of reinforcement learning, and that allow the artificial neural network to subsequently compute outputs for new stimuli. Note that the figure on page 72 is vastly simplified for comprehension's sake, as modern implementations have up to 50 or more layers and many different topologies.

The hidden layers are key to the power of artificial neural networks, but they also bring an important problem. It isn't possible (or at the very least it isn't easy) to interrogate an artificial neural network to find out how it came up with its solution (for example, how did it identify a particular person in a photograph?). In other words, artificial neural networks can lead to decision making for which the rationalization is hidden and unknowable, or un-inspectable, and possibly unjust, [513] a critical issue that is the subject of much research.[514]

To conclude this whirlwind tour of AI techniques and terminology, we will finish with three often-heard procedures: backpropagation, deep learning, and evolutionary learning.

Backpropagation

Backpropagation, short for backward propagation of errors, is an algorithm for the supervised learning of artificial neural networks. In our description of artificial networks, we described a process where the outputs of one layer of neurons influence the neurons in the next layer, a process that moves only in a forward direction. However, some artificial neural networks also involve information moving in a backward direction. The actual outcome of the artificial neural network is compared with the desired output, which in turn influences the neurons in the hidden layers and their weightings.

Deep Learning

An extension of machine learning is known as *deep learning*, which involves artificial neural network algorithms comprising many hidden layers and a process of iterative clustering. For example, once a deep-learning algorithm determines that a picture contains a particular shape, it cycles again to find other shapes, and then cycles again to identify the connections between those shapes, iterating repeatedly until it has recognized what it is looking at (for example, a face). Deep learning is the headline approach used by AlphaGo.

Evolutionary Machine Learning

An intriguing and cutting-edge field of research is evolutionary machine learning, an alternative approach to deep learning that uses a process

[513] O'Neil, C. (2017). *Weapons of Math Destruction*.

[514] Morcos, A.S., et al. "On the importance of single directions for generalization." ArXiv.org. http://arxiv.org/abs/1803.06959

inspired by Darwinian natural selection.[515] Evolutionary algorithms are the AI version of genetic algorithms,[516] which were introduced in 1960 by John Holland. While deep learning is focused on modeling what we already know, evolutionary machine learning is focused on creating solutions that do not yet exist. Instead of an AI engineer writing the final AI code, the evolutionary learning algorithm itself generates many pieces of random code, each of which it then evaluates for its fitness (Does the code do anything useful?). While code that is unsuccessful (is a poor fit) is abandoned, the code that is most successful (best fit) is then randomly mutated to produce many new pieces of code, all of which are again evaluated and subjected to survival of the fittest selection. This process is iterated many times, with the outcome being an AI-written new AI program. Evolutionary machine learning is currently the focus of much early research. Only time will tell what it will achieve.

[515] Charles Darwin. (1869). *On the Origin of Species by Means of Natural Selection: Or the Preservation of Favoured Races in the Struggle for Life*. D. Appleton.
[516] https://en.wikipedia.org/wiki/Genetic_algorithm

About CCR

Redesigning Education Standards

The Center for Curriculum Redesign (CCR) is an international convening body and research center seeking to expand humanity's potential and improve collective prosperity by redesigning K–12 education standards for the twenty-first century. In order to create a comprehensive set of frameworks, CCR brings together constituencies with diverse points of view—international organizations, jurisdictions, academic institutions, corporations, and nonprofit organizations including foundations—to consider and respond to the question: "*What* should students learn for the twenty-first century?"

The Center's Guiding Principles

A sustainable humanity—one in which collective potential is expanded, and collective prosperity improved—is orchestrated out of multiple social, economic, and environmental factors. Key among them: a relevant education, based on meaningful curriculum, is critical to creating sustainability, balance, and wellbeing.

While significant attention is being paid to teaching methods and pedagogy, the CCR argues that the *what* of K–12 education is at least as important as the *how*, and brings a singular focus to the what.

That twenty-first century what must take into account the accelerated pace of change we are experiencing, and shifts in societal and personal needs. Curriculum must be useful for the lives children will live and adapted accordingly.

Our ability to contribute a meaningful WHAT requires openness to different perspectives. Therefore, CCR avoids dogma and emphasizes innovation and synthesis—multiple inputs applied and organized for optimum clarity and impact.

We can—and will—shape the future we want.

Focus on the What

Exponential changes in technology make specific predictions about the future all the more unreliable, but one thing is certain: we must prepare children to deal with greater complexity than ever before. The last major curriculum reform occurred in the late 1800s, also in a time of rapidly changing needs. Well into the twenty-first century, we can ill afford to depend on a nineteenth century curriculum. Indeed, we cannot expect our children to thrive unless we deeply examine, redesign and deliver a curriculum consistent with twenty-first century needs—one that is balanced and flexible. To thrive will mean to be adaptable, versatile and wise.

In designing a curriculum framework around adaptability, versatility and wisdom we accomplish two main goals:

- Enhance the chances of an individual's personal and professional success and fulfillment.
- Provide a common base of understanding and ability to participate in society, for a sustainable humanity.

The Center's Work

The Center for Curriculum Redesign is not a program or intervention. The staff and CCR's partners approach their work holistically, actively engaging with policymakers, standard setters, curriculum and assessment developers, school administrators, heads of schools, department heads, key teachers, EdTech experts and other thought leaders and influencers to develop a thorough understanding of the needs and challenges of all education stakeholders. This is essential to creating the vision of meaningful, relevant twenty-first century education, and to enabling practical implementation.

The organization's research, findings and recommendations are actively disseminated through a wide variety of formats: CCR-sponsored conferences and seminars, active web presence and social media, consulting engagements and keynoting.

The following video serves to summarize our views, and can be shared freely: http://bit.ly/CCRintrovideo[517]

CENTER FOR CURRICULUM REDESIGN

[517] For the video on Vimeo, go to http://bit.ly/CCRintrovideovimeo

About the Authors

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