Practicing Connections: A Framework to Guide Instructional Design for Developing Understanding in Complex Domains

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Title: Practicing Connections: A Framework to Guide Instructional Design for Developing Understanding in Complex Domains

Authors: Laura Fries, Ji Y. Son, Karen B. Givvin, and James W. Stigler

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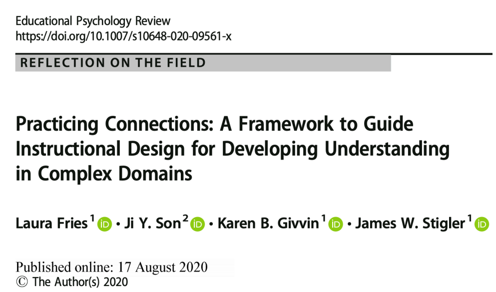
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REFLECTION ON THE FIELD

Practicing Connections: A Framework to Guide Instructional Design for Developing Understanding in Complex Domains

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Abstract

Research suggests that expert understanding is characterized by coherent mental representations featuring a high level of connectedness. This paper advances the idea that educators can facilitate this level of understanding in students through the practicing connections framework: a practical framework to guide instructional design for developing deep understanding and transferable knowledge in complex academic domains. We start by reviewing what we know from learning sciences about the nature and development of transferable knowledge, arguing that connectedness is key to the coherent mental schemas that underlie deep understanding and transferable skills. We then propose features of instruction that might uniquely facilitate deep understanding and [...] that the connections between a domain's core concepts, key representations, and contexts and pra[...] the world must be made explicit and practiced, over time, in order for students to develop coherent

understanding. We illustrate the practicing connections approach to instructional design in the context of a new online interactive introductory statistics textbook developed by the authors.

Citation

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CIRCL Primer: Persistence in Education

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Questions, or want to add to this topic or to a new topic? Contact CIRCL.

Overview

Perseverance has become part of the everyday language of education. The misconception that intellectual power alone can enable students to succeed in school and life is giving way to a deeper understanding that attaining long-term and higher-order goals can depend so much on how people deal with inevitable obstacles, setbacks, and challenges. This is consistent with extensive correlational research that shows, for example, that conscientiousness ("dependability and will to achieve") is as closely tied with academic success as intellectual ability (Poropat, 2009); for adults, it is also associated with income, wealth, and life satisfaction (Duckworth et al., 2012).

But what are grit, tenacity, and perseverance, and how can educators create environments and experiences that promote them?[1] While many people think of grit as a personality characteristic that resides within the student with little room to change, the fact is many different factors can contribute to grit—both externally in the environment and internally for the student. There are a variety of programs, approaches, and technologies that leverage different kinds of resources to get students on track with strong goals and support for their perseverance (see Key Lessons). For example, students are more likely to persevere when there is a fair and respectful climate, high expectations, and an emphasis on effort over ability. Technology can also be used to support the perseverance necessary to attain challenging academic goals. One example from the CIRCL community is the work of Arroyo, Stephens, Woolf, Maloy, Burleson, and Muldner, who are exploring new ways that technologies can be responsive to students' struggles as they learn. There are also important mindsets and skills that students can learn that can enhance their ability to persevere, such as knowing how to deal with specific obstacles when they arise. At the same time, there are some widespread misunderstandings and confusions that can get in the way and even be damaging to students learning to navigate a complex and challenging world (see Issues). For example, overemphasizing grit as a personality characteristic can undermine students' desire to persevere.

A Working Definition

Scholars have put forth a variety of definitions of grit, tenacity, and perseverance, as well as related terms, such as persistence and resilience. From these, for the purposes of our report, we synthesized a definition of "grit":

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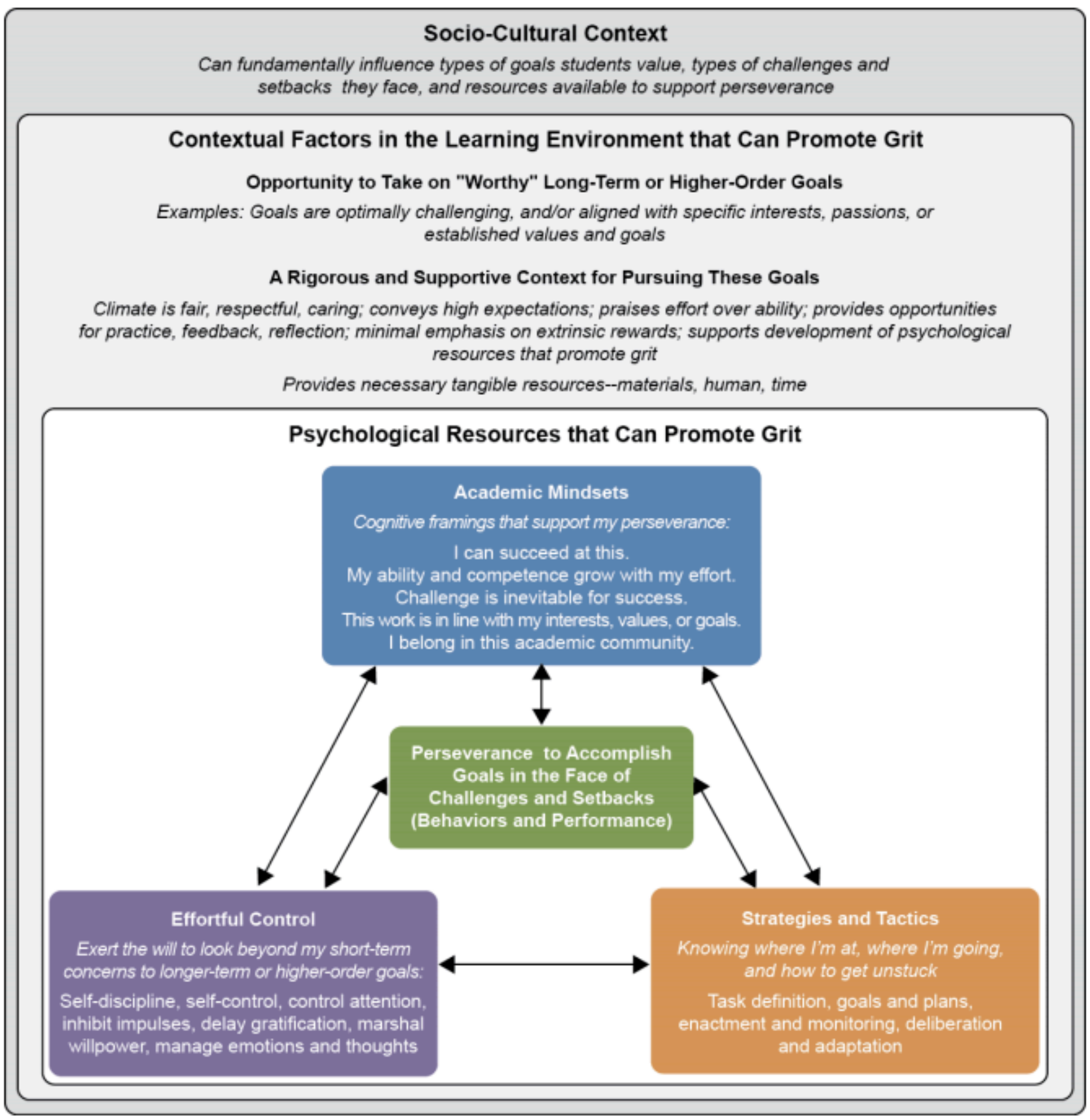
[1] This Primer summarizes findings from a report on a broad synthesis of research and practice based on interviews of 27 high-profile thought leaders and reviews of the pertinent research in education and psychology (see Shechtman et al., 2013). To prepare the report, the team also reviewed approximately 50 programs, practices, and technologies intended to promote perseverance in a variety of ways. This was not an exhaustive review, but it revealed key themes in the ways that educators are approaching these issues and suggested ways that digital technologies might be used to expand learning environments to support perseverance.

perseverance to accomplish long-term or higher-order goals in the face of challenges and setbacks, engaging students' psychological resources, such as their academic mindsets, effortful control, and strategies and tactics.

A Hypothesized Model

To support a more coherent understanding, we developed a hypothesized model of factors that can contribute to grit. The factors include qualities of the learning environment, the mindsets and skills that students can learn and draw on, and the broader sociocultural context. The model is intended to provide foundational knowledge to guide practice, research, and policy. We call this a hypothesized model because the research literature does not yet lend itself to a rigorously tested comprehensive theory. The following figure from page 17 of Shechtman, DeBarger, Dornsife, Rosier, & Yarnall (2013) presents the full model.



Key Lessons

The following are some of the key lessons from research and practice.

Learning environments can be designed to promote grit. We identified two core factors (and there may be others). These can be provided by the structure of activities and/or the kinds of practices that educators bring to supporting their students.

- **Opportunities to take on worthwhile goals**. Research provides extensive guidance about what constitutes worthwhile goals; for example, they should be aligned with what students value and be optimally challenging (not too hard, not too easy). Sometimes students may need help understanding why certain goals are worthwhile for them.
- **A rigorous and supportive environment to accomplish their goals**. Research shows, for example, that students are more likely to persevere when there is a fair and respectful climate, high expectations, and an emphasis on effort over ability. Tangible resources are also important—students need appropriate human support, time, and materials to get through challenging tasks.

Students can develop mindsets and skills to help them persevere. Research points to three core types of mindsets and skills, all of which have been shown to be malleable and teachable under certain conditions (see Dweck, Walton, & Cohen, 2011; Farrington et al., 2012).

- **Academic mindsets**. These are how students understand themselves as learners, their learning environment, and their relationships to the learning environment. Mindsets can have a powerful impact on how students behave and perform in the face of challenge. One core mindset that supports perseverance is called the "growth mindset"—knowing that "My ability and competence grow with my effort, strategies, and help from others." Many studies have shown that students can learn to have a growth mindset, and that this supports perseverance. Other key malleable mindsets that support perseverance are self-efficacy and a sense of belonging.
- **Strategies and tactics**. Students will be more likely to persevere when they are equipped with specific strategies and tactics to deal with the challenges and setbacks they face. They need skills for taking responsibility and being productive under conditions of uncertainty. Students can learn skills such as planning the tasks necessary to accomplish goals, time management, monitoring progress and recognizing problems, knowing how to change their course of action, and dealing with specific obstacles.
- **Effortful control**. Successful students marshal willpower and regulate their attention to stay on track for long-term goals. Research shows that students stronger in these skills are happier and better able to handle stress. Students can learn many different kinds of strategies to regulate their own attention and emotion in ways that help them stay focused, engaged, working well with others, and on track for success.

Sociocultural context can matter. All students encounter difficult challenges throughout their schooling, and contextual factors can support or hinder students' perseverance in the face of challenge. Factors such as socioeconomic conditions, ethnicity, and gender can all influence the types of goals students want to accomplish, the types of challenges they face, and the resources they have access to.

There are many programs, approaches, and technologies that have been promoting grit in various ways. While there is still a need for evaluation evidence, the following conceptual clusters illustrate some of the many ways leaders are designing learning environments and supporting the development of mindsets and strategies.

- **Preschool and early elementary programs that address executive functions**. Executive functions are key to developing the effortful control necessary to stay on track to accomplish goals. Approaches include training with games, aerobic exercise and sports, martial arts, and mindfulness practices. Many programs have substantial empirical evidence of their success.
- **Interventions that address mindsets and strategies**. Several studies show that brief targeted interventions (e.g., 2 to 10 hours) can help students develop the mindsets and strategies needed to persevere through challenging academic work. For example, mindset interventions may explicitly teach students to have a “growth mindset,” help students understand that struggle is inevitable to success, or provide students with opportunities to affirm their personal values. Strategy interventions may help students clarify their goals, anticipate in advance how to deal with likely specific obstacles, or develop general study skills or metacognitive skills.
- **Alternative school models and school-level reform approaches**. Many schools, charter network organizations, and other kinds of programs are developing new educational models with a deep focus on perseverance. Character education models, project-based learning, design thinking models, and school-level reform programs are key approaches. Such approaches focus on providing good opportunities for students to take on worthwhile goals, resources to build rigorous and supportive environments, and/or explicit ways of teaching critical mindsets and strategies. Anecdotal evidence of these models’ success is extensive, but further research is needed to determine impacts.
- **Informal learning programs**. Many informal learning programs provide the kinds of opportunities that help students develop important long-term goals, provide a support system for getting through school and accomplishing other goals, and opportunities to develop key mindsets and strategies for perseverance. Two important types of programs are those that provide structured social support networks for students who will be first in their families to go to college, and those that provide activities to spark and support interest and persistence in STEM professions. In most cases, there is considerable anecdotal evidence of program success, but further research is needed to determine impacts.
- **Digital technologies and environments**. While technology cannot provide quick fixes for supporting perseverance, there are many ways that it can provide the resources and rigor to help students persevere. For example, the online world provides a wealth of informational resources, organizational tools, and interpersonal networking that can enable learners to persist toward their goals. Also, digital learning environments can provide optimal challenge through adaptivity and scale up ways of promoting productive mindsets and strategies. Some research is beginning to show positive impacts of technologies on supporting both the noncognitive factors associated with perseverance and academic achievement.

Issues

The following major issues have been identified in research and practice. Most of these issues are general across all learning environments with or without technology, as work integrating design elements to promote grit into cyberlearning environments is still just beginning to emerge.

The need to integrate best practices to promote grit within disciplinary learning. This is an important Cyberlearning opportunity. There are a variety of challenges in learning math, science, ELA, and other disciplines. Some of these challenges, such as staying focused and organized through a long project, may require supports, mindsets, or strategies that are domain general. Other challenges, such as those associated with doing complex lab projects or writing papers, may require supports, mindsets, or strategies that are specific to the disciplinary domain. There are many important efforts to integrate practices to promote grit within discipline-specific curriculum and pedagogy.

Potentially damaging misconceptions and misapplications. There is little evidence that grit itself is harmful, but there are some misconceptions and misapplications that can potentially be problematic. For example, overemphasizing grit as a personality characteristic or pushing students to persevere to accomplish goals that are not appropriate for them can undermine their learning, engagement, and well-being. Also, being nice and encouraging to students is important and helpful, but more is needed to promote grit. Practitioners must be mindful of this, yet research offers little guidance. Research in this area will help educators gauge and fine-tune interventions, models, practices, and approaches.

Inconsistency in conceptual terminology as a barrier to collaboration and progress. To advance practice, policy, and research, there is a need to further clarify conceptual ideas and terminology within and across communities. Researchers must be clear about what exactly they mean by grit, tenacity, or perseverance in their own work. More generally, unified frameworks and collaborative activities that bring communities together can help bring clarity that is important to advance research and practice.

More work is needed to understand the transferability of grit across contexts. Are people who persevere in one context more likely to persevere in another? Research is needed to understand how individuals strive to accomplish goals in different contexts, and what mindsets and skills may or may not transfer.

Practitioners and policymakers need actionable research-based advice. While there are many programs and a strong research base, practitioners still need research-based advice about how to use approaches effectively across a variety of settings for a diversity of students. Policymakers need to make informed decisions about how to allocate resources in ways that best support student perseverance. Researchers can help bridge these gaps, for example, by translating technical research findings for general audiences, conducting field-based implementation research that partners with practitioners, and focusing efficacy research on variations across settings.

Moving forward. There are many sources of evidence that suggest that grit, tenacity, and perseverance can be malleable and teachable, and there is great potential to promote grit, tenacity, and perseverance in a deeper way for a wide variety of students. While there are no quick fixes in practice, research, or policy, there are many kinds of small changes that can contribute to incremental progress. There are also some deeper shifts needed in the culture of education that will take coordinated efforts across all communities of educational stakeholders.

Projects

Examples of NSF Cyberlearning projects that overlap with topics discussed in this primer.

- EXP: Tenacity: Self-Regulation of Attention and Its Relationship with Learning
- INT: Collaborative Research: Detecting, Predicting and Remediating Student Affect and Grit Using Computer Vision
- BCC-SBE/EHR: Developing Community & Capacity to Measure Noncognitive Factors in Digital Learning Environments
- DIP: Collaborative Research: Impact of Adaptive Interventions on Student Affect, Performance, and Learning

Resources

The following is a selection of programs and organizations associated with each cluster of approaches (see Key Lessons). This list is not meant to be exhaustive, but rather provide a starting place with a variety of approaches.

Preschool and Early Elementary Programs that Address Executive Functions:

- Tools of the Mind
- Promoting Alternative Thinking Strategies (PATHS)
- Chicago School Readiness Project (CSRP)

Interventions that Address Mindsets and Strategies:

- Project for Education Research that Scales (PERTS)
- Pathways to Improvement

Alternative School Models and School-Level Reform Approaches:

- Noel Academy for Strengths-Based Leadership and Education
- Compassionate Schools Initiative

Informal Learning Programs:

- College Track
- OneGoal
- Girls Inc.

Digital Technologies and Environments:

- CogMed
- WOOP
- Brainology
- This Is Grit

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Citation

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CIRCL Primer: Data Science Education

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Overview

Data Science is an interdisciplinary field that seeks to derive insights and knowledge from the analysis of typically very large data sets. While data science education is relatively new, there are currently many undergraduate and graduate degree programs available in data science. This primer is an overview of the early state of data science education in grades K-12.

New technology has made it easier than ever to capture, store, and arrange many forms of data about the world. Low-cost sensors capture and store scientific data from various environments. Optical character recognition (OCR) technology converts volumes of texts into data for analysis. Image recognition technology permits rapid search of photographic and graphic databases. Portable audio and video recording devices now collect many types of human interactions in different situations and settings.

Data science is the field that attempts to build knowledge from this newly available massive data store. While there is no consensus definition of data science, there is widespread agreement that data science goes beyond the application of traditional disciplinary or statistical methods. Drew Conway's Data Science Venn Diagram describes data science as the partial union of content expertise, math and statistics knowledge, and hacking (or computer science) skills. Some characteristics are:

- The investigator is "awash in data" (the dataset may at first be too overwhelming for there to be a clear path to analysis)
- The analysis requires "data moves" that go beyond application of known procedures (for instance, one may have to create a completely new visualization)
- The data are "unruly", meaning that a single observation may have many pieces of information
- The data are not typically easily stored in traditional data table format

While traditional statistical tools are central to data science, investigators may use more exploratory techniques such as machine learning or visualization to find patterns in data. Data science education introduces students to the tools, dispositions, and techniques:

- Running experiments and collecting data, typically in science class
- Conducting exploratory data analysis of one's own data or of others' data using different visualization tools
- Statistics, typically in mathematics class

At its core, data science requires students to engage in cross disciplinary thinking. While it is unrealistic to expect K-12 students to engage in all aspects of data science, especially in the elementary and middle grades, educators are beginning to understand how we can incorporate appropriate tools and techniques for each grade level, and create and manage engaging data science classroom activities.

Key Lessons

Integrating Data Science into the Curriculum and Informal Settings. Opportunities to engage with data in elementary and secondary grades most often take place in science courses because data analysis provides a hands-on way to see science concepts in action.
While there is concern that teachers may not have time to integrate the messier and more time-intensive aspects of data science into their already full curriculum, research has identified some promising strategies. These might be broadly characterized as activities that aggregate data across groups of students and focal activities that require students to confront specific data problems. As an example of an aggregated data activity, if a teacher has many students conduct many trials of an experiment (say with a ramp or a spring) — each time modifying more than one variable at a time — the class can then explore the resulting pooled dataset to identify relationships and patterns. As an example of a focal activity, a teacher can ask students to review existing data in two contrasting aspects of the environment, say rainfall and topographic altitude, and ask them to infer the underlying relations. In these ways, students can engage with data science while reinforcing their understanding of core scientific concepts.

Data exploration activities also can be integrated into informal learning settings, such as museums or at camps. For example, some citizen science projects ask participants to collect data that is stored in large public data sets, such as timing of migration, seasonal plant growth measurements, or the quality of air or water. However, the current challenge for informal education environments is to move beyond data collection activities and find ways that informal learners can search for patterns in large data sets.

Focusing on Particular Aspects of Data Science. Progress has been made in providing curricular tools to support data exploration. For examples, the Maine Data Literacy Project has created a framework to aid students in determining what type of analysis or visualization they should use. This framework has students consider the types of data they have and their analytic goals such as investigating variability, comparing groups, exploring correlations or relationships, investigating change over time, and investigating behaviors or characteristics of subgroups. Researchers have found that science teachers consider these goals appropriate and valuable, and that the framework can support students in thinking about data sets that might otherwise be overwhelming.

The Role of Technology. Advances in technology have brought about the data revolution, and technology has a key role in data science education activities. Though students can work with very small data sets or interpret data illustrations without technology, they cannot engage in the practice of data science without technology. Software designed for learning, with a low threshold for getting started, can get students excited about working with data across a wide variety of subjects.

Spreadsheets and simple databases comprise the most common forms of technology used to work with data sets, but while they may work well in a business setting, they do not necessarily do well at encouraging data exploration. For instance, Excel provides a set of standard graphs, but it does not provide students with the ability to fluidly explore relationships. Statistical analysis packages are typically designed for practitioners rather than learners, and may have a powerful, but complex, set of features that hamper rather than encourage exploration. However, there are technology tools designed explicitly for data science education that do a better job of encourage playing with data. For example, TinkerPlots allows students to manipulate data visualizations with an intuitive toolkit that emphasizes simple methods of dragging data points into meaningful plots. Newer efforts include Tuva and CODAP, which allow students to dynamically explore relationships and build visual representations. At present, Tuva tends toward single curated data sets, flat tables, and a single graph at a time. In contrast, CODAP allows for multiple linked representations, map data, and graphs with three or more variables. CODAP is unique in allowing learners to create and modify hierarchical structures, an important part of experiencing the doing of data science.

Issues

Serious thinking about how to integrate the new field of data science into K-12 education has barely begun. Much exploration and research are needed. Five issues of note are: framing data science education; identifying the barriers to integrating data science into educational contexts; establishing consensus around the goals of data science education; finding a path that both educates and protects students with regard to data ethics and privacy; and determining what research in data science education is needed.

Framing Data Science Education. Who will teach data science? Should data science become a subject in the school curriculum like calculus or American history, or should working with data be a part of every school subject? The path of least resistance is carve out a new discipline with its own courses likely not encountered until the high school level, and then by only some proportion of students. Most teachers would not have to worry about fitting data science concepts and skills into increasingly crowded content areas. A small number of well-trained subject matter specialists could teach the few, likely elective, courses. This path is doable immediately and, in fact, has been started in projects like Mobilize, a collaboration between Los Angeles Unified and UCLA.

The problem with carving out a separate discipline for data science at the school level is that it betrays the inherent interdisciplinary spirit of data science. Data are everywhere. Nearly all areas of work require familiarity with data. While relatively few of today's students will end up with the job title of data scientist, all of them will need to understand how to use data productively as workers and as citizens. This line of thinking leads to an arduous path at the end of which every teacher is integrating data science into whatever they teach and, mirroring the world outside school, students take for granted that data are part of all learning. Going down this path will require change at every level and in every subject, plus an unprecedented level of interdisciplinary coordination.

Identifying Barriers to Data Science Education. To achieve integration of data science into multiple subjects, the pervasive stovepiping of subject disciplines poses particular challenges.

Currently, from grades 6-12 (the grades at which, one can argue, students are most ready to engage in data science education), there is almost no collaboration across disciplines. This stovepiping permeates the standards developed for different disciplines, such as science and mathematics. It is challenging to change the standards or find ways for teachers to effectively collaborate across disciplines. Data science is not the only new field that challenges the stovepipe model; so does the field of computational thinking, which seeks to engage students in activities that employ principles of computer science in diverse courses and disciplines.

The lack of teacher knowledge and the limited time available for professional development pose additional challenges. The practice of data science goes beyond knowledge and requires the *experience* of actually working with and using data. Teachers can learn about a new field, which makes it possible for them to teach about it, but we want students (and their teachers) to experience data science by doing it. Data science requires a deep understanding of both disciplinary content and methods, and requires dispositions that run counter to common, efficiency-oriented teaching methods, such as a willingness to engage in ill-defined problems, follow paths that are ultimately not productive, and create new visual representations. It will be a significant effort to get math and science teachers comfortable with these new requirements. This concern is compounded for non-STEM teachers and elementary school teachers, who are typically less accustomed to the quantitative thinking that often accompanies working with data.

Establishing the Goals of Data Science Education. There is still not consensus on the goals of data science education. While producing more data scientists is important, building data fluency in all walks of life is a very important goal. Nearly all people will routinely be working with data and require some skills that fall into what is now called data science. Some specific goals include:

- Identify paradigmatic learning activities that exemplify what we mean by experiencing data science at different grade levels.
- Describe exemplary uses of technology in data science education.
- Formulate performance criteria for data science education.

In the broadest sense, the goal of data science education is to figure out how best to bring about effective learning with and about data. The field may move forward with that as the driver, and more specific goals will emerge.

Addressing Issues around Data Ethics and Privacy. Data science education should sensitize students to the potential impacts of data collection and analysis on groups, individuals, and entities. As people surf the web and interact with their devices, they leave evidence (a data "exhaust") that can be used to identify them and access their experiences and activities. The "quantified self" movement associated with wearable devices that gather data about health and activity presents obvious risks to privacy. Education researchers are only in the beginning to confront these issues and, as technology advances, they are likely to increase in importance.

Determining What Research is Needed in Data Science Education. A set of cutting-edge research agendas and processes needs to be defined for foundational data science education research to make impact. For example: What is the role of visualizations in data science education? How do students interpret visualizations of complex data? How can we help them create their own visualizations? How do learners conceive of data and learn to use data structures appropriate to particular contexts and questions? What are important “data habits of mind” and how do learners acquire them?

Projects

Examples of NSF Cyberlearning projects that overlap with topics discussed in this primer.

- Collaborative Research: Designing the Impact Studio -- Dynamic Visualizations in the Write4Change Networked Community
- DIP: Data Science Games - Student Immersion in Data Science Using Games for Learning in the Common Online Data Analysis Platform
- CAP: Data Science, Learning and Youth: Connecting Research and Creating Frameworks
- CAP: Innovating Data-driven Methodologies for Documenting and Studying Informal Learning
- DIP: Collaborative Research: STEM Literacy through Infographics

More posts: data-visualization

Resources

Data Science Education Technology Conference
Oceans of Data Institute
Coursera Catalog: Data Science Courses and Specializations

Readings

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CIRCL Primer: Broadening Youth Participation in Computer Science and Engineering

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Overview

Educators, companies, and governments around the world share the desire to support and engage underrepresented groups in science and engineering. Some programs have had success in the goal of increasing the interest and engagement of underrepresented groups in engineering and STEM. Many of these developed curriculum, intensive teacher training, student competitions, and other practices—such as providing mentors and same-gender/race role models, and using real motivating problems in the students' community—to engage underrepresented groups in engineering and design. In general, the most successful programs that have an impact on underrepresented groups are those that have role models that youth can identify with, and that develop appropriate situational, culturally relevant interactions with target youth (McGill, Decker, & Settle, 2015).

See also CIRCL Primer: Computational Thinking

Still, large disparities persist in innovation rates by socioeconomic class, race, and gender—and the gap is not explained by innate ability (e.g., early childhood test scores; Bell et al., 2017). Consider the College Board's Advanced Placement Program, which is one gateway to the STEM career pathway. While the number of high school students taking the AP Computer Science exam has been increasing annually, and the number of exam takers in 2016 rose 17%, female, Hispanic, and African American participation remains low; just 23% of exam takers were female, 11.5% were Latino, and 3.7% were African American. In 8 states, fewer than 10 girls took the exam, and in 2 states, no girls took the exam. Even when women, girls, and minorities enter a STEM career pathway, they leave at a higher rate—at multiple points—from middle school to community college to even tenured faculty in STEM (Burke & Mattis, 2007; Griffith, 2010). Margolis & Fischer (2003) interviewed women who were dropping out of computer science in college and found that professors favored men who had more experience in CS. What's going on here? From a social justice perspective (Bienkowski, 2018), even when anyone *can* take advantage of an opportunity (equality), not everyone comes to that opportunity *prepared* in the same way or *experiences* that opportunity the same way (equity).

Why worry about diversity in computing and engineering? Disparity in opportunity is not fair to individuals economically and educationally, and society needs everyone's perspectives and contributions to solve important problems. Inclusion is critical for innovation: diversity increases innovation (e.g., patents), partly because a variety of perspectives lead to new ideas, earlier identification of problems, and more effective science (Forbes Insights, 2011; Medin & Bang, 2014; Bienkowski, 2018). Bell and colleagues (2017) argue that if women, minorities, and children from low-income families were to invent at the same rate as white men from high-income families, the rate of innovation in America would quadruple; "There are many "lost Einsteins" – people who would have had highly impactful inventions had they been exposed to careers in innovation as children" (p. 1)—and had they been given continued opportunities, role models, mentors, and other support provided to those who are already highly rewarded.

Advancing educational, economic, and innovative opportunity requires special attention to issues that prevent equitable participation (Blikstein, 2018). Governments and funding agencies have responded with several initiatives—including NSF's CS4All and STEM+C programs. Expanding access to computer science has been announced as a priority by 40 states (Code.org, 2017), 27 states have enacted computer science curricula for their K-12 public schools, and 13 more are in the process of developing statewide CS standards (Blikstein, 2018). This primer reviews practices from selected work that that has helped broaden youth participation in computer science and engineering (see Key Lessons). These practices were drawn from the literature and from a review of selected successful programs (see Projects). We also discuss deeper issues of identity, interest, and self-efficacy that can hold youth back, and ways to impact youth interest and desire to pursue STEM and engineering careers.

Key Lessons

Mentors help youth develop interest, identity, and self-efficacy. As learners develop, they need others to help them. Teacher often play this role through formal instruction. Mentors use many of the same practices as good teachers, but mentoring relationships are often more informal and focused on offering advice from a perspective of experience. Mentors can help youth development their identity by promoting an interest, and over time, reshaping beliefs about an area of interest (e.g., seeing themselves as someone who could work in the area). A young person who has a mentor in computer science typically engages in more computer science education and also has a more diverse set of beliefs around who can be a computer scientist (Ko & Davis, 2017). Ko and Davis developed a 6-week course in which the teacher explicitly created mentoring relationships with each student that included a personal interest in their trajectory of learning (e.g., talking with them everyday, having end of the course mentorship conversation, and offering email support after the course ended). After the course, there was a significant increase in student interest in computing for students who had a mentor; the mentorship effect was more powerful than gender or socioeconomic status.

Youth need engineering role models who reflect their identities and interests. A role model is an image of someone admired, someone who an individual aspires to be like. Unlike a mentor or teacher, a role model may not play a direct role in the success of the individual. However, role models still provide inspiration and motivation. For example, girls are more likely to become inventors in a field if they simply grow up in an area with more female inventors (but not male inventors) in that field (Bell et al., 2017). In computer science specifically, having women as role models and mentors increases the likelihood that girls will pursue the field (Wang et al., 2015). Men can also serve as successful mentors and role models for girls if they do not conform to male computer science stereotypes (Cheryan et al., 2011). Having curriculum that avoids stereotypes, and teachers, facilitators, and peers who push back against stereotypes, helps youth feel included and appreciated (Ruiz, 2017).

Engaging existing relationships in youths' lives helps increase youth success. Youth express positive attitudes toward science when they experience success and receive support from important people in their lives at home, in school, and in their communities (Aschbacher, Li, & Roth, 2010). Family plays a critical role in encouraging youth and exposing them to opportunities, and it's especially helpful to engage parents in the effort to increase youth participation in computer science and related fields (Wang, Hong, Ravitz, Ivory, 2015). It is also helpful for educators to discuss with youth how STEM professionals think about people's needs while they work, and what the student could uniquely contribute if they were to pursue computer science or engineering. An exciting curriculum that youth connect with—like Hour of Code or attending a computer camp—can also be a "triggering event" that helps youth develop an initial interest in the subject (Ko & Davis, 2017).

Focus on real world interests to attract underrepresented youth. "Powerful learning experiences result when students have the opportunity to connect their interests from outside of school to learning opportunities in more academic contexts" (Reich & Mizuko, 2017). For girls and non-dominant youth, it's important to create entry points that support diverse interests (e.g., fashion, sports, dance, health). Margolis, Fisher, and Miller (1999) report that when asked why they are taking computer science, undergraduate males typically report interest in computers while about half of females describe their interest as it relates to areas of interest such as health, education, science, or art. Girls may be more interested in careers in health and medicine than engineering (Sadler et al., 2012). These interests provide an opportunity to highlight new pathways into engineering: many medical careers (such as biomedical engineers) work at the intersection of engineering, life sciences and medicine, so they need computer science background. McGee and Bentley (2017) report that African-American and Latinx students are more likely to want to go into science because of their interest in social justice and improvements to the social world that science could facilitate. Tapping into interests that different groups have is important for success.

Facilitate an extended, supported experience to enable success. As mentioned earlier, youth persist when they receive support and experience success (Aschbacher, Li, & Roth, 2010). In fact, if youth have a bad *first* experience with computing, it can turn them off completely (Ko, 2017): "Research shows over and over that most learners, people of all ages, start with low programming self-efficacy, and that without early, repeated successes in writing programs, this self-efficacy is quickly exhausted, causing youth to give up… [which] may lead to reduced interest in coding and lower programming self-efficacy. Female learners in particular are prone to internalizing these failures into their identity." It's best to ease youth into coding so they have a successful experience.

Issues

Lack of **opportunities** and **connections** explain part of the lower engagement of underrepresented groups in STEM and engineering. Even when opportunities are made available, deeper issues of **identity, interest,** and **self-efficacy** continue to hold youth back.

Identity is both an important part of, and a way to discuss, learning. Identity is more than an individual's beliefs about him or herself; it includes not only how you think of yourself but also your perception of how others see you and what is promoted by society as acceptable or desirable. From ambient messages in the culture, individuals perceive what others think of them and who is typically identified a certain way—for example, who is and can be an engineer. Identity surfaces as one way of understanding why we see robust underrepresentation of particular groups. People make important decisions about their future and how they engage in the pursuit of their careers based on identity. In many different ways, learners can feel marginalized or encouraged because of their identity. Developing learning environments that integrate learner interests, are sensitive to identity, and encourage all learners to be participants and take on new identities—especially in STEM fields—is challenging and needed work (Bell, Van Horne, Cheng, 2017). To develop STEM identities, young people need access to sustained, high quality experiences, and, particularly in the early adolescent years, they need to see others like themselves as role models.

Interest is a related component necessary to develop future STEM workers. Hidi and Renninger (2006) define interest as a person's heightened affect and predisposition towards a subject depending on their knowledge, feelings towards it, and value of it. Interest goes from an initial spark that requires extrinsic motivators to keep it going, to well-developed when it does not require extrinsic motivators. Of course, a learner will always benefit from external rewards or recognition around their interests, but a learner with well-developed interests in a topic will stay involved even without rewards or requirements. Ko and Davis (2017) discuss "triggering events" as important to helping develop an interest in computing, but that more is needed to develop it and sustain it. Hidi and Renninger (2006) describe interest development in a 4 phase model. At a high level, the 4 phases can be described as follows:

1. **Triggered Situational Interest**—sparked by events, personally relevant experiences, and novel or surprising events. Usually a precursor to further development.
2. **Maintained Situational Interest**-—sustained by meaningful tasks, and deeply engaging, personally relevant instructional projects can help this develop.
3. **Emerging Individual Interest**—marked by repeated engagement, positive affect, going beyond the requirements of the task.
4. **Well-Developed Individual Interest**—deeper knowledge, positive affect, generates new strategies for work, shows ability to self-regulate and understand their own knowledge.

Self-efficacy is another psychological lens to understanding why girls and non-dominant youth are not well-represented in the fields of STEM, including computer science and engineering. Self-efficacy is a self-assessment of how good one is at something. People who assess themselves as not good at a particular topic often avoid that topic. Girls and minority youth often have lower self-efficacy around computer science and engineering (Wilson et al., 2015). For girls and minority youth, improved self-efficacy has been linked to having role models "like oneself" and to pedagogy that includes hands-on, personally relevant, and cooperative work—pedagogical styles not typically seen in many STEM types of courses (Beyer, 2014). The surveys of youth will also include questions to assess their overall self-efficacy and their self-efficacy around computers and engineering.

Youth interest in STEM *may* be difficult to change. An evaluation of 13 programs in Massachusetts to increase youth interest in STEM found that only 5 of the programs produced evidence of increase in youth interest after the program (UMass Donahue Institute, 2011). The successful programs varied widely in their structure, and included an out-of-school high-school biotech internship, a middle school STEM summer camp, an elementary middle and elementary after school math program, an in-school elementary engineering program, and a middle school math program that reached thousands of students with a one-time experience. Almost all provided information on STEM careers, some included collaborative group work, nearly all focused on real-world applications, and all but one engaged youth over a series of several sessions. The program that found a measurable difference in student interest through a single classroom experience was the DIGITS program, in which a STEM professional visited a classroom to talk about their careers (focusing on positive aspects), and lead discussion and activities with the youth. The STEM professionals ("ambassadors") were trained by the program before the visit, and given a script and guidance for interacting with the youth. Still, it's possible that a ceiling effect could be in play in some of these programs to increase youth interest: If youth sign up for such optional STEM programs because they *already have* an interest in STEM, then the program itself may do little to grow their interest.

Projects

Examples of NSF Cyberlearning projects that overlap with topics discussed in this primer.

Computational Thinking

- EXP: Readily Available Learning Experiences: Turning the Entire Web into Progressive Examples to Bridge Conceptual Knowledge Gaps for Novice Web Developers
- EXP: Automatically Synthesizing Valid, Personalized, Formative Assessments of CS1 Concepts
- The cognitive and neural mechanisms of computer programming in young children: storytelling or solving puzzles?
- EAGER: Teaching Computational Thinking through Programming Wearable Devices as Finite State Machines
- EXP: Linking Eye Movements with Visual Attention to Enhance Cyberlearning

Computer and Information Science

- EXP: Readily Available Learning Experiences: Turning the Entire Web into Progressive Examples to Bridge Conceptual Knowledge Gaps for Novice Web Developers
- EXP: Automatically Synthesizing Valid, Personalized, Formative Assessments of CS1 Concepts
- The cognitive and neural mechanisms of computer programming in young children: storytelling or solving puzzles?
- EXP: Data-Driven Support for Novice Programmers
- CAREER: Designing a New Nexus: Examining the Social Construction of Electronics and Computing Toolkits to Broaden Participation and Deepen Learning

Engineering

- EXP: Paper Mechatronics: Advancing Engineering Education Through Computationally Enhanced Children's Papercrafts
- EAGER: Making with Understanding
- A Pedagogical Framework for Undergraduate Project-Based Engineering Design Courses
- DIP: Improving Collaborative Learning in Engineering Classes Through Integrated Tools
- EAGER: Collaborative Research: Cyber-Eye: Empowering Learning through Remote Visualizations using Unmanned Aerial Systems

In addition, the following projects were reviewed for this Primer.

FIRST Robotics. The mission of FIRST is to “inspire young people to be science and technology leaders and innovators, by engaging them in exciting **mentor-based** programs that build science, engineering, and technology skills, that inspire innovation, and that foster well-rounded life capabilities including self-efficacy, communication, and leadership.” FIRST is also committed to **diversity and inclusion**, increasing **underrepresented students’ interest in STEM** and “developing strategies that will ensure greater access to its programs and reduce inequalities.” FIRST offers 4 programs: LEGO League (middle school), LEGO League Jr. (elementary), Tech Challenge (middle school and high school), and Robotics Competition (high school), each with an accompanying **curriculum** that is **aligned to national science standards**. In the high school Robotics Competition (and similarly, in the Tech Challenge), students form **teams**, build robots, and program them with the help of coaches and mentors over the course of **2-3 months**. Each January, a new challenging game is introduced; for example, building a robot that can free-throw a basketball into the basket. The student teams and their mentors work together to solve the challenge, and then teams **showcase their work** in regional and district **competitions**. District champions go on to compete in a national competition in April. In 2017, the program reached 85,000 high school students across 3,400 teams in nearly every state in the U.S. Since the program began in 1989, it has engaged **more than half a million youth** across 59,000 teams creating almost 45,000 robots with the help of **150,000 mentors**, and has had substantial impact. Based on its research, FIRST reports that youth who participate in FIRST are more than 2 times as likely to show **gains in interest in STEM**, and those who participate for more than 1 year show significantly greater gains in STEM knowledge than those who leave after a single year. After participating, 87% plan to take a more challenging math or science course. Alumna are 2.6 times more likely to enroll in an engineering course in their first year of college, and more than 75% are in a STEM field as a student or professional. The impact on girls, in particular, is dramatic.

Technovation. Technovation “invites teams of girls from all over the world to learn and apply the skills needed to solve real-world problems through technology.” The goal of the program is to **inspire girls to change the world with technology** and pursue computer science as a **career**. During the intensive 12-week curriculum, small teams of girls work together face-to-face, with a **facilitator**, ask questions and interact with others in an online forum, and are matched up with **female mentors** to act as guides and role models. A key part of the program is engaging professional women to serve as **mentors and role models** to guide, encourage, and help girls overcome challenges, develop self efficacy, and learn to become entrepreneurs. Working with women mentors, the student teams identify a **problem in their local community**, design and develop a mobile app to address the problem, and then create a business plan and video to pitch their “startup” idea to investors. Since the program began in 2010, it has engaged more than 15,000 girls across 100+ countries and has had substantial impact. Technovation reports that after participating in the program, 78% of students reported more interest in computer science, 70% reported more interest in entrepreneurship, and 67% reported more interest in business leadership. Further, 58% enrolled in subsequent computer science courses and 26% declared a college major in CS, “65x the national rate of 0.4% of female college students majoring in CS”.

Digital Youth Network. Over the years, DYN has offered 5 different initiatives, Digital Youth Divas, Digital Queendom, Robotics, C21, and DYN TV. The DYN team works to develop young people and their technical, creative and analytical skills. They have dedicated spaces and work with Chicago youth over extended periods of time. They have developed diverse supportive environments for youth, and in their Digital Youth Divas (DYD), a **two-year, out of school program for middle school girls**, they work to have **non-dominant girls** build their own **interests and create their own STEM identities** (Pinkard et al., 2017). In their work, they created a digital badging program and say that others should try to reverse engineer their program "because youth everywhere benefit from stronger, connected learning and valuable digital badges." Badges give program creators a way to better understand what is being learned and learners a way to show what they have learned. Identity development is an explicit part of the program and participants document their interests and identity in their profile as their work; the youth may not realize they are documenting their identity, but that's what they are doing on the website.

ICT4Me. ICT4Me (formerly BuildIT) is a summer and afterschool program for middle school youth to develop interest, self efficacy, and skills in information technology (IT), and knowledge of possible related careers. The goal of the program is to provide underrepresented youth, and particularly girls, with opportunities to "experience the value of these careers through role models; engage in activities that connect their interests to technology and engineering; and experience success in these activities are powerful motivators for persisting in male-dominated ICT careers and developing their ICT fluency." The program includes a **6-unit curriculum** and assumes, at minimum, that the experience is supported by a manager, a facilitator, visiting IT professionals, and an opportunity ("Family Tech Night") for students to **showcase their work** to their family, peers, and the school community. Note that interaction with IT professionals is a key part of the experience: the developers recommend that **during each unit, at least two** IT professionals should interact with the students, and that "**The professionals should be the same gender and race as the youth you work with. Including more people of color and women is a plus.**" The site provides tips on how to recruit such professionals who can serve as relatable role models to help students see themselves as someone who could professionals in a variety of careers to encourage youth to consider an ICT career.

Resources

CIRCL Primer: Computational Thinking

CIRCL Spotlight: Principled Assessment of Computational Thinking

CIRCL Webinar Series: Computational Thinking for Teachers & Parents

Girls, Equity, and STEM in Informal Learning Settings: A Review of Literature

Big study about science interest

Code.org

Mentor Net

Readings

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Computational Thinking

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Overview

Computational thinking (CT), a term that experienced a surge of popularity in the 2000s, refers to a broad range of mental processes that help human beings find effective methods to solve problems, design systems, understand human behavior, and leverage the power of computing to automate a wide range of intellectual processes. Definitions vary, but there is general agreement that CT skills include the following:

- Formulating problems so that their solutions can be represented as computational steps and algorithms;
- Defining multiple layers of abstraction, understanding the relationships between the layers, and deciding which details need to be highlighted (and complementarily, which details can be ignored) in each layer when trying to understand, explain, and solve problems in different domains;
- Decomposing large complex tasks into manageable modular subtasks that supports parallel execution and multiple problem solvers;
- Iteratively developing solutions and systematically detecting and correcting errors;
- Analyzing the efficiency of various solutions;
- Reformulating seemingly difficult problems into solvable forms using reduction, transformation, recursion, and simulation.

While most existing definitions of CT describe it as a ‘thought process’, researchers in the field have increasingly realized the importance of focusing less on computational “thinking” and more on computational “doing”. CT becomes evident only in particular forms of epistemic practices that involve the generation and use of external representations (i.e., representations that are external to the mind) by computational scientists. This pedagogical perspective is important since it means that engaging students in computational representational practices like the process of developing abstractions is required in order to support the development of their CT skills. This perspective also aligns with the ‘learning-by-design pedagogy’, which suggests that students learn best when they engage in the design and consequential use of external representations for modeling and reasoning.

Discussions of computational thinking emerged, in large part, out of desire by computer scientists to communicate the ways in which their discipline was more than programming. Coding or programming is one way to apply and practice aspects of computational thinking, but many aspects of computational thinking — and therefore, computer science — can take place without engaging in coding. CT emphasizes conceptualization and developing ideas and algorithms for solving a problem rather than dealing with the rigid syntax of programming languages for producing artifacts that represent the solution to the problem. However, this does not mean that CT skills can be taught divorced from the use of computers. Though some CT concepts and principles can be introduced and explored through unplugged activities without the use of computers, prolonged use of such an approach deprives learners of crucial computational experiences. In other words, computers and other computational devices may not be synonymous with CT, but they are enablers of CT.

Also, it is noteworthy that though CT is often defined to draw on concepts fundamental to computer science, several CT skills are not exclusive to the field of computer science. For example, abstractions are used in all disciplines where modeling is a key enabler for conceptualization and problem solving, such as in science, engineering, mathematics, and economics. Similarly, logisticians and management scientists have studied scheduling extensively, and notions of tradeoff are central to the work of economists and engineers. Most disciplines involve problem solving, information retrieval and representation, modeling, debugging, testing, and efficiency considerations in some form or the other. Today, the wide spectrum of CT applications encompasses disciplines as diverse as science, mathematics, music, poetry, archaeology, and law.

Not surprisingly, CT is considered to represent a universally applicable attitude and skill set everyone, not just computer scientists, would be eager to learn and use. With the proliferation of computers in our society, understanding the fundamentals of how computational solutions are designed is important for everyone. Jeannette Wing, who coined the term 'Computational Thinking' in 2006, argued that it should be included as a determinant of every child's analytical ability along with reading, writing, and arithmetic by the middle of the 21st century. Just like young students initially learn to read so that they can later read to learn, they also need to learn to think computationally at an early age so they might later use it to learn complex concepts, represent solutions as computational steps, and solve problems using computational models and methods. It is no longer sufficient to wait until students are in college to introduce them to CT concepts. Students must begin to work with algorithmic problem solving and computational methods and tools during their K-12 years.

Increasing access to CT instruction is now widely discussed as a social justice issue. The stereotypical image of a computer scientist is that of a young white male bent over a keyboard, working in a room by himself. Focus on CT as a much broader, collaborative problem-solving process has potential to break this stereotype and broaden participation in the computer science field. Beyond broadening participation within computer science, CT skills can prove to be beneficial for all career fields. However, in spite of recognizing the need to introduce all students to CT concepts and practices from an early age, several CT-based programs and learning environments are still primarily used in informal and extracurricular settings like summer camps and after-school computer clubs. Engaging students in CT through motivational extracurricular CT-based activities may be a good first step, but CT eventually needs to be integrated into the K-12 curricula, either as a stand-alone discipline or integrated with existing disciplines like science and mathematics. Curricular integration will help remove the variables of self-selection, confidence, and willingness to opt for elective and extracurricular programs from the equation. This will provide all students, irrespective of gender and ethnicity, equal access to CT concepts and practices.

Key Lessons

Key lessons on Computational Thinking (CT) definitions and frameworks:

- CT skills have been defined as a three-dimensional framework comprising computational concepts, practices, and perspectives.
    - Computational concepts refer to elements, such as sequences, loops, parallelism, events, conditionals, operators, and data structures that are present in many programming languages.
    - Computational practices refer to activities, such as being incremental, reusing and remixing, testing and debugging, and modularizing and abstracting that designers use to create programs.
    - Computational perspectives, such as expressing, connecting, questioning, potential study and career path in computing, and personal relevancy of computing refer to worldviews that designers develop as they engage with digital media, and how they see themselves within the field and the realm of future careers.
- CT practices in Science and Mathematics contexts have been defined in the form of a taxonomy (Weintrop at al., 2016) consisting of four main categories:
    - **Data practices** – Collecting data, Creating data, Manipulating data, Analyzing data, and Visualizing data
    - **Modeling and simulation practices** – Using computational models to understand a concept, Using computational models to find and test solutions, Assessing computational models, Designing computational models, and Constructing computational models
    - **Computational problem solving practices** – Preparing problems for computational solutions, Computer programming, Choosing effective computational tools, Assessing different approaches/solutions to a problem, Developing modular computational solutions, Creating computational abstractions, Troubleshooting and debugging
    - **Systems thinking practices** – Investigating a complex system as a whole, Understanding the relationships within a system, Thinking in levels, Communicating information about a system, Defining systems and managing complexity.

Key lessons from CT-based research:

- CT skills can be taught in concert with skills in other domains, and this can make learning both easier than learning each separately. In fact, the ACM K-12 taskforce recommends integrating programming and computational methods with curricular domains, such as science and mathematics, rather than teaching programming as a separate topic at the K-12 levels. Using CT has also been added as a recommended practice by the Next Generation Science Standards.
- Well-designed computational thinking activities can enhance learning of other embedded topics, such as mathematics.
- Children as young as kindergarteners can engage in simpler aspects of computational thinking, such as sequencing.

- The language students use to engage in programming activities — in particular, whether a block-based or text based language is used — can impact what students understand about computational thinking.
- Assessments for measuring students' CT skills should not be tied to any programming language in particular, if possible.
- Increasing engagement and interest in CT may not necessarily be synonymous with increased understanding and use of CT concepts and practices.
- Teacher professional development and teacher-friendly resources and examples of CT are required in order to introduce CT in the K-12 curricula.
- Besides introducing CS curricula for K-12 students, integrating CT with existing science or mathematics curriculum can be an effective means for teaching CT skills, especially at the middle school level.

Issues

While the importance of introducing all students to CT skills from an early age is widely acknowledged, a number of issues still plague the field. Some important issues are listed below.

Efforts have primarily focused on engaging students in CT concepts and practices through motivating contexts like game-design, storytelling, robotics, and app-design in after-school workshops, summer camps, or as part of other extra-curricular activities, making CT accessible only to a selected few. Such efforts have naturally prioritized an interesting and engaging experience for students using computational tools instead of deep learning of CT concepts.

Many research studies on computational thinking demonstrate what students are capable of achieving at different grade levels, but there have been fewer systematic studies of how computational thinking instruction can be feasibly addressed in a typical school year. More studies of how programs can be implemented within the constraints of schools are needed.

Lack of systematic CT curricula have also resulted in dearth of research studying students' learning and developmental processes while learning CT skills and using CT-based learning environments.

Curricular integration of CT requires development of systematic CT assessments, an area that is under-investigated despite its importance being well recognized. Thorough assessments of computational thinking have yet to be developed, in part because the field lacks a shared understanding and vocabulary for what computational thinking entails.Such assessments can provide a thorough understanding of students' difficulties in using computational methods and tools, which can then lead to the development of systematic scaffolds to support students' development and use of CT skills.

While computational thinking is proclaimed to be a literacy appropriate for all students, it remains unclear where instruction for all should end and when instruction for only students with further interest in computer science should begin.

Projects

Examples of NSF Cyberlearning projects that overlap with topics discussed in this primer.

- Track 2: CS10K: BJC-STARS: Scaling CS Principles through STARS community & leadership development
- EXP: Learning Parallel Programming Concepts Through an Adaptive Game
- EXP: Understanding Computational Thinking Process and Practices in Open-Ended Programming Environments
- CAREER: Constructing Modern and Inclusive Trajectories for Computer Science Learning
- DIP: Extending CTSiM: An Adaptive Computational Thinking Environment for Learning Science through Modeling and Simulation in Middle School Classrooms

Principled Assessment of Computational Thinking – Applying the ECD approach to create assessments that support valid inferences about computational thinking practices, and is using the assessments and other measures to investigate how CS curriculum implementation impacts students' computational thinking practices.

Learning Trajectories for Everyday Computing (LTEC) – Developing learning trajectories for computational thinking (CT) in K-5 and addressing which aspects of CT might be integrated with math instruction in elementary school.

CTSiM: Computational Thinking using Simulation and Modeling – Leverages the synergy between CT and STEM in middle school contexts. Students use an agent-based visual programming language to build computational models of different science phenomena, which they can then simulate and compare against the results generated by expert simulations. Student learning is guided by online resources and an adaptive scaffolding framework.

CTSTEM – Promoting CT in high school science and math to empower all students to participate in a computational future.

Resources

Conferences & Organizations:

- ICLS – International Conference of the Learning Sciences
- SIGCSE – Special Interest Group on Computer Science Education
- SPLASH-E – Systems, Programming, Languages and Applications: Software for Humanity – Education Track
- AERA SIG/ATL and SIG/LS (Special Interest Groups in Advanced Technologies for
- Learning and Learning Sciences)
- Computer Science for All NYC

- RESPECT – Research on Equity and Sustained Participation in Engineering, Computing, and Technology

Videos:

- Computational Thinking by Grady Booch (an ACM webinar)
- NSF 2016 Video Showcase videos on computational thinking
- Code.org Video Library

Social Media/Web:

- CS Education DIscussion Forum on Facebook
- Computing Education Blog by Mark Guzdial
- CIRCL Project Spotlight: Principled Assessment of Computational Thinking
- CIRCL Perspective on Matthias Hauswirth and his blog Learning to program? Or programming to learn?
- How to teach computational thinking, by Stephen Wolfram and response to the article: The keys to a well-rounded computer science education (by Hadi Partovi of code.org)

Curriculum:

- Exploring Computer Science (ECS) for high school students, with a focus on creating equal access to computing for students who are traditionally underrepresented in the computing workforce. A lot of schools are using this.
- Computer Science Principles (CSP) advanced placement course
- Mobile CSP – focuses on mobile computing
- Code.org curriculum for elementary, middle school, and high school
- Computational Thinking in Simulation and Model-Building (CTSiM) from Vanderbilt has Science + CT Curricular Units you can request access to
- Computational Thinking in Science and Math (CT-STEM) at Northwestern University has lessons and assessments you can request access to
- Exploring Computational Thinking (ECT) by Google for Education
- Zoombinis computational thinking game by TERC
- CS Unplugged learning activities

Standards and Assessment:

- K-12 Computer Science framework (release date September 2016)
- Advanced Placement Computer Science Principles
- CSTA K–12 Computer Science Standards
- Assessments for ECS Units 1-4 developed by PACT (need a CS10K account; free)

Teacher Resources:

- CS10K Community – where teachers of ECS and CSP can come to connect with each other and with the resources and expertise they need
- Computational Thinking for Educators – A free online course helping educators integrate computational thinking into their curriculum
- ScratchEd online community – where Scratch educators share stories and resources
- CSTA – Computer Science Teachers Association

Tools:

- Scratch, Dr. Scratch (assessment), and ScratchX (extensions)
- Alice
- Modkit
- Arduino
- ARIS
- MIT App Inventor
- VENVI
- Blocky Talky
- Ready, Steady, Code
- SiMSAM
- Sketching with Electronics
- App Lab
- Ear Sketch
- CodeCombat
- Tree House
- CodeAcademy
- StarLogo Nova
- Snap!
- Minecraft Modeling

Readings

References and key readings documenting the thinking behind the concept, important milestones in the work, foundational examples to build from, and summaries along the way.

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Margolis, J. (2010). Stuck in the Shallow End: Education, Race, and Computing. Cambridge, MA: MIT Press.

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Hemmendinger, D. (2010). A plea for modesty. Acm Inroads, 1(2), 4-7.

Grover, S., & Pea, R. (2013). Computational Thinking in K–12 A Review of the State of the Field. Educational Researcher, 42(1), 38-43.

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Basawapatna, A. R., Repenning, A., & Koh, K. H. (2015, February). Closing The Cyberlearning Loop: Enabling Teachers To Formatively Assess Student Programming Projects. In Proceedings of the 46th ACM Technical Symposium on Computer Science Education (pp. 12-17). ACM.

Bienkowski, M., Snow, E., Rutstein, D. W., & Grover, S. (2015). Assessment design patterns for computational thinking practices in secondary computer science: A first look (SRI technical report). Menlo Park, CA: SRI International.

Clements, D. H., & Sarama, J. (1997). Research on Logo: A decade of Progress. In C. D. Maddux & D. L. Johnson (Eds.), Logo: A retrospective (pp. 9-46). New York, NY: The Haworth Press.

Peters-Burton, E. E., Cleary, T. J., & Kitsantas, A. (2015). The Development of Computational Thinking in the Context of Science and Engineering Practices: A Self-Regulated Learning Approach. International Association for Development of the Information Society.

Weintrop, D., Beheshti, E., Horn, M., Orton, K., Jona, K., Trouille, L., & Wilensky, U. (2016). Defining computational thinking for mathematics and science classrooms. Journal of Science Education and Technology, 25(1), 127-147.

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- Katie Rich – University of Chicago
- Patricia Schank – SRI International
- Michelle Wilkerson – University of California, Berkeley

CIRCL Primer: Assessing Computational Thinking

Authors: Quinn Burke, Cinamon Sunrise Bailey, and Pati Ruiz
Questions, or want to add to this topic or to a new topic? Contact CIRCL.

Overview

Computational thinking (CT) is increasingly being recognized as a crucial educational literacy characteristic of 21st century learning as well as a requisite skill for the 21st century economy, which relies on computing as an essential component of commerce. CT is broadly defined as a way of "solving problems, designing systems and understanding human behavior by drawing on the concepts fundamental to computer science" (Wing, 2006, p. 33).The term "computational thinking" can be dated back to the 1980s when Seymour Papert's Mindstorms book brought to the mainstream the idea of using computers in K-12 schools as "objects to think with". However, it was Jeannette Wing's influential 2006 article on CT that helped spark CT as an educational imperative for schools. Since 2006, a total of forty (40) states have enacted--or are in the process of enacting--computer science (CS) standards and frameworks for their K-12 schools (Code.org, 2018). In high school, CS is typically a stand-alone course offering; however, on the K-8 levels, many states and districts are largely focusing on integrating computing into existing coursework, be it math, science, social studies, and/or language arts. With this curricular integration on K-8 levels, the goal is twofold: First, to foster children's capacity to formulate and address problems systematically; and second, to direct and reinforce learning within existing academic disciplines through the refinement of such problem solving skills.

One of the primary challenges of computational thinking as an integrative, cross disciplinary competency is of **assessment**. In assessing CT, one could consider evaluating a student with regards to any or all of the three dimensions of CT:

(1) **computational concepts**: the fundamental concepts students engage with as they program or engage in CT oriented practices-such as algorithmic thinking, decomposition, abstraction, parallelism, and pattern generalization

(2) **computational practices**: the actual practices students develop as they encounter and engage with the concepts; this includes collecting and sorting data, designing and remixing computational models, debugging simulations, documenting one's work, and collaboratively breaking down complex problems to their requisite parts

(3) **computational perspectives**: the perspectives students form about the world around them and about themselves as they comprehend these concepts and engage in such practices; perspectives here refers to learners' own sense of agency and technology fluency, as well as a

wider appreciation as to how systems function, why they break down and how they can be improved

Given the imperative to integrate CT into existing school subjects, especially on the K-8 levels, there are questions as to how to define CT as a skill and as a knowledge. *Is CT best assessed as a series of learned concepts? How does understanding such concepts measurably inform CT practices? How does CT learning transfer across academic subject areas and how does its subject matter integration inform the dimensions of CT that can be be assessed?* Alongside these pressing questions, there are then other persistent variables to consider that are characteristic of assessing any type of learning. *How do teaching practices and purported learning styles inform the way CT is assessed, and how do these assessments relate to grade level expectations and expected competencies?*

There is general consensus from the research (Aiken et al., 2012; Dorling, 2016; Duncan, 2018; Grover, Cooper, & Pea, 2014; Grover & Pea, 2013; Snow et al., 2012; & Wentrop et al., 2015) that computational thinking represents a more robust and practical goal for K-12 schools than the more nebulous goal of “digital literacies”, which too often is driven by for-profit companies promoting particular apps and products.

Yet there is still considerable debate over the precise meaning of computational thinking, and much of this stems directly back to this question of effective and consistent assessment. Being able to effectively assess CT within different content areas allows for a greater understanding as to how it may best be implemented into a range of academic content areas. More rigorous and systematic assessment also could informs what pedagogies better facilitate learners' understanding of its various components. In the same manner, changes could be made to the wider school curricula in order to address changing student and workforce needs. Finally, gaining a stronger grasp on the ways and means CT is (and could be) assessed offers a sharper examination of equity of access and educational experience within schools with regards to which students are encountering such content and to the degree they are comprehending it.

Key Lessons

The following lessons stem from research that has been conducted regarding defining and assessing CT concepts, CT practices, and CT perspectives:

Assessing Computational Concepts

Researchers have defined several CT concepts that are highly useful when students/designers understand them and are able to apply them in various academic and non-academic contexts:

- iterative, recursive, and parallel thinking; sequences; loops; events; conditionals; operators; data; abstraction; evaluation; algorithmic thinking/design; decomposition;

automation; pattern generalization; pattern recognition; systematic processing of information; symbol systems and representations; conditional logic; efficiency and performance constraints; debugging; and systematic error detection (Basu, Mustafaraj, & Rich, 2016; Brennan & Resnick, 2012; Grover & Pea, 2013)

Methods for Measuring CT Concepts. Guided by their design of the Three-Dimensional Integrated Assessment (TDIA) framework, Zhong, Wang, and Chen (2016) developed assessment tasks that aimed to comprehensively assess the three dimensions of CT: computational concepts, practices, and perspectives. There have been several methods proposed for measuring CT concepts. These include:

- Designed based assessments and/or software engineering metrics:

    - Dr. Scratch, a free, open source software assessment tool for Scratch; Fairy Performance Assessment as an Alice program to analyze thinking algorithmically and making effective use of abstraction and modeling (Werner, Denner, Campe, & Kawamoto, 2012); REACT-Real Time Evaluation and Assessment of Computational Thinking (Koh, Basawapatna, Nickerson, & Repenning, 2010); Bebras tasks-aimed at choosing interesting tasks, which motivate learners to deal with informatics and to think deeper about technology (Román-González, Moreno-León, & Robles, 2017)

- Accumulative content knowledge based assessments:

    - Computational Thinking Test (CTt): designed for primary and middle school; aligned with the CSTA Computer Science Standards for the 7th and 8th grade; multiple choice; each item measures one or more of seven computational concepts; this has been used in content area research (i.e. language arts) (Román-González, 2015; Román-González, Pérez-González, & Jiménez-Fernández, 2016; Román-González, Pérez-González, & Jiménez-Fernández, 2017)

    - Commutative Assessment Test: evaluate “if and how programming modality affects learnability”. (Weintrop & Wilensky, 2015, p.4)

- Assessment of computational language/vocabulary as a measurement of CT conceptual knowledge

- Surveys/Interviews/Feedback forms:
    - Artifact-Based interviews (Brennan and Rosnick, 2012); questionnaires, journal entries, and semi-structured interviews (Chalmers, 2018); Relational Screening Model: “Personal Information Form” (Durak & Saritepeci, 2017); The CTP

Video-Prompt Survey (Marsall, 2011); and teacher feedback through online forms (Duncan, 2018)

Assessing Computational Practices

CT skills can be applicable across disciplines. For example, a student studying Spanish could identify patterns in word and sentence structure, compare these patterns to ones that could be found in English, and then explain the similarities and differences in these patterns to a classmate. These are skills that can be classified as 'systems thinking' CT practices.

By transferring CT skills and practices across school subjects, students ought to be able to use different approaches and perspectives in order create more innovative solutions in other fields, including language arts, science, mathematics, social science, and humanities. Researchers have organized CT Practices into the following areas:

- Data practices (collecting data, creating data, manipulating data, logically organizing and analyzing data, visualizing data)

- Modeling and simulation practices (using computational models to understand a concept, using computational models to find and test solutions, assessing computational models, designing and drafting computational models)

- Computational problem solving practices (formulating problems in a way that enables us to use a computer and other tools to help solve them, choosing effective computational tools, approaching the problem using programmatic thinking techniques, assessing different approaches/solutions to a problem, breaking down problems into manageable components, generalizing this problem-solving process to a wide variety of problems, developing modular computational solutions, creating computational abstractions, troubleshooting and debugging)

- Systems thinking practices (investigating a complex system as a whole, understanding the relationship within a system, thinking in levels, communicating information about a system, generalizing and transferring this problem solving process to a wide variety of problems, defining systems and managing complexity)

Methods for Measuring CT Practices. There have been several methods proposed for measuring CT practices. These include:

- CT skill-transfer: aimed at assessing the students' transfer of their CT skills to different types of problems

        - Bebras Task measures transfer to 'real life' problems (Dagiene & Futschek, 2008)
        - CTP-Quiz: analyzes the transfer of CT to the context of scientific simulations (Basawapatna, Koh, Repenning, Webb, & Marshall, 2011)

    - Student-generated portfolios & rubrics
        - Project portfolio analysis (Brennan & Rosnick, 2012)
        - Rubrics designed to evaluate student work across five dimensions: general factors, design mechanics, user experience, basic coding constructs, and advanced coding constructs (Grover, Basu, & Schank, 2018)

    - Audio and video capture/observation of Students engaged in CT practices

    - Direct observation of student performances using field notes to document progress

    - Assessments based on real-time manual input (i.e. keystroke/ time spent on task)

Assessing Computational Perspectives

As students interact and participate with CT tools and artifacts, their relationships to others as well as the world around them purportedly evolves. CT attitudes and perspectives involve elements related to that evolving understanding of self that students experience. Basically, it is how a student sees themselves, their relationship with others, and the computational thinking world around them.

Engaging students in computational thinking practices could help develop their perspectives/ dispositions, which can then potentially enhance their academic and career success. The Computer Science Teachers Association (CSTA) and the International Society for Technology in Education (ISTE) (2011) identify "confidence in dealing with complexity, persistence in working with difficult problems, tolerance for ambiguity, the ability to deal with open-ended problems, and the ability to communicate and work with others to achieve a common goal or solution" as dispositions or attitudes that are essential dimensions of CT.

Method for Measuring CT Perceptions. Examples of methods proposed for measuring CT perceptions include:

    - CT Perceptions-Attitudes scales/tests/rubrics

        - Computational Thinking Scales (CTS): five-point Likert scale; examines creativity, algorithmic thinking, cooperativity; critical thinking; and problem solving (Korkmaz, Çakir, & Özden, 2017). Though this study was done in a turkish post-secondary setting, it did show validity.

- The Computational Thinking Test (CTt) as a means to predict if 'computationally talented' students can be detected prior to learning a CT task (can levels of success be predicted prior to learning and how can this contribute to the development of more individualized lesson plans) (Román-González, Pérez-González, Moreno-León, & Robles, 2018)

- Rubric on learning dispositions (Dorling, 2016)

- Self-efficacy survey five point Likert scale: assesses problem solving skills and ability to think computationally (Weese & Feldhausen, 2017)

- Computational Thinking Pattern Analysis (CTPA): implements computational thinking patterns in a student-created game and uses the game's tutorial "norm" as a gauge of creativity. (Bennett, Koh, & Repenning, 2013)

Issues

While computational thinking is increasingly being recognized as a crucial skill for K-12 students, there are a number of challenges associated with its integration into schools and effectively assessing it.

CT Definitions. First, as noted earlier, there is still a lack of consensus with regards to how to define CT knowledge and skill acquisition. Do students have to demonstrate knowledge and abilities in all dimensions of CT (concepts, practices, and perspectives), or are we able to ascertain that they have CT knowledge/skills if they only obtain/express partial knowledge in one domain? For example, if a student is able to analyze data but has not displayed knowledge of systems-thinking practices (investigating a complex system as a whole, understanding the relationship within a system, and managing complexity), can we still say this student has CT knowledge even though they have only displayed knowledge/skills in data practice? More research needs to occur in order to develop a shared understanding and vocabulary of what computational thinking encompasses.

Multiple CT Dimensions. Second, while an exact definition of CT is still a matter of debate, as the prior section details, there has been wider consensus that CT entails concepts, practices, and perspectives. Accordingly, to assess a student or program with regards to only one of these dimensions provides an incomplete picture of CT. In developing and articulating a computational thinking framework, all three of the dimensions of CT ought to be addressed. In this regard, multiple means of assessments (i.e., artifact analysis, surveys, field note observations) may very well be necessary in order to fully evaluate a student's nascent CT knowledge and abilities. Without this, there is a risk of missing key pieces of information and contributing factors, which could affect CT development and implementation (i.e. cognitive and personality traits, learning styles, age and gender specific factors, environmental effects, and curriculum contributions).

Correlations between CT Dimensions. Third, studies evaluating the acquisition of CT increasingly need to consider correlation between conceptual knowledge, practical application, and wider shifts in personal perspectives. If a student successfully completes an activity, does this simultaneously demonstrate understanding of the CT concept as well as the achievement of a particular CT practice and a broader understanding of computing's role in society? At this point, with assessing CT still in a fledgling stage, researchers have a responsibility for developing metrics for each of these dimensions and examining to what degree conceptual gains correspond to documented changes in practice and personal perspectives. Arguably the second dimension related to CT practices is the most difficult to document and ascertain. Conceptual understanding can be often be gauged by the analysis of student projects as well as through simple quizzes and puzzles related to particular CT concepts. Pre-and post surveys coupled with participant interviews meanwhile capture shifts in perspectives. Assessing actual practice however relies heavily on direct observation and field note documentation, which is especially labor-intensive and time-consuming. Real-time digital assessments, such as documenting participants' keystrokes and the time spent online on a particular task, offer more immediate sources of data around practices, but these require considerable analyses on the back-end and are rarely telling metrics without corresponding measures, such as artifact analysis and participant survey responses.

Integrating CT into Curriculum. Finally, while the question of skills transfer is not a new one, it has renewed significance as schools are increasingly attempting to integrate CT across a range of academic subject areas. While there are numerous studies documenting CT's integration into math, science, ELA, and social sciences coursework, we still altogether lack substantial research how to optimally integrate CT into the curriculum and how to assess it in terms of the content area with which it is aligned. Additional questions could include asking to what degree CT can or should be assessed as a distinct skill set, as a series of goal-directed activities or regulatory processes, and/or as part of the normal formative and summative assessment processes that are already occurring within an academic content area.

Projects & People

Examples of NSF Cyberlearning projects that overlap with topics discussed in this primer.

Computational Thinking

- Synthesis and Design Workshop: Distributed Collaboration in STEM-Rich Project-Based Learning
- Synthesis and Design Workshop: Digital Science and Data Analytic Learning Environments at Small Liberal Arts Institutions

- EXP: Readily Available Learning Experiences: Turning the Entire Web into Progressive Examples to Bridge Conceptual Knowledge Gaps for Novice Web Developers
- EXP: Automatically Synthesizing Valid, Personalized, Formative Assessments of CS1 Concepts
- The cognitive and neural mechanisms of computer programming in young children: storytelling or solving puzzles?

Other related projects :

- CIRCL Spotlight: Principled Assessment of Computational Thinking (PACT) - NSF-funded project that applies evidence centered design (ECD) to create assessments that support valid inferences about computational thinking practices; see also Assessment Design Patterns for Computational Thinking Practices in Secondary Computer Science: A First Look, a technical report from the PACT project.
- CIRCL Spotlight: Computational Thinking & The Game Zoombinis - an NSF-funded project to study the development of CT for upper elementary and middle grades students.
- Real Time Assessment of Computational Thinking (REACT) - an NSF-funded assessment tool that allows teachers to determine level of student CT skill acquisition as they code in real time

Related CIRCL Perspectives:

- Marie Bienkowski - NSF Project: Principled Assessment of Computational Thinking; Investigators: Eric Snow, Marie Bienkowski
- Deborah Fields - NSF Project: EXP: Macro Data for Micro Learning: Developing FUN! for Automated Assessment of Computational Thinking in Scratch; Investigators: Deborah Fields, Sarah Brasiel, Taylor Martin
- Mark Guzdial - Course and tool development for CS1 Course: Media Computation; FCS1 (with student, Allison Elliott Tew), the first validated test of introductory CS knowledge designed to be multilingual; replicated by SCS1 (with student, Miranda Parker)
- Yasmin Kafai - NSF Project: Collaborative Research: ET-ECS: Electronic Textiles for Exploring Computer Science with High School Students and Teachers to Promote Computational Thinking and Participation for All; Investigators: Yasmin Kafai, Jane Margolis, Joanna Goode
- Pati Ruiz - 2016 NSF Video Showcase: Broadening Participation
- Aman Yadav - NSF Project: PD4CS (Professional Development for Computer Science); CPATH-2: Computer Science Pathways for Educators

Resources

Related CIRCL Primers:

- CIRCL Primer: Computational Thinking - an overview of computational thinking definitions, frameworks, and research by the Cyberlearning 2016 working group.
- CIRCL PRimer: Evidence-Centered Design (ECD) - an approach to designing educational assessments, which measure their intended constructs and yield to evidential arguments.

Conferences & Organizations:

- AERA SIG/ATL and SIG/LS - Special Interest Groups in Advanced Technologies for
- Learning and Learning Sciences
- CSforAll - Resources for districts, schools, and classrooms to help provide all K-12 students with an effective computer science education.
- CSTA - Computer Science Teachers Association
- Code.org - Online resource for learning and teaching coding practices (aim: increase access to computer science in schools)
- ICLS - International Conference of the Learning Sciences
- ISTE - The International Society for Technology in Education
- K12CS - K–12 Computer Science Framework
- RESPECT - Research on Equity and Sustained Participation in Engineering, Computing, and Technology
- SIGCSE - Special Interest Group on Computer Science Education

Videos:

- Integrating Computational Thinking into Mathematics Instruction in Rural and Urban Preschools - Brief overview of project with: CT learning blueprint; CT/math alignment document (preschool math Building Blocks curriculum); hands-on activity prototypes that focus on the CT concepts (sequencing, debugging, and modularity); and brief discussion on ways to assess preschool students' CT learning and preschool teachers' CT understanding
- Principled Assessment of Computational Thinking (PACT): Assessing Computational Thinking in High School - An overview of what PACT has accomplished and future plans. Two ECS teachers also discuss their use of the ECS assessments developed by the PACT team.
- ScratchEd Webinar-Assessing Computational Thinking: May 2012 -- ScratchEd Team discusses different approaches to assessing students' understandings of computational thinking

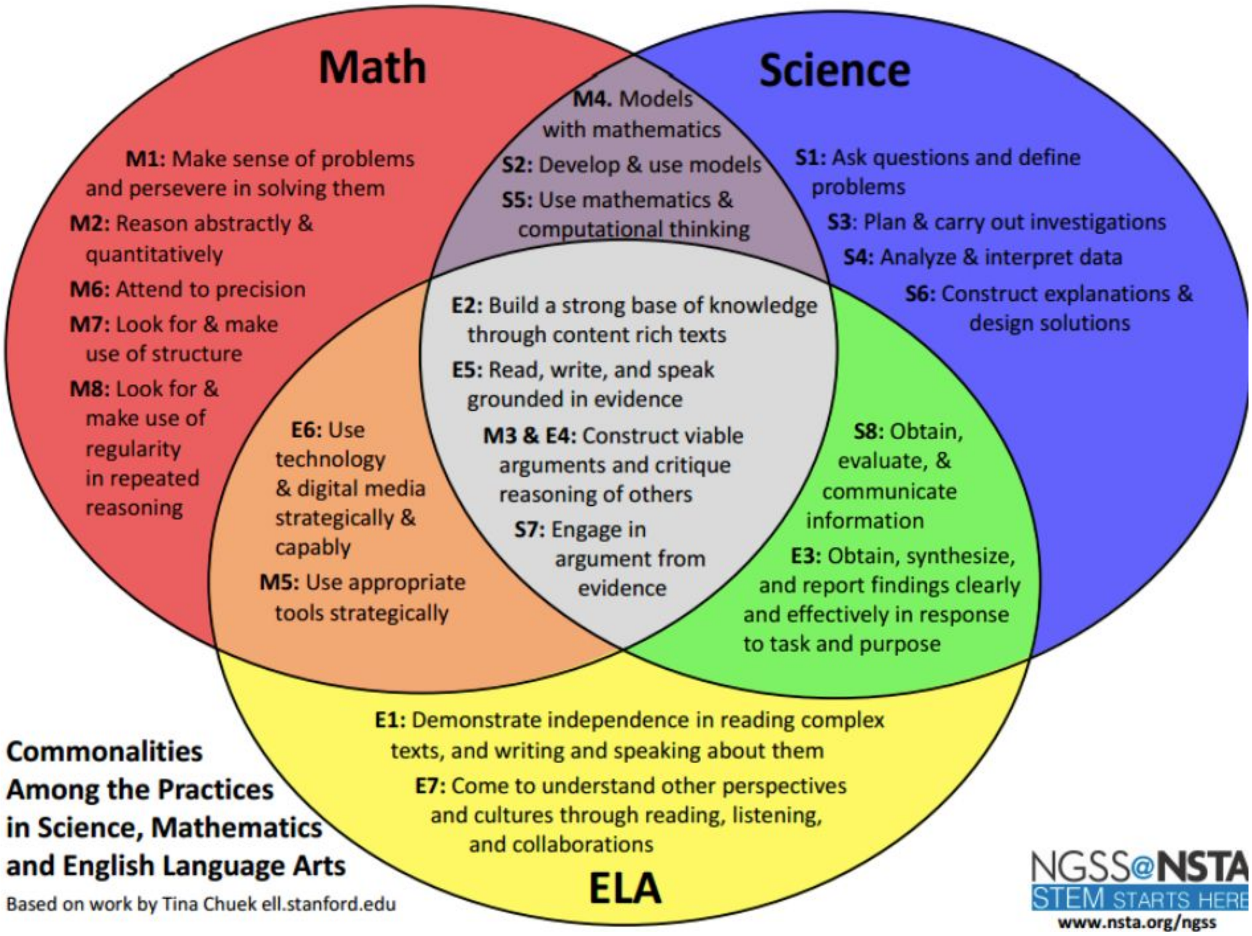
Digital Media:

- 7 Computational Strategies - e-school news provides seven computational thinking strategies to equip students with problem-solving abilities
- Computational Thinking Concepts Guide - concepts, definitions, and teaching tips
- Computational Thinking in Cyberlearning in K-12 - an accumulation of digital articles on CT and cyberlearning
- Cyberlearning Community Report: The State of Cyberlearning and the Future of Learning With Technology: describes six design themes emerging across multiple NSF-funded cyberlearning projects: Community Mapping: Moving and Discovering Across Contexts; Expressive Construction: Enabling Learners to Represent Powerful Ideas; Enhancing Collaboration and Learning through Touch Screen Interface; Virtual Peers and Coaches: Social and Cognitive Support for Learning; Classrooms as Digital Performance Spaces; and Remote Scientific Labs: Authenticity at Distance
- Fairy Performance Assessment: Measuring Computational Thinking in Middle School - preliminary results of a performance assessment tool for measuring CT in middle school (game-based design)
- Operational Definition of Computational Thinking for K–12 - The Computer Science Teachers Association (CSTA) and the International Society for Technology in Education (ISTE)

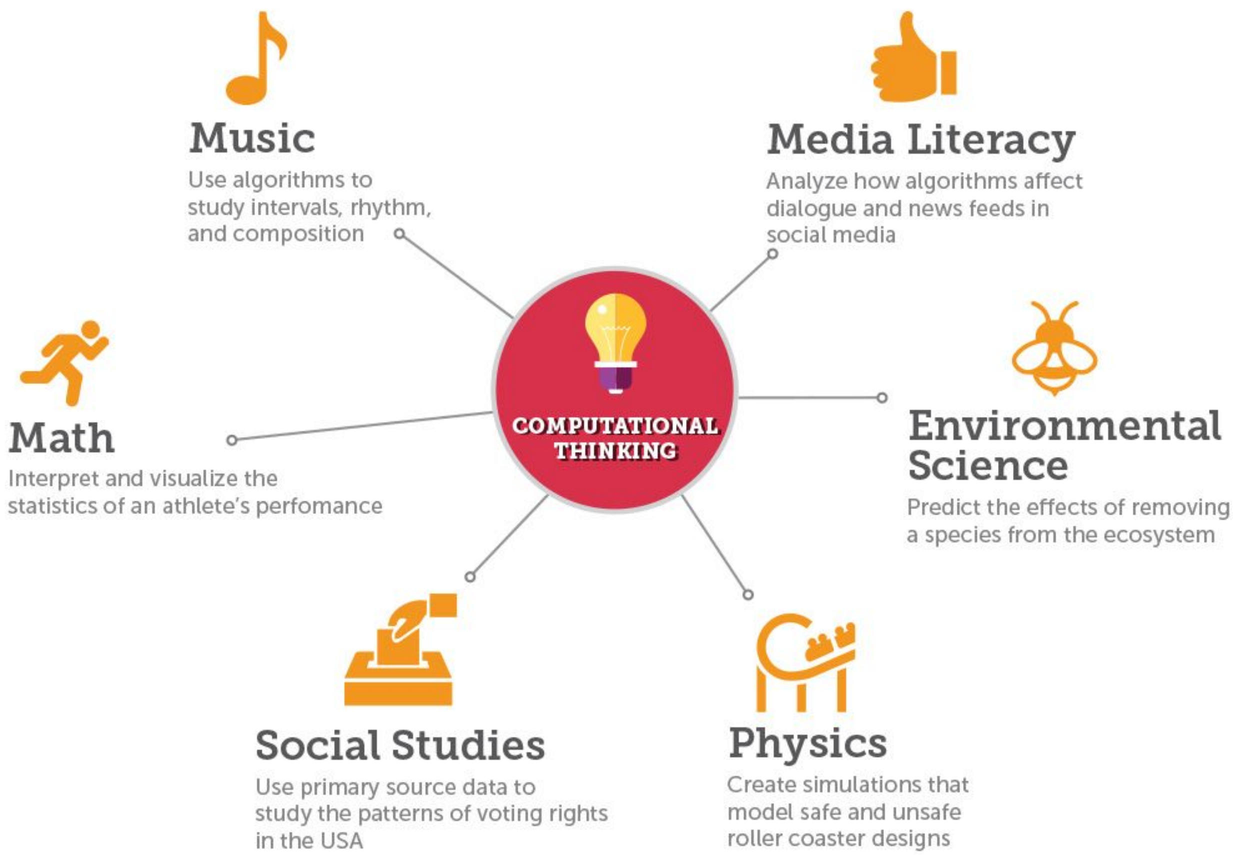
Tools:

- AgentSheets
- Alice
- App Lab
- Arduino
- ARIS
- Blocky Talky
- Dr. Scratch
- EarSketch
- Hummingbird Robotics
- MIT App Inventor
- Modkit
- Ready, Steady, Code
- Scratch
- Tree House

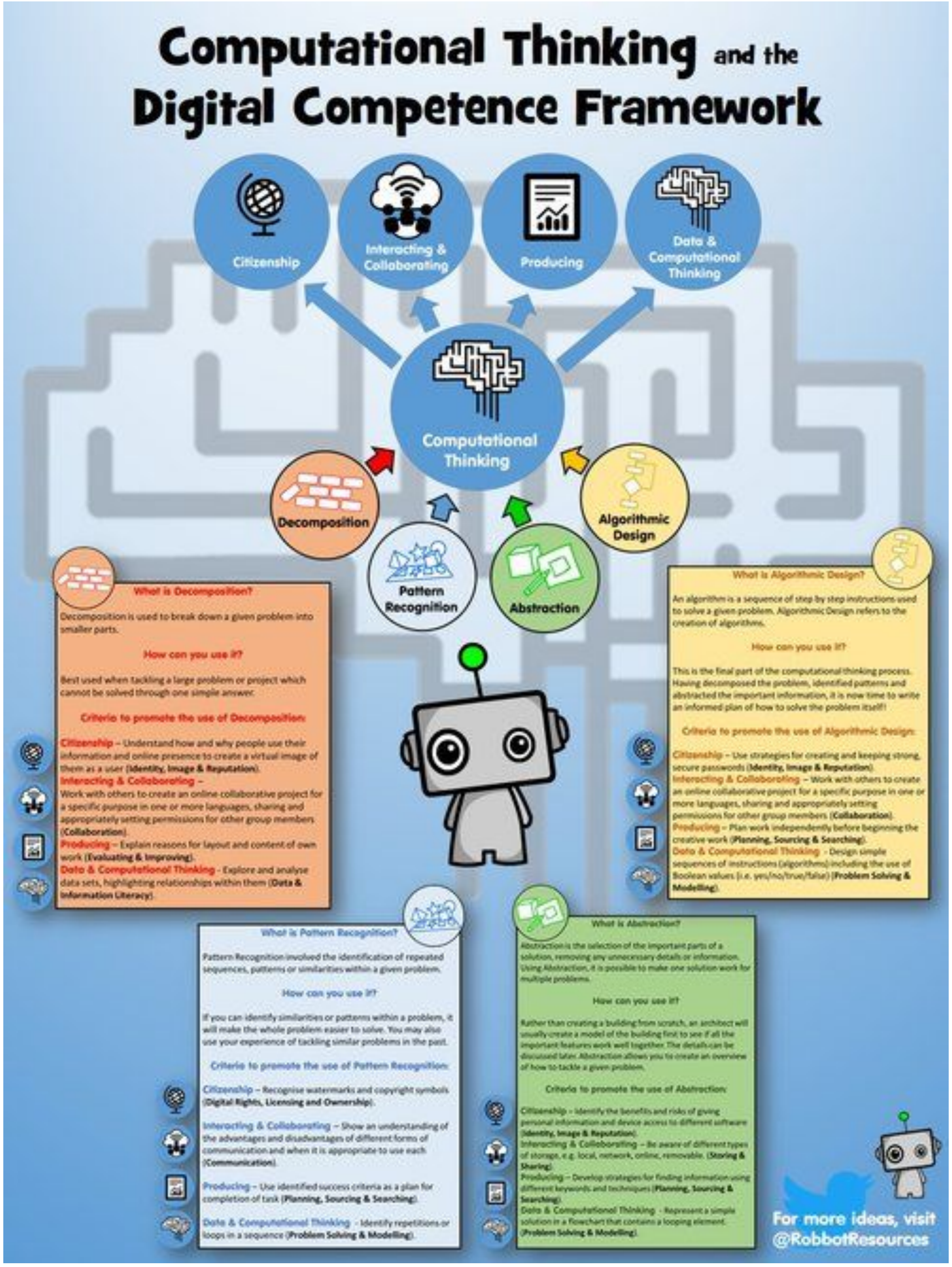
Computational Thinking Frameworks:



From [presentation by P. McLaren & J. Solek]



From Angevine, C. (2017). Advancing computational thinking across K-12 disciplines.



From [Rob-Bot Resources]()

Readings

References and key readings used in this primer on the dimensions of CT thinking (concepts, perspectives, and practices) as well as research on assessment in these areas are listed below.

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Citation

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CIRCL Primer: Virtual Reality in Education

Authors: Britte Cheng and Cynthia D'Angelo
Questions, or want to add to this topic or to a new topic? Contact CIRCL.

Overview

Virtual reality (VR) is an emerging platform for creating meaningful, engaging user experiences. VR typically refers to a computer-generated experience of a fictional or real place that you can interact with through words and gesture. Done well, VR can make people feel that they are physically present in the virtual world — and react as if they are in a real world — because the brain buys into the illusion that the experience is, in fact, real. In gaming, VR headsets, hand-held remote controllers, and wearable gloves and suits offer new levels of immersion and interactivity. Beyond gaming, VR is being used in the workplace to help doctors practice surgery, customer-service employees improve understanding of body language, and colleagues feel connected in virtual meetings. VR can even help people develop empathy around (for example) climate change, understand scientific phenomena they can't see, and experience historical events they otherwise couldn't experience (Bailenson, 2018).

From a learning science perspective, VR ties into long-standing themes around how dynamic representations and visualization can support conceptual learning. It opens new opportunities to consider how affect and cognition are mutually supportive in learning processes. And it raises challenging issues of how groups collaborate in virtual spaces, or how learning moves among virtual and everyday group spaces and contexts. As learning scientists, we see an opportunity here, if we are careful. The next sections of this primer present some key learning science lessons and issues for VR. But first, to orient the reader, we provide a brief overview (below) of VR technologies and the related concepts of virtual, augmented, and mixed reality.

VR Technologies. VR is making inroads into education as it becomes more user friendly and economically accessible. VR technologies differ in the amount of immersiveness that they afford, from relatively non-immersive 2D computer-based environments to fully interactive spaces in which you can walk around and interact with objects using headsets and other devices. Headsets typically use either smartphones or computers to drive screen graphics.

smartphone headsets (e.g., Cardboard, HTC Vive, Google Daydream, Samsung VR Gear) offer mobility, but are limited in their processing power and display resolution, which impacts how visually immersive an experience can be. Alternatively, computer-based headsets (e.g., Playstation VR, Oculus Rift) have the benefit of more processing power and better resolution, but restrict the mobility of the user and require special Input devices for each setup. The forms of interaction possible range from no input (e.g., Cardboard), to basic controllers for selecting things within the VR (e.g., Gear, Vive), to additional features like tracking the motion of the user (e.g., Oculus).

Augmented reality. In many discussions of VR in education, there is also a mention of augmented reality (AR). While VR **replaces** your current view with a simulated one, AR **overlays** virtual objects (e.g., labels) onto your current view. A well-known example is Pokemon Go. In this app, your phone's camera shows you a live view of the world around you, and sometimes a virtual Pokemon creature appears in the screen as part of the game. You can then interact with the creature using your phone. Although AR technologies currently lag behind VR technologies, applications of AR are promising for a variety of learning applications: For example, AR applications could project accurately sized dinosaurs into a classroom to helps students to understand scale, support hearing impaired learners by projecting interpreter's signs in the same field of vision as the object, and add additional context or scaffolded support to hands-on activities.

Mixed reality. Features of virtual and augmented reality technology are combined in mixed reality — usually by projecting virtual objects into a real space that is more immersive than augmented reality. For example, the Concord Consortium and University of Virginia have developed a mixed-reality gas laws activity that allows students to interact with a visual molecular dynamics simulation of a gas through tactile inputs spatially aligned with objects in the simulation. Commercial devices like Microsoft HoloLens allow users to interact with the environment without a physical controller.

Key Lessons

What are the potential benefits of using VR in educational settings and/or for educational purposes?

While potential benefits of using VR in educational settings is still being established, there are some key aspects of various VR experiences that are likely to enhance learning as part of well-designed learning activities. Here we discuss a common set of ideas that characterise the VR experience in order to explore the potential benefits for learning.

Immersion vs. presence. In much of the literature on experiences in VR, for learning or otherwise, the dual concepts of immersion and presence are the primary drivers of VR's impact. Intuitively, these ideas make sense, but they should be specified in order to better understand how they are operating. Immersion is the degree to which VR technology can provide an experience of being in a non-physical world by surrounding the user of the VR system in images, sound, or other stimuli that provide an engrossing total environment. Presence is the extent to which the user perceives themselves to be in a non-physical world (e.g., you can see you own hands interacting with objects in the environment). Thus, different systems with same level of immersion may produce different levels of presence for the same user.

Derived directly from arguments that immersion and presence of VR environments can support learning, VR content that mimics visiting or experiencing other places/phenomena is among the most readily available (i.e., "the magic school bus on steroids"). Google Expeditions offers a library of hundreds of "tours" of places and experiences — such as scuba diving in coral reefs, the craters of Mars, and the human respiratory system of a cell. Each is designed to accompany K-12 lessons. Based on a similar principle, higher ed VR uses include access to virtual science labs and tools that would otherwise be too costly or dangerous to provide in real life.

Taking immersion and presence a step further, some VR content is aimed at deepening social and psychological experiences. Virtual journalism aims at placing individuals in the midst of current news stories to develop better understanding of issues and events, but also to establish empathy among users in ways that more traditional news reporting can not. Research on VR has shown its potential to develop more than empathy among users. Bailenson and colleagues have shown that users can experience and reduce impacts of stereotype threat when appearing as a person other than themselves in a VR world (being immersed in another's shoes).

What are lessons learned for designing curriculum and instruction or for designing future research?

While examples of the potential benefits of immersion and presence to support learning (and beyond) spark our imagination, a key question becomes how to best design lessons that employ VR. Like all other learning technologies, the activities in which the VR devices are embedded are the lead factor determining the extent to which the tech can enhance or impede learning. Based on this idea, a foundational principle for using VR in educational settings is to leverage known learning science mechanisms as part of VR activities. For example, embedding VR in constructivist activities, activities that leverage student collaboration, or activities that require students to apply prior or new knowledge in authentic problem contexts is more likely to to draw on the affordances of VR to support student learning. In this vein, two examples of recent research illustrate attempts to establish how VR might extend the impact of known LS mechanisms.

VR and embodied learning. Recent research on embodied learning posits that one's body and one's physical experience play an important part in student learning (Lindgren & Johnson-Glenberg, 2013). In VR learning environments, students can have embodied experiences in and with physical spaces that go well beyond classroom walls. However, the vast majority of VR content available and feasible to classroom teachers is limited to head-mounted VR. Thus, in many cases, the full range of bodily movement is not available.

Augmented and mixed-reality technologies blur the boundaries of one's physical environment and virtual spaces by enabling more freedom of movement within the classroom (or any physical environment), further extending the possibilities of embodied learning.

VR to support science learning. The benefits of the use of simulation in science instruction is well-documented (D'Angelo et al., 2014). The ability to experience and interact with phenomena is extended with immersive technologies like VR. Researchers recently put this idea to the test by comparing student learning in three study conditions wherein students either used VR, photospheric digital media, or panoramic images as part of two science lesson. In one lesson, students who used VR achieved higher gains as measured by pre and post tests, and in the second lesson there were no learning differences by condition (for more details, see Cheng et al, 2018).

This study, among many calls from education researchers, points to the need to further analyze and study the alignment of the particular VR technology and content with the content and learning goals of the lesson in which VR is being used. One approach to specifying this alignment is described by the study researchers as identifying the overlap or coordination of the structure and sequence of learning activities (in which VR will be used), the pedagogical practices that will be employed in the lesson, and the affordances (and constraints) of the VR technology and content to be used. This approach is common among best practices of use of any learning technology, specifically those that are still being explored, but will result in principles of use specific to VR.

Issues

There isn't yet much research available on the uses of VR within educational settings, especially classrooms or informal learning spaces. Thus, we don't know what key dimensions of VR content need to be considered in design of educational content and activities that goes beyond our general understanding of how to implement technologies within educational spaces (see Key Lessons section). However, there are some issues that are specific to VR that need to be considered going forward:

1. **Little current research on how best to align affordances of specific VR tech and content with known learning mechanisms**. The alignment of learning goals with the affordances of specific content in a particular type of VR with particular students is an important consideration of any instructional design. Because there is little research so far into the various affordances of different content within various types of VR, it will be difficult to know the proper alignment of these factors for a while. Research goals for VR might focus on questions around specific **subject matter integration** (social science and science are often given as examples — but what about math and English language arts?), **grade level optimization** (does it provide too much novelty for younger children? What ages best suited?) and **assessment** (such as quasi experimental studies investigating whether students retain content more ably with vs. without VR).

2. **Amount and format of content is limited right now.** While there is a growing amount of content available for VR, it still does not include the wide variety of learning content available in other more accessible formats. There are also very limited resources and tools available for teachers and students to generate their own content or edit content that is available; for many, this will mean using existing content and/or lessons, which may not suit their particular needs very well.
3. P**hysical limitations of using VR with a wide variety of students.** There are a number of issues surrounding the physical limitations of VR: the physical discomfort of some versions of VR that typically increase with the amount of time spent in VR; age limitations on many versions of VR, including Expeditions, which recommends not using it with kids under 13; and students with vision difficulties that may not be able to see the VR content.
4. **Resources required (both financial and technical) in order to implement VR-related instruction in classrooms and educational spaces.** VR technologies, like any new technology, are generally expensive and require a significant investment by the educational agency or group to implement them with any amount of scale. Even less expensive versions of VR, like Cardboard, require fairly recent version of smartphones to be used in the headsets. Other VR technologies are almost prohibitively expensive to be used in classrooms (e.g., a HTC Vive set-up is $500) where they are a supplemental technology. There are also other technology and infrastructure resources that are needed to successful implement these kinds of technologies: charging stations, up-to-date devices, reliable wi-fi (or local networks), ample storage room, and troubleshooting experience or help.

Collaboration among and between students in VR systems is still in its infancy, and there is much work to do in this space. Some VR technologies, such as smartphones, allow for a pseudo-VR mode where, instead of putting the phone up to your eyes, you can keep it at arm's length and use the phone or tablet as a window into a virtual world. This kind of setup could facilitate more collaboration and shared views among students, although it does this at the expense of much of the immersive quality of VR. But again, depending on your learning goals, this might be an appropriate trade-off.

The sheer novelty of VR can also be an issue in classrooms that can impact instruction in multiple ways. First, students could be distracted by their excitement in using a new technology. **Since such excitement fades over time, instructional designers may want to build in extra time in early uses of new technology to get the novelty out of the way so it does not conflict with learning.** Further, short uses of novel technology could over-emphasize the significance of the technology rather than on the content that will result in improved learning outcomes. In other words, the excitement might lead to a spurt of increased student engagement in the lesson but because the excitement wears off, the learning gains may primarily be due to the novelty rather than the actual benefits of the instruction. Research on longer-term use of VR technologies is needed to disentangle this novelty issue and establish more precise thresholds distinguishing between novelty and substantial student engagement.

Projects

Examples of NSF Cyberlearning projects that overlap with topics discussed in this primer.

Augmented and Virtual Reality:

- Catalyzing Scientific Inquiry and Engineering through Wearable Intersubjective Sensation Devices
- EAGER: Making with Understanding
- EXP: Collaborative Research: Cultivating Apprenticeship Learning for Architecture, Engineering, and Construction Using Mixed Reality
- EXP: Collaborative Research: Extracting Salient Scenarios from Interaction Logs (ESSIL)
- DIP: Collaborative Research: Interactive Science Through Technology Enhanced Play (iSTEP)

Stanford Ocean Acidification Experience. A virtual underwater ecosystem where you can experience firsthand what coral reefs are expected to look like by the end of the century if we do not curb our CO_2 emissions. Watch the ocean absorb invisible CO_2 molecules, a coral reef degrade and marine life disappear as the ocean acidifies.

Resources

Google Expeditions – virtual field trips for classroom use
ThingLink – annotate 360 videos and images
zSpace – all-in-one computer with VR and AR capabilities with a suite of learning apps
Alchemy VR – creator of compelling immersive experiences
Immersive VR Education – tools for teachers to create their own content in virtual classrooms
AltSpaceVR – social platform for VR

Readings

References and key readings documenting the thinking behind the concept, important milestones in the work, foundational examples to build from, and summaries along the way.

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Neural Network Models for Natural Language Processing

In addition to original primers, CIRCL occasionally features relevant primers found in the literature. We welcome new primers on similar topics, but written more specifically to address the needs of the cyberlearning community. Have a primer to recommend? Contact CIRCL.

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Title: A Primer on Neural Network Models for Natural Language Processing

Author: Yoav Goldberg, Bar-Ilan University, Israel

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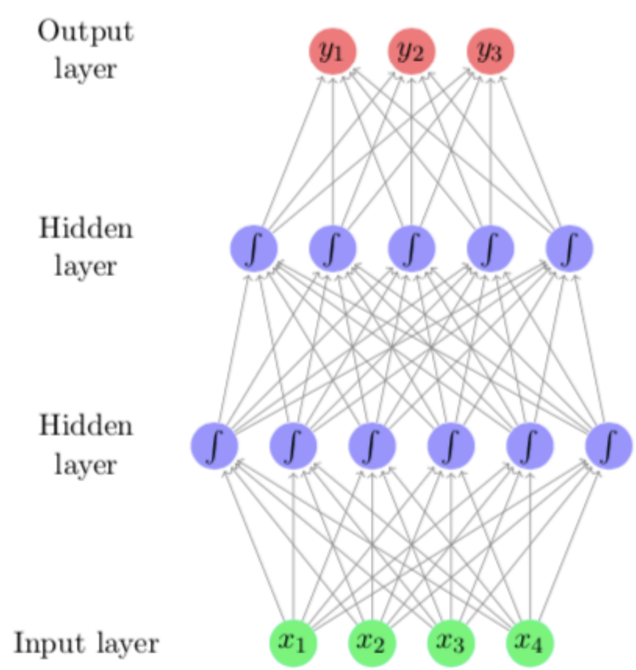

Figure 2: Feed-forward neural network with two hid

Abstract

Over the past few years, neural networks have re-emerged as powerful machine-learning models, yielding state-of-the-art results in fields such as image recognition and speech processing. More recently, neural network models started to be applied also to textual natural language signals, again with very promising results. This tutorial surveys neural network models from the perspective of natural language processing research, in an attempt to bring natural-language

researchers up to speed with the neural techniques. The tutorial covers input encoding for natural language tasks, feed-forward networks, convolutional networks, recurrent networks and recursive networks, as well as the computation graph abstraction for automatic gradient computation.

Citation

Goldberg, Y. (2016). A primer on neural network models for natural language processing. Journal of Artificial Intelligence Research, 57, 345-420.

← Situated Cognition

What is AI Literacy? Competencies and Design Considerations →

This material is based upon work supported by the National Science Foundation under grants 1837463 and 1233722. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the National Science Foundation.

Situated Cognition

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Title: A Short Primer on Situated Cognition

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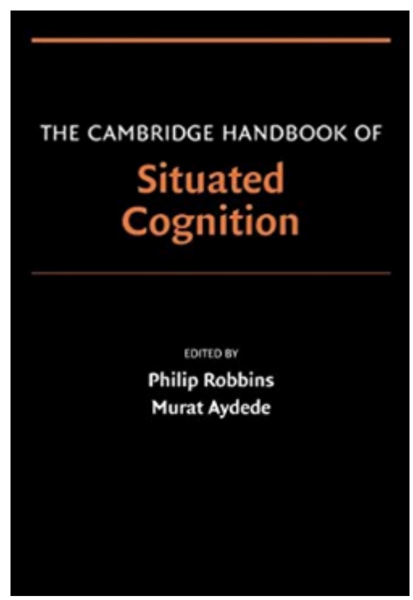
Author: Philip Robbins and Murat Aydede



Abstract

In recent years there has been a lot of buzz about a new trend in cognitive science. The trend is associated with terms like *embodiment, enactivism, distributed cognition*, and *the extended mind*. The ideas expressed using these terms are a diverse and sundry lot, but three of them stand out as especially central. First, cognition depends not just on the brain but also on the body (the embodiment thesis). Second, cognitive activity routinely exploits structure in the natural and social environment (the embedding thesis). Third, the boundaries of cognition extend beyond the boundaries of individual organisms (the extension thesis)… In this brief introductory chapter, we present a bird's-eye view of the conceptual landscape of situated cognition as seen from each of the three angles noted previously: embodiment, embedding, and extension. Our aim is to orient the reader, if only in a rough and preliminary way, to the sprawling territory of this [Cambridge] handbook.

Citation

Robbins, P., & Aydede, M. (2009). A short primer on situated cognition. The Cambridge handbook of situated cognition, 3-10.

Neural Network Models for Natural Language Processing →

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What is AI Literacy? Competencies and Design Considerations

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Title: What is AI Literacy? Competencies and Design Considerations

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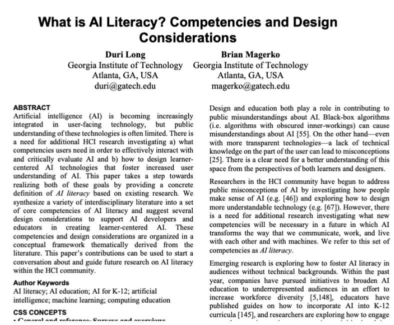
Author: Duri Long and Brian Magerko, Georgia Tech



What is AI Literacy? Competencies and Design Considerations

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ABSTRACT
Artificial intelligence (AI) is becoming increasingly integrated in user-facing technology, but public understanding of these technologies is often limited. There is a need for additional HCI research investigating a) what competencies users need in order to effectively interact with and critically evaluate AI and b) how to design learner-centered AI technologies that foster increased user understanding of AI. This paper takes a step towards realizing both of these goals by providing a concrete definition of *AI literacy* based on existing research. We synthesize a variety of interdisciplinary literature into a set of core competencies of AI literacy and suggest several design considerations to support AI developers and educators in creating learner-centered AI. These competencies and design considerations are organized in a conceptual framework thematically derived from the literature. This paper's contributions can be used to start a conversation about and guide future research on AI literacy within the HCI community.

Author Keywords
AI literacy; AI education; AI for K-12; artificial intelligence; machine learning; computing education

CSS CONCEPTS

Design and education both play a role in contributing to public misunderstandings about AI. Black-box algorithms (i.e. algorithms with obscured inner-workings) can cause misunderstandings about AI [55]. On the other hand—even with more transparent technologies—a lack of technical knowledge on the part of the user can lead to misconceptions [25]. There is a clear need for a better understanding of this space from the perspectives of both learners and designers.

Researchers in the HCI community have begun to address public misconceptions of AI by investigating how people make sense of AI (e.g. [46]) and exploring how to design more understandable technology (e.g. [67]). However, there is a need for additional research investigating what new competencies will be necessary in a future in which AI transforms the way that we communicate, work, and live with each other and with machines. We refer to this set of competencies as *AI literacy*.

Emerging research is exploring how to foster AI literacy in audiences without technical backgrounds. Within the past year, companies have pursued initiatives to broaden AI education to underrepresented audiences in an effort to increase workforce diversity [5,148], educators have published guides on how to incorporate AI into K-12 curricula [145], and researchers are exploring how to engage

Abstract

Artificial intelligence (AI) is becoming increasingly integrated in user-facing technology, but public understanding of these technologies is often limited. There is a need for additional HCI research investigating a) what competencies users need in order to effectively interact with and critically evaluate AI and b) how to design learnercentered AI technologies that foster increased user understanding of AI. This paper takes a step towards realizing both of these goals by providing a concrete definition of AI literacy based on existing research. We synthesize a variety of interdisciplinary literature into a set of core competencies of AI literacy and suggest several design considerations to support AI developers and educators in creating learner centered AI. These competencies and design considerations are organized in a conceptual framework thematically derived from the literature. This paper's contributions can be used to start a conversation about and guide future research on AI literacy within the HCI community.

Citation

Duri Long and Brian Magerko. What is AI Literacy? Competencies and Design Considerations. Accepted to Proceedings of the 2019 ACM Conference on Human Factors in Computing Systems (CHI 2020) (24.3% acceptance rate, Best Paper Honorable Mention).

← Neural Network Models for Natural Language Processing

Mining Big Data in Education: Affordances and Challenges →

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CIRCL Primer: Neuroscience And Education

Contributors: *Judi Fusco*, *Jodi Asbell-Clarke*, *and* *Bernadette Sibuma*
Questions, or want to add to this topic or to a new topic? Contact CIRCL.

Overview

Cyberlearning researchers and neuroscientists are beginning to explore new methods to understand connections between classroom practice, neuroscience, and educational neuroscience. Together, they are investigating questions such as: How can neuroscience impact learning and teaching in the classroom? How can learning and teaching practices inform neuroscience models? What exciting opportunities and questions lie ahead at the convergence of neuroscience and educational research? What ethical and logistical considerations must we keep in mind while designing a research agenda in this area?

From neuroscience to cyberlearning may seem like a far reach. Why now? Advances in technology are enabling researchers to explore connections between neuroscience and learning science in new ways. For example, new methods enable the integration of multiple streams of data to build on multimodal models of learning, using electroencephalogram EEG and other physiological data gathered in classrooms (or labs). More portable and affordable neurological and physiological sensors now make it possible to do brain-based research outside of the lab in more authentic learning contexts, such as classrooms and gaming environments.

The convergence of neuroscience and cyberlearning could provide new insights into why particular interventions help some learners but not others. Perspectives from neuroscience can help refine our understanding about who is helped, how much they are helped, and under what conditions will the interventions may help. Cyberlearning has a key role to play in educational research, particularly as tools and methods enable feasible studies “in the wild” of classrooms and everyday activity. This primer discusses some of the key lessons and issues related to the convergence of neuroscience and educational research. In the next section, we provide a brief overview of neuroscience concepts.

Background Concepts

Generally, research on **cognitive neuroscience** seeks to understand the relationships between brain structures and functions, such as perception, thinking, and learning. For example, cognitive neuroscience research can examine the role of the prefrontal cortex in executive functions and the hippocampus in memory formation. Findings in cognitive neuroscience research may converge with cognitive psychology research. Cognitive neuroscience and **affective neuroscience** research also overlap in the investigation of the relationship between emotional and cognitive processes. Affective neuroscience considers the neural mechanisms involved in emotion. Initially, research on cognitive aspects of learning was separate from research on emotions, but recently neuroscience has shown how some of the same brain regions are involved in both emotional processing and cognitive processing. This relationship has implications for the design and development of learning environments.

In addition, the emerging area of **educational neuroscience** (sometimes called Mind, Brain, Education or MBE) links cognitive neuroscience with educational and learning theories. While some might consider educational neuroscience as a subset that overlaps different fields, others consider educational neuroscience a distinct collaborative attempt to build tools, methods, and frameworks across (human cognitive) neuroscience, (cognitive) psychology, and educational practice "without imposing a knowledge hierarchy" (Howard-Jones, et al., 2016). In the rest of this section we discuss methods, tools, and concepts that are foundational to neuroscience, cyberlearning, and/or to their convergence.

Techniques to Measure Neural Activity. Although direct measures of spatial neural activation and imaging of the brain using fMRI (functional Magnetic Resonance Imaging) or PET (Positron Emission Topography) are not practical in the classroom, there are portable physiological measures—such as fNIRS (functional near infrared spectroscopy), EEG (electroencephalogram), and eye-tracking—that can give an indication of where activity is occurring in the brain in real-world learning environments. Using such portable and less expensive tools, researchers have begun to examine the connections between brain activity and the process of learning in classrooms and everyday settings. In addition, researchers can bring students, teachers, or other types of learners to a lab so that neurophysiological recordings (fMRI or PET) can be collected before and then again after a classroom or other learning experience.

Attention and Executive Function. Attention and executive function are processes that impact how learners take in new information and build knowledge. Learners must attend to salient information, practice the coding of information repeatedly, and recode the information in a variety of contexts. Executive functions include a set of cognitive processes (including metacognition, self-regulation, as well as working memory, arousal, problem-solving, shifting activities, organizing, and self-monitoring) that are fundamental to learners' ability to process and retain new information.

Attention has been argued to be a precursor to executive function, while others argue that executive function is an underlying ability of attention. Cognitive neuroscience studies have examined attention and executive function-related processes that affect performance. For example, brain research supports theories about how the stress or anxiety caused by stereotype threat can hurt performance by putting extra load on a person and reducing their working memory capacity in that situation (Hofmann, Schmeichel, & Baddeley, 2012; Rydell, McConnell, & Beilock, 2009; Mangels, et al., 2012); we also know that media multitasking negatively affects performance on a task (Moisala, et al., 2016).

Several different types of instructional activities have been designed to support attention and executive functions. Digital and non-digital games as well as curriculum interventions have been designed to focus on improving executive functions. In addition, many neurogames that include attention and executive function tasks inspired by neuroscience research are being examined to determine if they can serve as reliable measures of performance. Cyberlearning technologies could potentially link non-classroom types of interventions with classroom work to create new technologies and genres for learning. NSF has sponsored work on executive functions in educational neuroscience to better understand if multi-factor EF training through a novel-game based approach leads to better academic achievement, especially in math and reading.

Social-Emotional Connections. Cognitive, socio-emotional, and physiological process are part of all learning processes. Neuroscience has shown that cognitive functions depend on activity from areas of the brain traditionally thought of as “emotional” areas (e.g., amygdala and hypothalamus) thus emotional functions are actually part of systems traditionally thought of as cognitive (Pessoa, 2008). From neuropsychology, Damasio (1999) found that in patients suffering from brain damage to areas associated with emotional processing but who otherwise had cognitive processing areas intact, performance was compromised on cognitive tasks such as decision making and learning. In educational neuroscience, Immordino-Yang (2015) examines how emotional activation can help with learning. Lindquist and colleagues (2012) add evidence to the need for unifying the cognitive and emotional views and propose a more psychological constructionist (Lindquist and Barrett, 2008) approach to thinking about emotion. This and related research may have implications for thinking about affect and emotion in cyberlearning research.

Mirror neurons or mirror systems have been investigated as part of how we connect with others. The mirror system is a network of brain areas which process other people’s actions in a way that is similar to how our own actions are carried out. The mirror system may play a role in how we learn through observation, how people empathize with one another, and how language developed in our species (Rizzolatti, Fogassi, Gallese, 2006). Related research has shown that when we see an individual who we find likeable experiencing pain, we show an empathic response to his or her pain. However, if we see someone for whom we feel that the pain might be justified (e.g., as a punishment for unfair actions), fMRI scans show that we find satisfaction from their pain—men more so than women (Singer, Seymour, O’Doherty, Stephan, Dolan, & Frith, 2006). Research from psychology and neuroscience related to mirror systems, Theory of Mind, empathy, and social cognition might serve to inform the structuring of social interactions that could be relevant to cyberlearning researchers as they design learning environments. In addition, the activity of neural mirroring systems when researching observational learning (e.g., skill acquisition) should be considered.

The default mode network (DMN) of the brain (Raichle, 2015), or the “resting state” of the brain, may be important for understanding learning and learning environments (Howard-Jones, Jay, Mason, & Jones, 2015; Immordino-Yang, Christodoulou, & Singh, 2012). The DMN is typically not active during cognitive tasks, but is active during tasks involving episodic memory or understanding the self in relation to the work in “constructive internal reflection” (Immordino-Yang, 2016). Other research on the DMN shows that it overlaps with areas of the brain that are responsible for tasks related to social cognition (Mars, Neubert, Noonan, et al., 2012; Li, Mai, & Liu, 2014; Lieberman, 2013). Recent research shows that connectivity of the DMN to the prefrontal cortex can be affected by trauma and poverty (Weissman, et al., 2018). The functional role of the DMN is still being determined; it may play a role to help with automatic responses as well as an important role in the transition between cognitive tasks and not just resting state (Smith, et al., 2018; Vatansever, et al., 2017). Much research is underway to better understand the role and function of the DMN.

Neuroscience research on social cognition and learning shows us how social interactions are important in learning, and how they seem to be required for learning language in infants (Kuhl, 2011). From this literature we may gain ideas about how to design cyberlearning systems in ways that will facilitate the socially-contingent aspects of learning. This, in turn, may help improve learning outcomes (Lieberman, 2013; Lieberman, 2012; Davachi, Mitchell, & Wagner, 2003; Mitchell, Macrae, & Banaji, 2004). Much work in the learning sciences is guided by the importance of social interactions (Lave & Wenger, 1991; Vygotsky, 1978) and research findings from neuroscience that show how “our brains are wired to connect” provide additional evidence for the importance of social interactions in learning and that learning is a very social endeavor for humans (Lieberman, 2013).

Much research has been done on the emotional response of stress, since it influences learning in profound ways. Early stressful life situations, such as poverty or trauma to the child or in the family, can cause delays to the development of executive functions (Barr, 2018). From research we learn that stress can be toxic and alter brain structures. Animal models suggest stress leads to excess corticosterone secretion and that leads to neurotoxicity in areas of the brain such as the hippocampus and prefrontal cortex, two areas involved in memory and executive function (Carrion & Wong, 2012). The way caring adults (parents, teachers, or others who are invested) respond can have positive or negative effects. The research on stress and emotion from the neuroscience perspective should be considered by learning researchers since there may be important implications for cyberlearning work.

Key Lessons

In this section, we discuss lessons learned from projects that have helped show the benefits of neuroscientists and learning or education researchers working together.

Computer Games, School Learning, and Neuroscience. Providing evidence of changes in the brain, McCandliss (2010) reports on results from a randomized control trial where kindergarten children played Graphogame, a game to help children master the association between a letter and its corresponding sound. Behind the scenes, algorithms analyzed a child's performance to provide lessons that were challenging and engaging but not too difficult to be frustrating. Repeated measures fMRI showed that in the course of 8 weeks with on average 224 minutes of gameplay, the "brain circuit of the visual system and the language system" that is necessary for reading developed more in those who played the game (Brem et al., 2010). Reading researchers can also see when the reading circuit isn't developed and new interventions can be developed. Research by Bers and colleagues is using fMRI to examine the cognitive and neural basis of computer programming in young children and how it engages the brain regions used in language learning (fronto-temporal) vs. general problem solving (fronto-parietal) to better understand effective learning trajectories.

Spatial Thinking Skills and STEM Achievement. Some evidence links spatial ability with future STEM attainment. Understanding the mechanism for why spatial skills help in future STEM attainment could lead to new interventions to help close the gap between those who achieve later success and those who don't. For example, an NSF project led by Adam Green is examining the effects of spatial thinking skills on high school students studying geoscience and whether spatial training might reduce gender differences. In particular, the project is looking at neural, behavioral, and educational data from students in a geospatial course designed to improve spatial thinking with such data from peers in a non-spatially-based advanced STEM course. This project bridges classroom experiences with neuroscience by doing pre and post course MRIs (both functional and structural) and serves as one model for doing work that brings together the classroom and neuroscience.

Embodiment and What it Means to Have an Embodied Learning Experience. Recent neuroscience research has shown that thinking—even in domains considered very conceptual and symbolic (e.g., mathematics)—is linked to an embodied understanding through our sensory motor system (Gallese & Lakoff, 2005; Beilock, 2016). Similar to research showing that emotion and cognition are linked; for example, imaging studies show how sensory systems such as vision and touch integrate with each other and with brain systems typically considered to be "cognitive" (e.g., those involved in conceptual understanding, planning, and imagination; Gallese & Lakoff, 2005). NSF cyberlearning researchers Abrahamson and Lindgren (2014) discuss embodiment and embodied design in learning activities and environments; see also Lindgren's GRASP project.

Virtual Reality and Neuroscience. Cyberlearning and neuroscience are both investigating virtual reality (VR). Concepts developed in cognitive neuroscience are important to understand and improve VR technology (Herbelin, Salomon, Serino, & Blanke, 2016). Some people call VR an embodied technology for the ability it has to give the user an experience of "presence" in a non-physical world and can allow for immersive experiences not possible in the real world. Since VR can manipulate perception and engagement, VR may lead to different ways of learning. Findings from neuroscience and learning are likely to inform one another and lead to a more convergent understanding of learner perception in VR.

Multimodal Research. Portable measures of brain activity such as fNIRS or EEG, and eye tracking, have led to studies of the mind-body connection through multimodal analysis as well as neurogaming research and development. Multimodal analysis uses data detected from different modalities (e.g., face, voice, posture, text) and physiological measures to create a more nuanced picture of the effects of different environmental stimuli and activities on the learner. By examining the time course of changes in activation across different streams of data from physiological sensors and data from logs of clicks that are generated in games or other digital environments, researchers can better understand the information processing occurring in the brain. The data may converge to relay a coherent image of a learner's state, or indicate discrepancies that may not be apparent. Emerging neurocognitive measures are being developed for working memory capacity, the role of the frontal lobe in tasks, and cognitive load using EEG, pupillometry, eye tracking, and fNRIS (Meiri, et al., 2012; Klinger, 2010; Antonenko, Paas, Grabner, & Van Gog, 2010).

An especially relevant area for cyberlearning is multimodal analysis of user data in human computer interaction studies associated with the development of affective computing interfaces, which seek to use information about a user's emotional state to better tailor a response. Predictions of emotional states can be made through various modality measures and multimodal analysis. With the increasing affordability and portability of EEG, researchers can now use patterns of brain activity as a modality measure in response to specific stimuli or events using event-related potentials (ERPs), which may lead to more accurate assessments of an individual's emotional state. Theoretical understanding of the response of the brain during feedback-based learning is now mature enough to begin looking at these ERPs in real-world learning situations. Researchers are also using multimodal analysis to study collaborative learning and socio-emotional experiences through changes in gaze, gesture, and posture (Worsley, 2017). Multimodal research, generally, could help cyberlearning researchers better understand what is happening in learners during different individual and collaborative tasks and in different environments. A recent review by Lane & D'Mello (2019) discusses physiological monitoring and intelligent learning environments.

Issues

In 1997, the gap between education and neuroscience was said to be too wide to bridge (Bruer, 1997). In 2008, Varma and colleagues discussed scientific concerns around methods, data, theory, and philosophy as well as more pragmatic concerns about costs, timing, locus of control, and pay-offs as differences and opportunities. Twenty years after the discussion of the "too wide" of gap, there are still discussions about differences and very real scientific and pragmatic concerns, but the literature suggests that the gap is narrowing. There has been a real "initial attempt to locate educational neuroscience within the learning sciences" even if it is still very nascent (Bruer, 2016).

In a recent debate, Bowers (2016), Gabrieli (2016), and Howard-Jones and colleagues (2016) exchanged their perspectives on the **promise of educational neuroscience to inform education**. Bowers (2016) initially argued that neuroscience (cognitive neuroscience) would not be useful to improving teaching in the classroom or for the development of interventions for those with learning difficulties. He states that neuroscience does not add anything to the enterprise above what psychology already does, and goes further to claim that some things neuroscience tells us are "trivial" (e.g., the importance of sleep in the learning process and that a child who lives in fear will have a hard time learning). Gabrieli counters that educational neuroscience is better conceived as a basic science that seeks to inform education topics, such as the relationship between brain development and learning differences, rather than being focused on practical applications to improve classroom teaching more immediately. Gabrieli maintains that research in educational neuroscience should not be evaluated based on immediate practical results. On the other hand, understanding the relationship between cognitive systems and emotional systems during the learning process—and designing environments to support those processes—seems like important convergent work for neuroscience and other educational research.

A bridge between neuroscience and education is starting to occur, but still in early stages. Tommerdahl (2010) suggested a way for thinking about a bridge between neuroscience and education and proposed a model to link neuroscience, cognitive neuroscience, psychological theories, educational theory, and the classroom. She proposed that a translation has to be done through those five levels to have rigorous, high quality methods for the classroom that work well in the classroom. Schwartz, Blair, and Tsang (2012) discuss two ways for bridging between education and neuroscience. One way, the most prevalent way, is when the neuroscientist looks for potential applications of their work in education; the second way is when educational researchers take theoretical problems to neuroscience and work convergently with neuroscientists to see if they can solve these together. Like Tommerdahl, Schwartz and colleagues also suggest that the different levels, from neuroscience to the classroom, need to explain the same phenomenon and make links between the different levels. Both papers argue for the importance of this convergence.

"**Neuromyths**" that are perpetuated by popular culture add to common misunderstandings about the brain and learning. Commercial "brain-based" products promising improved knowledge and cognition (often in an easy, fun manner) with no evidence behind their claims take advantage of neuromyths. Some common examples of such myths include thinking that individuals only use 10% of their brain, individuals are "left-brained" or "right-brained", or that listening to music by Mozart will increase intelligence. One approach to linking education and neuroscience has been to give teachers and practitioners a better understanding of neuroscience so they can determine what findings from neuroscience research are scientifically rigorous and may be most applicable to their classroom practice (Dubinsky, 2010).

If practitioners, parents, and administrators have a better understanding of how the brain works, they can help resist the "brain enhancing" products that have been inaccurately labeled as "backed by brain sciences" by marketing departments (Pasquinelli, 2012). Many of these products have not had rigorous testing and may or may not work. There are potential products that could help people learn or help them focus their executive function abilities. Ideally, research from neuroimaging could help create educational interventions for reading and mathematics (e.g., Boets et al, 2013; Hoeft, et al, 2011; Schlagger & McCandliss, 2007) but much of this research is still in development. However, there is a need to make sure that we make changes based on evidence and understand if they work in classrooms and what they bring to the learning process. In this, teachers and learning scientists should be an integral part of the process. Cyberlearning research opens the door for studying the promise and efficacy of applying new neuroscience technologies and methods in real world learning situations, including classrooms and informal settings.

Projects

Examples of NSF Cyberlearning projects that overlap with topics discussed in this primer.

Neuroscience

> The cognitive and neural mechanisms of computer programming in young children: storytelling or solving puzzles?

Multimodal Data/Environments

EAGER: Leveraging Behavioral and Physiological Feedback in the Design of Affect-Sensitive Distance Learning

EXP: Paper Mechatronics: Advancing Engineering Education Through Computationally Enhanced Children's Papercrafts

EAGER: Developing Teaching Assistant Expertise with a Sensor-Based Learning System

EAGER: Mobile City Science: Youth Mapping Community Learning Opportunities

EXP: Linking Eye Movements with Visual Attention to Enhance Cyberlearning

Other related projects:

Collaborative Research: Revealing the Invisible: Data-Intensive Research Using Cognitive, Psychological, and Physiological Measures to Optimize STEM Learning uses neuro-imaging to measure student engagement and learning (NSF grants 1417967, 1417456, 1418122)

GRASP (GestuRe Augmented Simulations for supporting exPlanations) is an NSF-funded collaboration between the University of Illinois at Urbana-Champaign and Concord Consortium that aims to understand the role that gestures play in reasoning about critical concepts in science.

SL-CN: Contributions of Executive Function Subdomains to Math and Reading Cognition in the Classroom examines how executive functions contribute to academic performance and whether weak EFs can be enhanced with cognitive training.

Cognitive and Neural Indicators of School-based Improvements in Spatial Problem Solving (NSF 1420481) and Neural and Cognitive Strengthening of Conceptual Knowledge and Reasoning in Classroom-based Spatial Education (NSF 1661065) examine the link between spatial ability and future STEM attainment and how spatial training may reduce gender differences.

Resources

CIRCL Webinar: Neuroscience and Cyberlearning: A Convergence Conversation

NSF

Cognitive Neuroscience Program
Science of Learning Program

Understanding the Brain

Journals

Mind, Brain, and Education
Social, Cognitive, Affective Neuroscience (SCAN)
Trends in Neuroscience and Education

Associations

American Educational Research Association (AERA) Special Interest Group on Brain, Neuroscience and Education

British Educational Research Association (BERA) Special Interest Group on Neuroscience & Education

Cognitive Neuroscience Society (CNS)

International Mind, Brain and Education Society (IMBES)
Learning & the Brain Conference

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Mining Big Data in Education: Affordances and Challenges

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Abstract
The emergence of big data in educational contexts has led to new data-driven approaches to support informed decision making and efforts to improve educational effectiveness. Digital traces of student behavior promise more scalable and finer-grained understanding and support of learning processes, which were previously too costly to obtain with traditional data sources and methodologies. This synthetic review describes the affordances and applications of microlevel (e.g., clickstream data), mesolevel (e.g., text data), and macrolevel (e.g., institutional data) big data. For instance, clickstream data are often used to operationalize and understand knowledge, cognitive strategies, and behavioral processes in order to personalize and enhance instruction and learning. Corpora of student writing are often analyzed with natural language processing techniques to relate linguistic features to cognitive, social, behavioral, and affective processes. Institutional data are often used to improve student and administrational decision making through course guidance systems and early-warning systems. Furthermore, this chapter outlines current challenges of accessing, analyzing, and using big data. Such challenges include balancing data privacy and protection with data sharing and research, training researchers in educational data science methodologies,

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analyzing, and using big data. Such challenges include balancing data privacy and protection with data sharing and research, training researchers in educational data science methodologies, and navigating the tensions between explanation and prediction. We argue that addressing these challenges is worthwhile given the potential benefits of mining big data in education.

Citation

Fischer, C., Pardos, Z. A., Baker, R. S., Williams, J. J., Smyth, P., Yu, R., … Warschauer, M. (2020). Mining Big Data in Education: Affordances and Challenges. Review of Research in Education, 44(1), 130–160. https://doi.org/10.3102/0091732X20903304

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Algorithmic Fairness in Education →

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Authors: René F. Kizilcec and Hansol Lee

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[Submitted on 10 Jul 2020]

Algorithmic Fairness in Education

René F. Kizilcec, Hansol Lee

Data-driven predictive models are increasingly used in education to support students, instructors, and administrators. However, there are concerns about the fairness of the predictions and uses of these algorithmic systems. In this introduction to algorithmic fairness in education, we draw parallels to prior literature on educational access, bias, and discrimination, and we examine core components of algorithmic systems (measurement, model learning, and action) to identify sources of bias and discrimination in the process of developing and deploying these systems. Statistical, similarity-based, and causal notions of fairness are reviewed and contrasted in the way they apply in educational contexts. Recommendations for policy makers and developers of educational technology offer guidance for how to promote algorithmic fairness in education.

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Abstract

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Kizilcec, R. F., Lee, H. (Forthcoming). Algorithmic Fairness in Education In W. Holmes & K. Porayska-Pomsta (Eds.), Ethics in Artificial Intelligence in Education, Taylor & Francis.

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Authors: Alexander Richter, Tamara Gačić, Bernhard Kölmel, Lukas Waidelich, and Patrice Glaser

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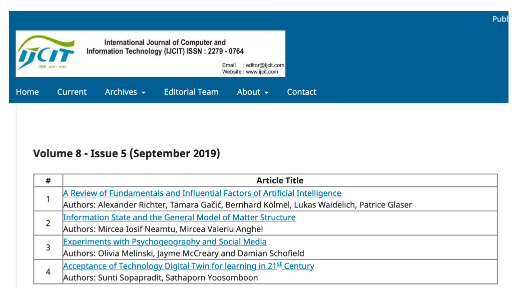
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4	Acceptance of Technology Digital Twin for learning in 21st Century Authors: Sunti Sopapradit, Sathaporn Yoosomboon

Abstract

Artificial intelligence (AI) is a trend that is currently leading to controversial discussions. On the one hand, it is a hyped technology with great potential to change the way people live and work.On the other hand, humans fear the possible consequences of misguided superintelligence based on the example of well-known movies. There are also numerous prominent scientists and technology pioneers who have very different opinions on this topic. In order to contribute to that discussion, this paper presents the drivers, advantages, disadvantages and challenges for the use of AI applications based on a literature search. In addition, historical developments, common definitions, types and functionalities of AI are described.

Citation

Richter, A., Gačić, T., Kölmel, B., Waidelich, L., & Glaser, P. (2019). Algorithmic Fairness in Education. *International Journal of Computer and Information Technology*, 8(5), 142-156.

← Algorithmic Fairness in Education

Practicing Connections: A Framework to Guide Instructional Design for Developing Understanding in Complex Domains →

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Smart and Connected Communities for Learning

Contributors: Judi Fusco, Julie Remold, Jeremy Roschelle and Patti Schank
Questions, or want to add to this topic or to a new topic? Contact CIRCL.

Overview

Smart and connected communities for learning (SCCL) leverage networks and technology to foster lifelong, lifewide learning that spans multiple settings or locations. Successful efforts to bridge learning experiences across settings demonstrate marked improvement in (a) participants' awareness of opportunities for learning in their locale, (b) their ability to engage in and sustain related learning experiences within and across multiple places, and (c) their experience of their community as interconnected in support of learning.

SCCL often happens in **more than one place** (across communities) and **leverages technology** (such as cyber physical sensors, Internet of Things, wearable technologies, mobile systems, and big data) to provide continuity across settings. SCCL takes place in both formal or informal learning environments, across neighboring communities, in a "smart city", or even across the country or world. Another key element of an SCCL is that it addresses needs or **solves problems that come from the communities**. A goal should be to make "more livable, workable, sustainable, connected communities" with citizens who are able to contribute and continue to improve their world. Smart and connected also involves **distributed human and social capital to solve problems**. In SCCLs, a team of educators, community representatives, researchers, and others design, implement, and evaluate potential solutions to a problem identified by the community (e.g., local environmental concern, food desert, workforce issues).

An example of an SCCL might be an program that links outside of school activities with in-school activities to allow learners to make meaning of or apply what they have learned in school (e.g., use math practices introduced in school to visualize data on a local environmental issue), and reach out to the community to share their learning and potentially impact on a related community issue. The New York Harbor School's Billion Oyster Project is an instance of this: schools, businesses, nonprofits, and individuals are working together (10 partners) to restore 1 billion live oysters to NY Harbor and restore the ecology and economy of their local marine environment.

As Eamonn Kelly reminds us (Kelly et al., 2016), in working with communities, it is important to remember all of the connections they have, and that they are part of a larger, complex system that involves citizens, a need for privacy, natural disasters, changing politics, and other issues. A change to one part of the system may affect other parts of the system in ways that are unanticipated. The intervention activities undertaken in a community will likely need to be iterative, flexible, and collaborative; unintended consequences should be documented, accounted for, and or addressed as possible.

Research on SCCLs should lead to new "powerful and resilient models and solutions, efficiencies in resources, advances in science and engineering knowledge and practices, and STEM education practices and research" (Kelly, STELAR webinar). Qualitative and quantitative indicators that allow researchers to quantify subjective outcomes including "personal quality of life, community and environmental health, social well-being, educational achievement, or overall economic growth and stability" (NSF DCL) are necessary. Models should include community roles and capacity-building for educators. Finally, SCCLs need to document their progress and share data and methods to help the field build new models and scale impact. Smart and connected communities for learning is a natural progression and could partner with projects on smart cities as well as work on learning across settings (or "crossover learning"; Sharples et. al., 2015). Gianni & Divitini (2015, p. 30) note that "While the role of technology in Smart Cities has been widely recognized and addressed, there seems to be no established field of research that connects Smart Cities to Learning." In the article, they go on to outline the learning theories and research methods, types of research and technologies used in articles linking learning and Smart Cities. The also note that Internet of Things is not well explored in the research. The methods and learning theories in the Smart City Learning literature could inform SCCL. What seems to make SCCL distinct from Smart City Learning is SCCL's focus of connecting people across settings to enhance learning.

Related Work

Related CIRCL Primer: The Cutting Edge of Informal Learning
The ideas behind SCCLs come from the growing body of research on smart cities and from research on the relationship between learning across settings.

Smart Cities. As populations continue to increase in urban areas, with a projected 70% of the population of the world concentrated in cities by 2050, there is a huge challenge, need, and opportunity to make cities "smart." Smart Cities work began around 2005, but the definition of what "smart" means is still being debated (Angelidou, 2015). Many of the approaches include a focus on energy-efficiency for green cities, smart technologies to improve or monitor water use or conditions, transportation options that are more convenient and accessible, urban manufacturing, and urban farming to improve housing, jobs, quality of life, and sustainable growth; and security for data and people.

Smart approaches in Smart Cities engage citizens in unobtrusive ways through the Internet of Things, sensors, wearable technologies, and mobile systems, leveraging infrastructure to integrate and use the data across agencies, schools, and informal settings. Nam and Pardo (2011) discuss three dimensions: technological (the integration of infrastructures and technology-mediated services), human (social learning for strengthening human infrastructure), and institutional (governance for institutional improvement and citizen engagement). Buchem and Pérez-Sanagustín (2013), take a humanistic perspective where smart cities are thought of as ecosystems that include technologies and technological infrastructures but go on to support the transformation of people into smart, engaged citizens who are learning and participating. The focus on people is purposeful; if just a technological focus is taken, it may result in passive people who live in the city rich with technological infrastructure. People are crucial for solving societal, environmental, political, and economic challenges. The humanistic perspective is essential to help us understand how technology can foster lifelong, lifewide learning across settings in communities.

Learning across settings and connected learning. Through engagement in activities based on personal interest and with others, connected learning strives to foster critical thinking and collaboration between learners and others in the community (Ito et al., 2012). Connected learning can also be seen as context-aware and ubiquitous learning; Yang, Okamoto, Tseng (2008) identify mobility, location awareness, interoperability, seamlessness, situation awareness, social awareness, adaptability, and pervasiveness and key characteristics. Regardless, learners and their interests are the main focus, and digital media and networked systems are used to engage diverse youth in authentic experiences that provide new pathways to learning. Three principles of connected learning are that it:

1. Is **production centered**. Because the work is production centered, it allows for active, engaged, hands-on learning. When the production involves digital tools and media, the work can be easily shared, remixed, and curated.
2. Has a **shared purpose**. The shared purpose or common goals of the work naturally help foster intergenerational and cross-cultural interactions with experts and interested others; artistic

expression, civic projects, or other collaborations or competitions are ways of creating meaningful shared purposes.

3. Is **openly networked**. Openly networked means that youth can more easily make connections to resources and cross boundaries between school and informal settings with their work.

Connected learning tries to create multiple points of entry to meaningful participation in areas of youth interest to help prepare youth for both formal work and a social life that includes civil society, family, and community life. Connected learning aims to be at the intersection of youth personal interests, academic focus of schools, and peer culture, connecting these three areas purposefully and selectively to further learning goals (related to the 3 principles above) by (a) connecting youth with resources in different settings and with institutional support, (b) helping them make connections from their interest to academic relevance, and © helping them make social connections with peers or adults who can further their learning. As Ito and colleagues (2012, p. 76) summarize, “Learning is most resilient when it is linked and reinforced across settings of home, school, peer culture and community.” Technology can help achieve this goal for learning because of the ways it can help connect people, classrooms, community, and home, and help learners create and contribute.

Issues

- How to design for community-scale learning using emerging technology affordances?
- How to connect learning across settings while leveraging the context in each setting?
- What projects, communities, and people should be involved in each project?
- How to measure and reward learning for individuals, groups, and communities?
- How to use data to continuously improve smart and connected learning communities while insuring data privacy? What issues may arise?
- How can different institutions with overlapping goals establish sustainable partnerships for SCCL?
- How might institutions of knowledge, places for learning, and the roles of mentors develop and evolve within connected learning communities? What are ways projects can connect to each other?
- What new research about learning becomes possible in smart and connected learning communities?
- How do we ensure that youth get exposed to points of entry in smart communities? (Maybe a “smart situation” could help more youth find their interests, make potentials connections, and create more opportunities?)

Projects

Examples of NSF Cyberlearning projects that overlap with topics discussed in this primer.

- DIP: ScienceKit for ScienceEverywhere - A Seamless Scientizing Ecosystem for Raising Scientifically-Minded Children
- DIP: Developing Frameworks, Tools and Social Practices to Support Effective Instructor use of Online Social Learning Networks in Blended Learning Models

Science Everywhere is an NSF funded research study aimed at understanding how technology can engage entire communities in science learning.

The Digital Youth Network, an infrastructure for connecting youth to each other in after-school contexts that includes a variety of tools for digital inquiry and expression.

The Chicago City of Learning is an initiative that joins together learning opportunities for young people in a way that allows them to think about, pursue, and develop their interests.

The Remake Learning Network is a professional network of educators and innovators working together to shape the future of teaching and learning in the Greater Pittsburgh Region.

Curriculum and Community Enterprise for New York Harbor Restoration in New York City Public Schools, an NSF TEST/ICER project.

Queens 2020 is an initiative to create a partnership between the museum and the communities it serves.

Creating a STEM Pipeline for Low Income and Immigrant Youth, an NSF ITEST Collaborative Research project.

Several ITEST projects discussed in this STELAR Webinar

Resources

STELAR Webinar: Smart and Connected Communities: An ITEST Perspective. Webinar recording, with presenters Eamonn Kelly, John Cherniavsky, Lauren Birney, and Leslie Rupert Herrenkohl.

NSF Press Release (Sept 2015): Cultivating smart and connected communities.

NSF DCL: Supporting Research Advances in Smart and Connected Communities to stimulate research and new technologies to enable more livable, workable, sustainable, and connected communities.
Connected Learning DML Research Hub

Smart Cities:

Bannan, B. (2015). A Smart City Case Example: Toward an Integrative Learning Design Framework for Research, Design and Analysis (Presentation).

Lapowsky, I. (2016). The White House Wants You to Build Tools to Improve Our Cities. WIRED blog post.
Market Place of the European Innovation Partnership on Smart Cities and Communities, including Barcelona is the World's Smartest City 2015 and Students in Mechelen, Belgium more at ease than teachers with cross sector approach.

Correa, D. (2015). Tackling Local Challenges through Smart Cities (slides). White House Office of Science and Technology Policy.

NSF Workshop on Smart Cities Dec. 3 & 4, 2015 – Links to pdfs from talks, including the one from Dan Correa.

Smart Cities to Smart Regions workshop from EC-TEL 2015 and promoted by the ASLERD (Association for Smart Learning Ecosystems and Regional Development) links to papers from it are available.

Readings

References and key readings documenting the thinking behind the concept, important milestones in the work, foundational examples to build from, and summaries along the way.

Angelidou, M. (2015). Smart cities: A conjuncture of four forces. Cities, 47, 95-106.

Bollier, D. (2016.) The city as platform: How digital networks are changing urban life and governance. Washington, D. C.: Aspen Institute.

Buchem, I.; Pérez-Sanagustín, M. (2013). Personal Learning Environments in Smart Cities: Current Approaches and Future Scenarios. Learning and Diversity in the Cities of the Future. Proposes Personal Learning Environments (PLE) that are constructed as a person moves in physical and virtual spaces. This merging of physical and virtual extend the experience and bring in new information that is not spatially bounded to allow for flow across times, topics, and locations and to create opportunities for learning to occur networked spaces. Could involve augmented reality, mobile tagging (with QR codes or geotagging), digital badges, mobile social media, smart objects, and wearable technologies. The pedagogical strategies and technological uses need to be designed and studied for effectiveness.

Caldwell, G., Foth, M. Guaralda, M. (2013). An urban informatics approach to smart city learning in architecture and urban design education. Interaction Design and Architecture(s) Journal – IxD&A, N. 17, pp. 7-28

Christopoulou, E., & Ringas, D. (2013). Learning Activities in a Sociable Smart City. Interaction Design and Architecture(s) Journal – IxD&A, N. 17, 2013, pp. 29-42.

Del Fatto, V., & Dodero, G. (2013). Geographic Learning Objects in Smart Cities Context. Interaction Design and Architecture(s) Journal – IxD&A, N. 17, 2013, pp. 53-66

Diaz, P., Divitini, M., & Ramos, F., (Eds.) (2015). Smart City Learning: Opportunities and Challenges. N. 27, Special Issue. Includes a focus section on “Innovation in Human Computer Interaction: What can we learn from Design Thinking?”

Gianni, F., & Divitini, M. (2015). Technology-enhanced Smart City Learning: a Systematic Mapping of the Literature. In Smart City Learning: Opportunities and Challenges (Special Issue).

Ito, M. Gutierrez, Livingstone, K. S., Penuel, B., Rhodes, J., Salen, K., Schor, J., Sefton-Green, J., & Watkins, S. C. (2012). Connected Learning: An Agenda for Research and Design.

Mikulecký, P. (2012), Smart Environments for Smart Learning. DIVAI 2012 – 9th International Scientific Conference on Distance Learning in Applied Informatics.

Pérez-Sanagustín, M.; Buchem, I.; Delgado Kloos, C. (2013). Multi-channel, multi-objective, multi-context services: The glue of the smart cities learning ecosystem. Interaction Design and Architecture(s) Journal – IxD&A, 17, pp. 43-52. Discusses needed services to connect and orchestrate the technology-enhanced learning ecosystems ecosystem, to help mediate the information flow. They highlight multi-channel, multi-objective, and multi-context as key attributes to support active and participatory processes.

President's Council of Advisors on Science and Technology (2016). PCAST Report to the President on Technology and the Future of Cities, February 2016.

Sharples, M., Adams, A., Alozie, N., Ferguson, R., Fitzgerald, E., Gaved, M., McAndrew, P, Means, B., Remold, J., Rienties, B., Roschelle, J., Vogt, K., Whitelock, D., & Yarnall, L. (2015). Innovating Pedagogy 2015: Open University Innovation Report 4. Milton Keynes: The Open University.

Yang, S. J. H., Okamoto, T., & Tseng, S..S. (2008). Context-Aware and Ubiquitous Learning (Guest Editorial), Educational Technology & Society, 11 (2), pp. 1-2.

Zhang, B., David, B., Yin, C., & Chalon, R., (2013). Contextual Mobile Learning for professionals working in the "Smart City". Interaction Design and Architecture(s) Journal – IxD&A, N. 17, 2013, pp. 67-76.

The Center for Innovative Research in CyberLearning

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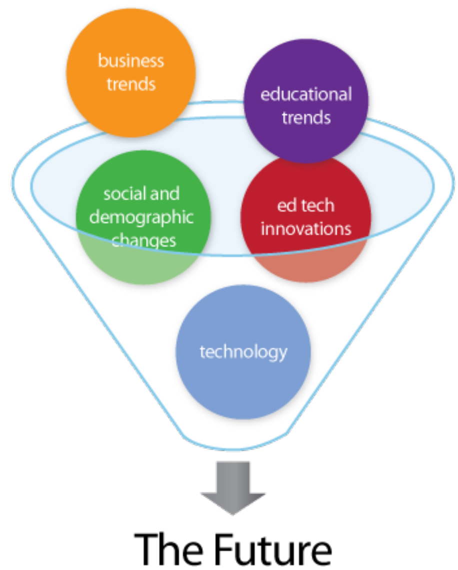
Looking Ahead: Trends that Will Shape Cyberlearning

Contributors: Avron Barr and Joyce Malyn-Smith
Questions, or want to add to this topic or a new topic? Contact CIRCL.
Latest update: Added 2016 Internet Trends Report (6/21/16)

Overview – Five Kinds of Trends to Watch

The ambition of cyberlearning research is to have a broad and profound impact on the products and methodologies used by learners and adults who support their learning (including teachers, coaches, mentors, etc.). To increase the relevance of our work, innovators should try to understand how learning is changing, which changes will have enduring importance, and what kind of adoption timeframes they should anticipate. Technology is not the only driver of change in learning. This primer paints a broad-brush picture of the landscape at this moment. The Resources section suggests some of places to find up-to-date coverage of trends and issues, such as the NMC Horizon Reports.



This primer organizes two dozen current trends that we feel are most relevant into five categories: **social and demographic changes**, **general technology developments**, **innovations in educational technology**, **changes in the way we teach**, and**business trends**. While we focus on the United States, other markets are experiencing similar changes. Where possible, we've tried to suggest some of the implications for cyberlearning research.

The Trends

Social and demographic changes

Education systems respond to social needs. Looking back at the design of school in the early 1900s, for example, the goal was to transform rural and immigrant children into literate factory workers. It's easy to point to ways that our system is already out of date, but society continues to evolve in ways that will change its demands on the education system.

Skill needs and national economic policy. Today's intense efforts to find innovative solutions to STEM education reflects the importance of changing workforce needs in a global economy driven by technology. Today it's computer programming, next year it may be an intense effort to improve the way we teach foreign languages to youngsters. Many jobs require high-levels of preparation and continuous learning. There is a general belief that in the post-industrial age, our country's economic well-being is linked to the ability of our citizens to think, create, and innovate using the affordances of technology. In addition to the 3Rs, and traditional employability skills, workers need new types of skills to innovate and solve problems, including techniques to support complex communication, collaboration, computational thinking, intergenerational workplaces, and the ability to use and customize the technology-enabled tools and information resources.

Demands of today's learner. Rapid advances and the ubiquity of technology have altered the ways today's learners learn. Trends like rising digital literacy benchmarks, anywhere/anytime learning, digital entertainment, and the emergence of a new culture of power users of technology, have resulted in a generation of learners who expect high-fidelity interactions, require more control over their learning environments, and demand the ability to adapt their technologies to their own purposes.

Part-time learners. We're seeing a dramatic rise in the number of students who opt out of full-time schooling because they can't afford full-time, because they're busy with a job and/or a family, or because they just don't want to be a full-time student. For example, economic realities and questions about the value of a 4-year residential experience have created a growing population of higher-ed students who opt for part-time.

Independent learners. There is a growing segment of learners who are not associated with an educational institution or who are linked part-time to several providers. They may, for example, be working toward certification in a particular job-related skill or attending individual courses from a school or an online provider.

Disappearing middle class students. After the second world war in the US, the GI bill opened the 4-year residential college experience to the masses. Education in turn allowed people to move into middle class, professional jobs. Today, it is no longer certain that college, or society, will offer that kind of upward social mobility in the future. Furthermore, the cost of college creates hardship for the middle class because income guidelines prevent middle class families from qualifying for financial aid. Many students today, even those with professional, post-graduate degrees, leave school heavily in debt from college loans and then have difficulty finding work in chosen career fields. The consequences ripple through the economy: loan defaults; delay in starting a family and owning a home; underemployment; lower tax revenues; and so on.

Gender and racial diversity. As the student population changes, the fact that major gaps in the educational achievement of women and racial minorities still exist, and in fact are growing, will become more salient. Recognizing that diversity sparks creativity and innovation, new industry/education partnerships addressing this issue will continue to emerge.

General technology developments

Moore's law, Internet, mobile, cloud, ubiquity. The amount of computing power that is always available, everywhere, to every teacher and every learner, will continue the rapid rise driven by Moore's law, the Internet, mobile computing, cloud computing, wearable computing, Bring Your Own Device, and so on. The Internet of Things will allow lab instruments, peripheral devices, tools, sensors, and appliances to be monitored and controlled by the computing devices we carry and wear.

Increasingly "natural" human-computer interaction. As research advances in neuroscience and computer science, human/computer interaction will become seamless. Technologies like speech understanding, facial affect recognition, gesture analysis, avatars, and human-like robots will result in more human-like interaction with learning activities (and with computing generally). Robots and avatars that can speak, listen, understand gestures, and read facial expressions and body language will relate to learners in qualitatively different ways. Advances in assistive technologies have the potential, for example, of drawing more disabled learners into the mainstream of education and work.

Artificial intelligence. Whether they walk, roll, or fly, drones, avatars, and robots that can see, hear, and respond intelligently are on the horizon. AI technologies allow computer systems to understand what they see and hear and to communicate with people and with each other. They can see invisible patterns in vast amounts of data, demonstrate logical reasoning, and never forget a face or a fact. These systems are smart and getting smarter. Continued research and more powerful computing devices will make human-like interaction and intelligent responses as essential in future computer products as color screens are today.

Big data and analytics. A related area of computer science that will continue to advance rapidly and change our expectations about the products we use is the ability to find patterns in the increasingly large amounts of data that are generated during our use of computer systems. This technology allows computer systems to learn things about us based on the data trails we leave during our online activities. Patterns in the behavior of online students, for example, are already being used to flag students who are likely to drop a course unless a teacher intervenes. Caveats about the use of big data abound, however. See, for example, Why Machines Discriminate — and How to Fix Them, an interview with Kate Crawford and Suresh Venkatasubramanian.

Immersive environments. The contexts in which we interact with computer programs will change. Virtual reality, virtual laboratories, and simulated practice environments will become more commonplace. Elements of game technology will continue to be used to increase motivation. Augmented reality — the ability to superimpose relevant, computer-generated information (visual, auditory, haptic) via devices like Google Glass or the Apple iWatch, along with advances in speech-based interaction, will continue to make computing systems more useful in every aspect of our lives. In enterprise training, the use of augmented reality on the job is already blurring the distinction between training and just-in-time performance support.

Video. Video has become a major part of how we all use our devices — and part of how we learn. In our day-to-day lives, YouTube is the first place one looks for lessons about how to fix a dishwasher or tune a guitar. In education, video-based innovations include lecture capture, the Khan Academy, and MOOCs. With video, learners have the opportunity to start watching when convenient, stop in the middle, resume any time, and backup to catch something that went by too fast. If the student population becomes increasingly accustomed to getting its information as video, then pedagogy, curricula, and tools will have to adjust.

3D printing. Fabrication in the real world of anything that can be designed on a computer offers fascinating opportunities for manufacturing, construction, and even art. Often a part of the Makers Movement in education, 3D printing technology motivates learners of all ages to think about design and learn to use modeling tools; to create and innovate by translating their concepts/ideas into concrete objects.

Social computing – learner designed learning environments. Much of our online-time is spent interacting with other people, forming along the way new kinds of social structures, large and small. The online networks that we are all building, maintaining, and using every day for work and play will continue to redefine learning environments, change the teacher-student and teacher-parent dynamics, expose teachers and students to new ideas and new products, and empower individuals and groups to take action and make changes.

Public Awareness and Market Adoption of Educational Technology

Researchers and product developers are exploring every possible way that advances in computer technology might improve teaching and learning. Here are some of the key trends in innovation that are broadly considered of commercial interest circa early 2016, when this primer was written. (The Resources section will be kept up-to-date with more current discussions.) Please note that broadly discussed educational trends and "cyberlearning themes" do not necessarily exactly align; the market is influenced as much by general industry developments and the situation in the schools as it is by learning sciences research.

Learning analytics, data-driven design, personalization. The ability to extract meaningful information about students, teams, schools, and learning materials from large bodies of data collected online will change the way schools and teachers make decisions about administration, teaching, and procurement. New products will analyze the data and help teachers use it effectively in the classroom. Adaptive teaching materials will use the data to personalize the learners experience.

Teacher's dashboard, email, social networking. Teachers, learners, and parents will be more connected, more responsive, and more informed.

Data privacy, student data lockers. Good administrative and instructional decisions require data about learners and their past activities. The need for data access is even more acute for AI-enhanced tools like Intelligent Tutoring Systems, since their power comes from making inferences based on data about the student's knowledge and history. There is a natural conflict between the need to share data across systems vs. the need to protect learners from inappropriate access to their data. One proposed solutions is the personal data locker — a private, online data store administered by learners (and their parents), who then can grant appropriate access to teachers, educational institutions, and publishers. Institutions and jurisdictions that solve this problem will have overcome a major barrier in advancing their use of educational technology.

Adaptive learning materials, immersive practice, and stealth assessments. Using data about students background, knowledge, and recent performance, many products now offer learning experiences that are personalized and that adapt to the learner as she progresses through the material. Combining techniques from digital gaming, simulation, virtual reality, and augmented reality with stealth assessment and a deep model of the learner based on her past experience in multiple learning environments will make for much more effective digital learning products.

Badges, independent certification, and e-portfolios. Perhaps no other innovation has the potential to change the educational landscape at all levels than does independent certification and the use of "work done" portfolios instead of traditional transcripts in evaluating students' progress and ability. Independent certification on specific job skills is already a major factor in hiring and advancement in the software industry and other tech sectors. Recently, a coalition of 80 colleges and universities, called the Coalition for Access, Affordability and Success, proposed a new admissions framework based on an online platform for building a portfolio of the applicant's work, starting in 9th grade.

Intelligent tutoring systems, robo-graders, personal learning assistants. Artificial intelligence research has promised for many years to offer each student the individualized attention of a personal tutor. Some products based on this research are already available, demonstrating not only subject-matter expertise, but also teaching skills that have been distilled from expert tutors. As AI has demonstrated in other applications (Siri, face recognition, self-driving cars) the early products may not seem so smart, but they learn fast.

Ebooks for education. Just as has happened with publishing in general, the use of tablet computers as a major platform for the delivery of educational materials is an inevitability. Educational publishers, following the publishing industry trend, have embraced the idea of delivering textbooks and other educational materials digitally. But their vision of the ebook started from the paper books they already create — plus some nice, tablet-enabled features like portability, search for keywords, embedded video, and interactive graphics. Eventually, when every student's schoolwork is tablet based, the marketplace will abandon the idea of the book altogether. How will authors and publishers create new products that make use of a hand-held, mobile, Internet-enabled computer with tons of embedded technology (GPS, camera, mic, motion, orientation, touch, gesture, wifi, bluetooth) to advance the state of education and training? The educational publishing industry is being disrupted, and every aspect of the relationships among publishers, institutions, teachers, and students is subject to change.

Pedagogical Trends

Several forces are driving change in the way we teach:

- What we teach — what the learners need to know — is changing. Beyond politically sensitive issues like evolution or global warming, there are serious questions about what students need to know to earn a living and take part in social discourse. Their educational needs are also shaped by the fact that they will likely be connected to the Internet every day for their entire lives.
- We have new insights into how people learn from research in psychology and neuroscience, and from studies of the efficacy of earlier innovations. See for example, CIRCL's Primer on Learning Sciences.
- As teachers and students acquire and work with technology, they invent new techniques and approaches that are enabled by the technology itself.
-

Cyberlearning researchers are familiar with a wide range of new pedagogical approaches: flipped classrooms, experiential learning, collaborative learning, competency-based education, and so on. The recently released Innovating Pedagogy 2015 report from the Open University and SRI Education reviews a dozen new ideas about how we teach. While some approaches, liked flipped classrooms, have seen relatively broad adoption and classroom experimentation, most are not in everyday use. We may find ourselves, over the next decade, in an extended period of experimentation by educators, trying different approaches to teaching using new products that support these innovations.

Business trends

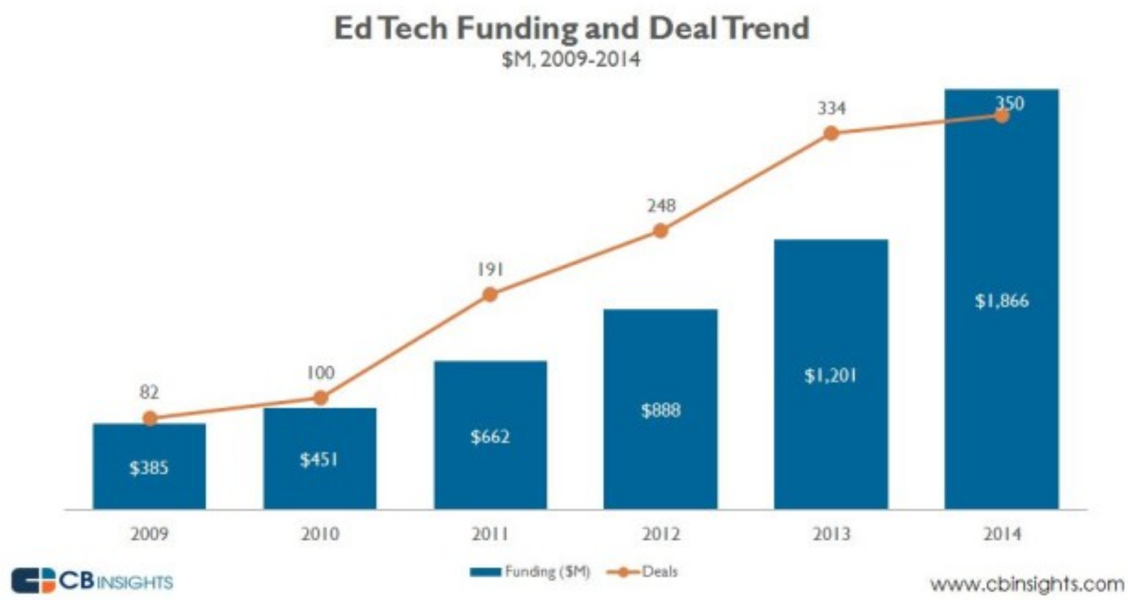
From the business perspective, there are obvious shifts in how education will be conducted. From for-profit and charter schools to online offerings like Khan Academy and Coursera, the fundamentals of the education business are changing. The following trends are worth watching.

New procurement models, aggregators, OER. Teachers can find learning materials and tools of all types online, disrupting the publisher-district supply chain for textbooks and other content. Teacher communities allow members to review and recommend materials. Schools are experimenting with new ways of working with publishers — e.g. buying just one chapter of a textbook. The trend is for more materials and a wider variety of materials to be available from publishers and from other sources (government agencies, non-profits, teacher-entrepreneurs). Aggregators, à la Netflix or Amazon, could offer not only large catalogs, but also reviews and recommendations. In 2015, according to Inside Higher Ed, some college textbooks for advanced courses now cost upwards of $400. In education there may be a much larger presence than in other industries of freely shared Open Educational Resources and open source software.

Platforms and data sharing. Some publishers and technology vendors are introducing tablet- or PC-based "platforms" for managing learning in schools and classrooms, and some are opening their platform to third party content. In addition the major publishers' platforms include data frameworks that allow all of their course materials to store and share student data securely in one place. While this trend may lead, in the short term, to proprietary school-wide or district-wide solutions, educators will likely find that multi-vendor solutions have advantages. As students and teachers become more sophisticated in their use of technology, they will want to incorporate best-of-breed products in different categories and not be "locked-in" to one vendor. The evolution of the school ecosystem will shape the commercial introduction of products incorporating new functionality like learning analytics, affect recognition, and adaptive testing.

Disruption. Almost every aspect of education is experiencing business pressure. Decreased demand for 4-year residential programs might cause an increase in college closures. Fewer students and increased use of MOOC-like technology in the large undergraduate courses may reduce the number of faculty jobs available for new PhD's. For-profit schools will, at least in the short term, continue to expand in some educational markets. Will traditional publishers make the leap to digital, or will K12 content be produced by companies like Disney or by new firms among the hundreds of ed tech startups? As the role of community colleges continues to focus on preparing people for jobs, will they build closer relationships with local employers?

Investment trends. According to EdTech Digest, venture investment in ed tech companies was below $200M per year from 2000 through 2008, and then things changed. This graph below from CB Insights via Geekwire, shows a compound annual growth rate of 30% per year from 2009 through 2014. Of course, venture funding is a boom and bust phenomenon — there's always a new, promising investment area to focus on. Continued investment of new ed tech companies and products depends in large part on the success of the early entrants.



Systems integration, learning engineering, and interoperability standards. Every educational situation is different. Innovative administrators rely on systems engineers to put together solutions that will work for their institution or jurisdiction. These "learning engineers" must be familiar with the underlying learning science, but they must also know about all of the available products and tools; historical efforts that have worked in similar situations elsewhere (and why some didn't work); relevant regulations; and the details of the already installed systems. We are just beginning to see the emergence of graduate programs to train this type of engineer (see, for example, CMU's Masters of Educational Technology and Applied Learning Science program.) These savvy ed tech "customers" often insist that the products they buy conform to software standards that allow solutions to be constructed from multiple vendors' products.

Issues – The Long View

There are so many innovations, disruptions, and trends to track, it's difficult to know which will impact what aspects of education and learning science research in the short term. In taking a longer view, however, some issues clearly warrant attention from cyberlearning researchers.

There are winds of change in education from charter preschools to the university-based MOOCs. Change creates opportunities for innovation and for new technology. The rapid advances in educational technology have created products that offer educators and learners an ever broadening array of features and functionality. In fact, today's students, many of whom are power users of technology, increasingly demand that advanced computing and communications resources be available to facilitate their learning. But technology is not the only driver. Technology creates the possibilities; the market creates success. In the process, institutions, companies, business models, and whole industries can break apart and recombine. For example, will US public schools, currently responsible for sheltering, teaching, socializing, and certifying the preparedness of our children, continue to exist as a single institution?

One could argue that if K-12 or higher-education institutions in the US were meeting the market's needs in an effective and efficient manner, technological innovations in teaching and learning would never find a major niche here. However, the cost of higher education, indeed the cost of textbooks alone, have become national issues. There is open debate about the value of a college degree; vouchers to support alternatives to the public education system; homeschooling; and the decline of the high school diploma. A college degree is no longer a guarantee of upward social mobility, or even a job. And for-profit companies claim that they can do a better job than our public schools at just about any aspect of education — and do it cheaper. New teachers receive little training in what today's ed tech can do or how to use it.

Public discussions about the cost, effectiveness, relevance, and even the goal of education are commonplace and will in all likelihood influence research funding as well as the nature of the problems faced by schools, teachers, and learners — the problems researchers must address if their work is to realize its potential impact. Implications for cyberlearning are not limited to formal education (K-20+). Learning environments will no longer be defined solely as school-based. Innovations resulting from the emergence and application of new technologies to learning will influence the ways individuals of all ages learn as they live, attend schools, and work in the 21st century.

The purpose of education. Looking out 10 years, will we have the same percentage of high school students going to college? Will trade and professional education continue its growth? Will we adopt a more European model of limited, merit-based (test-based) advancement to secondary and postsecondary education? Will independent certification for specific job skills change the value of a high-school diploma? Will a high-school diploma mean anything to prospective employers? Will the lack of upward social mobility dramatically reduce demand for a college degree? Will life-long learning be a bigger factor in the global demand for education? Will countries decide that mandatory education could be completed by age 16 instead of 18, or that 18-year-olds need to know twice as much as we are teaching them today? The way people approach these macro questions, and the policies that result, have a direct effect on the funding of research and, ultimately, on its relevance.

Rise of informal learning and independent certification. Where and how learners access information is not only changing our assumptions about how we define “learning environments,” it is also challenging formal educators in new ways. How will educators evaluate and leverage informal learning? How will they assess students’ prior out-of-school learning against prescribed curricula and make adjustments in order to reach/teach each student? How will educators recognize and build upon students’ independently acquired expertise to nurture their talents? How will formal learning be organized (e.g. flipped classrooms) to engage student’s informal learning skills/interests? Will the role of informal educators change? And if so, what types of new trainings/certifications might be needed of them? What new technologies/systems/practices will formal educators use to design, manage, assess and integrate students’ out-of-school learning into the formal education curriculum?

School infrastructure. Researchers should be aware that the classroom infrastructure is changing — Bring Your Own Device is just the beginning. It is hard to predict how the many general and education-specific technology trends will shape our research and the commercial impact of cyberlearning. One surprising possibility for cyberlearning researchers: historically, schools and classrooms had IT infrastructure that was years behind what we had in our labs. As schools, districts, and colleges build innovative solutions incorporating multiple advanced systems and products, researchers may find their lab’s IT infrastructure falling behind the schools they study. More of the research may have to be done in the field and in cooperation with commercial product vendors.

Online economics. Will schools and colleges routinely use online offerings to reduce labor costs and supplement their course catalogs in areas where qualified faculty are in short supply (e.g. computer programming or Chinese language)? Will online students be critical to the business models of all colleges, not just the for-profit institutions? How will residential programs differentiate themselves? In what ways will the online courses, independent certification, and other technological trends impact faculty staffing at the university and, in turn the demand for PhD’s to teach? How could a country without an effective literacy infrastructure, for example, find ways to educate their populations without building schools?

AI. Automated tutors and assistants are going to get smarter and more human-like — think bots that understand and use speech, gestures, facial expressions, etc. What kinds of tools will teachers need in order to manage 20, or 200, students who each employ multiple AI's that in turn are scheduling, teaching, assessing, coaching, and advising them? Will smart products change the role of humans in the education process? How will today's public education systems manage this change?

Secure data sharing. Smart systems require data: data about the learner's objectives, preferences, and history, and data about the available resources (activities, assessment instruments, courses, …) and their interdependencies. While student data privacy is a legitimate political issue, we must find a way for smart systems to securely share information about learners — not just grades, but their interests, preferences, activity streams, history, and details from the complex student models these systems build. Using data about the learner accumulated by other systems will be critical for the acceptance of AI-enhanced products like intelligent tutoring systems, personal learning assistants, adaptive drill and practice systems, learning games, smart books, and learning analytics engines.

Educational publishing and the marketplace. Who will mass produce the advanced learning activities envisioned by researchers using technologies like games, virtual reality, augmented reality, learning analytics, video, GPS, affect recognition, and AI? Will it be today's textbook publishers, game companies, tablet platform vendors, university professors, or a new category of provider? How will these offerings be sold to school districts and how will they be used in the classroom? How will administrators, teachers, parents, and learners discover, evaluate, acquire, use, review, and recommend the myriad of technology-based educational offerings? Will there be an Amazon for teachers?

There are surely many additional issues of great consequence to education and to research. Following these trends increases the likelihood that our research will remain relevant to the practice of education.

Resources

Some recommendations for keeping up with the various trends that will impact cyberlearning and related research. Please contact CIRCL if you have additional suggestions for ways to keep up with the trends that affect cyberlearning.

Edsurge is a great weekly newsletter for following ed tech trends, investments, and startups. Other publications that cover ed tech trends include:

- Inside Higher Ed
- Ed Tech Digest
- Hack Education
- Campus Technology
- The Journal

The New Media Consortium's several Annual NMC Horizon Reports looks at emerging trends and technologies in K12, Higher Ed, Libraries, Museums and Schools.

Many conferences focus on emerging ed tech and its application in the various education and training market segments. The keynotes from these events are often made available on line. Worth mentioning are:

- SXSWedu
- ASU-GSV Summit
- BETT Show, London
- DevLearn, focused on enterprise training technology
- I/ITSEC, focused on military training technology

To track technology trends more generally:

- Look for annual review articles in tech publications like ComputerWorld and Wired
- Also, periodic reviews from industry analysts like Deloitte and Gartner
- Computing Community Consortium
- The Internet Trends Report

Trends in education, pedagogy, and classrooms:

- Edutopia
- International Society for Technology in Education
- Association for Supervision and Curriculum Development
- The Center for Public Education
- UNESCO
- education.com

Some recent reviews of Social and Demographic trends:

- Pew Research Center
- The US Department of Labor
- The National Center for Educational Statistics publishes multiple trends reports

Business trends in education and publishing:

- Michael Jay's monthly Ed Table Talk podcast often focuses on publishing issues
- The AAP's Annual Content in Context Conference
- The SIIA's Education Technology Industry Network
- Publishing Trends
- University Business
- EducationDIVE
- District Administration
- EdWeek
- Independent Book Publishers Association
- GetElastic

Readings

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Evidence-Centered Design

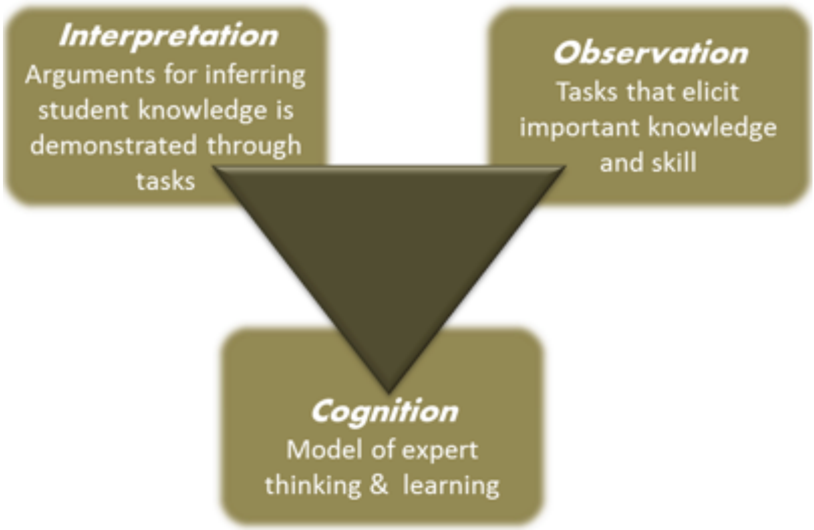
Contributors: Louise Yarnall and Geneva Haertel
Questions, or want to add to this topic or to a new topic? Contact CIRCL.

Overview

Evidence-centered design, or ECD for short, takes the art of test design and turns it into a science. Test development usually involves assembling various items into a test and then using statistical techniques and expert review to check for technical quality. ECD reduces the trial-and-error process, and leads to better measures. ECD involves justifying many design decisions *before* the first test item is selected or developed. Through ECD process, test developers create a list of the types of evidence known to accurately reflect what someone knows and can do. Creating this list is particularly valuable when designing tests of hard-to-measure knowledge, skills, and psychological states. ECD is becoming a testing industry standard and provides the kind of documentation that is often imperative in legal situations when evidence of a test's validity is required. This primer will provide a quick overview of this assessment design practice and both its benefits and costs.

To begin the ECD process, test developers study relevant learning sciences research, gather input from subject matter experts, and review previous tests, assessment tasks, scoring rubrics, and scales. Such initial groundwork is important because test designers rarely develop an accurate and reliable measure on their first try. All this upfront work is carefully documented so that later, after the test is administered, ECD test designers may refer back to this rich documentation to systematically review and revise items and tasks to increase comprehensibility, precision and reliability. Moreover, the ECD documentation means that the designers have **evidence** on which to base each subsequent revision to the test questions, media representations, or scoring rules. They also can reuse these documents to efficiently create tests of similar knowledge and skills.

While large-scale testing companies may engage professional item designers and measurement experts in using ECD, the basic ECD principles can serve as a useful guide to teachers and human resources professionals when selecting testing materials for use. These principles may also be helpful to parents and students when considering the fairness of tests administered in schools and elsewhere, especially when high stakes decisions are being made (e.g., admission to a university, a certification examination, for use as evidence of an instructor's competency). This primer summarizes the three core concepts that must be considered when of designing assessments—Cognition, Observation, and Interpretation (presented in the assessment triangle below), and how they align with the ECD process to contribute to better test design and test product selection.



The Assessment Triangle.
(Pellegrino, Chudowsky, & Glaser, 2001, p. 44)

Key Lessons

The ECD process is a dance around this triangle. In the first move of the dance, the assessment designer jumps to the cognition point at the bottom of the assessment triangle by consulting **research evidence** to understand expert thinking and core problems of novice learning in a subject domain. The assessment designer then steps to the upper right point of the triangle by selecting or creating tasks that create **observable evidence** of the desired, research-based knowledge and skills. Finally, the assessment designer steps to the upper left of the triangle by analyzing how well the test tasks produce **measurable, valid and consistent evidence** of a learner's proficiency. Using the design documentation produced during the ECD process, the assessment designer then goes back to each of these three steps and adjusts the specifics--the model of learning, the observable evidence being collected, and the interpretation of the scores. In practice, the assessment designer is moving among all three points of the assessment triangle in a fluid, iterative way.

Cognition: ECD test developers first refer to learning science research so they can better understand the concepts, reasoning and skills required for individuals to perform successfully in subject area domains. Over the past 40 years, learning scientists have documented the knowledge, skills, and reasoning of domain experts and compared these to novices' knowledge structures and reasoning procedures. They have studied how experts and novices play chess, construct geometry proofs, write computer programs, simplify algebraic equations, evaluate historical evidence, read school textbooks, write argumentative essays, and reason using non-intuitive system models in biology, chemistry, and economics. Learning science has also posited various motivational factors that influence learning, such as effort and confidence. Taken as a group, these cognitive and motivational processes provide greater explanatory power about why some students attain better learning outcomes than others. In the ECD view, tests based on such learning science research can better flag when students are successful in engaging in such learning processes, and when they are engaging in counterproductive practices. Tests that successfully make such distinctions offer a powerful starting point for instructional intervention. In ECD, all these psychological elements associated with learning a subject are documented for future reference in the test design process. The review of this background research is referred to as **domain analysis** and is the initial step in the ECD process.

Observation: In the next step in the ECD process, test developers select or create items that are intended to elicit observable evidence of the underlying cognitive or motivational forms of knowledge and skill from the examinee. At this point the assessment designers have identified task features that they believe will elicit observable behavioral evidence of these knowledge, skills and psychological **constructs**, as psychologists call them. After gathering items relevant to the constructs to be measured, the test developers may find that these items share common task features, such as ways of wording a test question or directing learners to interact with media, and they may find some item scoring criteria are likely to differentiate learners along a useful scoring scale. If no such items or scales are found among the existing tests, ECD assessment designers may construct new items and scales so that the desired knowledge, skills, and psychological states may be observed and measured. Often the first items that assessment developers design around a hard-to-measure construct are embedded within a scenario which presents a short storyline and the learner is asked to reason about the content and provide a short narrative response. In other cases assessment designers may create "stand-alone" items to inform the design of shorter and easier-to-score items. The observations provide data that developers use to score and make inferences about student performance.

Interpretation: After ECD test designers have developed a test, it is time to administer it to learners and check the test for its technical quality (reliability and validity). By having experts in the field review the test items, the ECD test designer can document the **content validity** of the test, meaning that the critical types of knowledge and skills are being tested in the assessment. Through initial pilot testing, the designer observes and interviews learners as they engage in responding to these new test items to determine whether they elicit the targeted knowledge and skill to be measured, or have **construct validity**. Pilot tests can also be conducted to tell test designers how similarly the same results will occur if the test is administered multiple times to the same students—in other words, how consistently will the test measure the construct for the same students, what test statisticians call **test-retest reliability**. Other technical qualities include examining how much overlap there is among certain items designed to measure similar or related underlying psychological states, or **inter item correlation coefficient**; which items are likely to be difficult for most students or correctly answered by students of high- or low-ability levels, or **item difficulty estimates**. These and other technical qualities of the assessment may be studied and used to inform the revision of the test. Through ECD, test developers may then adjust task features to improve the scoring logic or refine their definitions of what psychological constructs are being measured. As a result of this evidence-based approach, the interpretation of the scores produced by the test are strengthened and the test designer has greater confidence that the inference made about what a student knows and can do is valid.

Issues

ECD involves **greater upfront costs** than traditional test development.

Developing careful and explicit design documentation before creating items and tasks **formalizes a step in the test design process that may seem burdensome to some test developers**. Although most test developers are familiar with the production of a test blueprint, fewer regularly engage in creating design patterns that specify the psychological construct being measured. Subject matter experts may resist applying such a principled approach because they believe their content expertise alone is sufficient for creating good test items. In addition, the increased use of technology-enhanced items and tests puts an additional cognitive load on students as they navigate different browsers and use new interfaces and item types (e.g., simulations, drag-and-drop, dynamic graphing). The use of ECD with its emphasis on thoughtful documentation may reduce the number of iterative development cycles needed to produce valid and reliable computer-enhanced tasks

However, there is often **limited guidance** available about how to link higher order psychological constructs, including subject matter content and the steps in complex reasoning processes to the design of assessment tasks and scoring systems. This results in some trial and error in the test development process. Routinely we find an absence of data on the technical quality of many assessments that instructors use from textbooks, item banks, or their own self-designed tests. ECD creates templates that designers may use to create items and tasks that are more likely to have adequate technical quality and support for the valid interpretation of scores. Such documentation may help drive down costs for computer-based tasks, such as interactive simulations.

Projects

Examples of NSF Cyberlearning projects that overlap with topics discussed in this primer.

- EXP: Understanding Computational Thinking Process and Practices in Open-Ended Programming Environments
- EXP: Learning Lens: An Evidence-Centered Tool for 21st Century Assessment
- BCC-SBE/EHR: Developing Community & Capacity to Measure Noncognitive Factors in Digital Learning Environments

Other projects

Principled Assessment Designs for Inquiry – Providing a practical, theory-based approach to developing quality assessments of science inquiry by combining developments in cognitive psychology and research on science inquiry with advances in measurement theory and technology.

Principled Assessment of Computational Thinking – Applying the ECD approach to create assessments that support valid inferences about computational thinking practices, and is using the assessments and other measures to investigate how CS curriculum implementation impacts students' computational thinking practices

Large-scale science assessment – Applying ECD to advance assessment design for large groups of examinees, typically numbering in the thousands, and often administered to make high-stakes decisions.

Next Generation Science Assessment – Developing NGSS-aligned assessments and curricula for the next generation of K-12 students.

Resources

Principled Assessment Designs for Inquiry (PADI) – Advancing Evidence-Centered Assessment design work atpadi.sri.com and ecd.sri.com

Next Generation Science Assessments developed with ECD

In the ETS database of technical papers, the following titles pertain to ECD:

- A Brief Introduction to Evidence-Centered Design
- Monitoring and Fostering Learning through Games and Embedded Assessments
- Designing Adaptive, Diagnostic Math Assessments for Individuals with and without Visual Disabilities
- Supporting Efficient, Evidence-Centered Item Development for the GRE Verbal Measure
- Evidence-Centered Assessment Design for Reasoning about Accommodations for Individuals with Disabilities in NAEP Reading and Mathematics

ECD-developed assessments for learners with disabilities:

- Cameto, R., Haertel, G., & Morrison, K. (2011). Technical Report 5: Synergistic Use of Evidence-Centered Design and Universal Design for Learning for Improved Assessment Design
- Cameto, R., Haertel, G., Haydel-DeBarger, A., & Morrison, K. (2011). Technical Report 1: Project Overview: Applying Evidence-Centered Design to Alternate Assessments in English Language Arts/Reading for Students with Significant Cognitive Disabilities

Readings

References and key readings documenting the thinking behind the concept, important milestones in the work, foundational examples to build from, and summaries along the way.

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Understanding Universal Design for Learning

Contributors: Gabrielle Rappolt-Schlichtmann, Marianne Bakia, Jose Blackorby, David Rose
Questions, or want to add to this topic or to a new topic? Contact CIRCL.

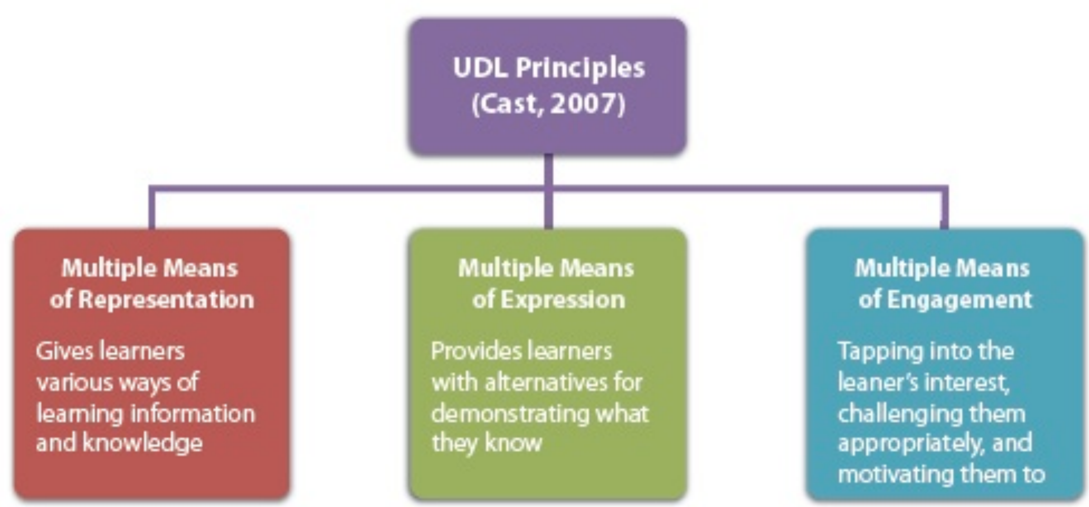
Overview

Universal Design for Learning (UDL) is a research-based framework intended to guide the design of learning technologies that are accessible and effective for all students, including those who are struggling academically and those with special needs. Inspired by the concept of universal design in architecture, the framework was first conceived in the early 1990s and developed over the intervening decades. UDL has entered the public consciousness as many local, state, national and international education settings have moved to adopt the framework. For example, UDL has influenced the design of more accessible museum exhibits and usable K12 curricula for low-vision/blind students. The Higher Education Opportunity Act (HEOA) of 2008 established the statutory definition for UDL, emphasizing that pre-service teacher training incorporate instruction on strategies consistent with UDL. More recently, the U.S. Department of Education's National Educational Technology Plans (2010 and 2015 in preparation), which is meant to guide the use of technologies in transforming education, refers to UDL as a framework that reduces barriers and maximizes learning opportunities for all students.

This attention to UDL within the field of education reflects and leads a broader conceptual shift away from "one size fits all" solutions and toward greater interest in providing "personalized" learning experiences for everyone. The UDL approach takes human diversity as its starting point rather than as an unexpected complication that will later require expensive modification or accommodation. Moreover, by attending early to the challenges of people who may be "in the margins" because they may have a different set of abilities, the UDL approach provides a foundation for educational designs that are powerful and flexible enough to optimize outcomes for all learners.

The theory and practices of UDL depend upon advances in two domains: modern learning sciences and modern learning technologies. From the learning sciences – cognitive neuroscience, affective neuroscience, cognitive science, educational sciences – UDL draws upon research that articulates the consequential differences between learners, differences that must be addressed for a learning technology to be successful for the full spectrum of learners. From modern learning technologies – such as interactive multimedia and networked learning environments – UDL takes advantage of the enormous capacity for personalization and adaptivity that these new technologies offer but that is usually insufficiently realized.

Just as universally designed buildings provide options that accommodate a broad spectrum of users, tools and curricula that are designed using the UDL framework offer a range of options for accessing and engaging with learning materials. The UDL principles can be applied to design of curricula, instructional practices, and assessments and the following three principles (along with actionable guidelines) address challenges that must be addressed to reach all students, and that can be addressed with modern learning technologies: (1) providing multiple means of presentation (e.g., perception, language, comprehension), (2) providing multiple means of action and response (e.g., action, expression, communication), and (3) providing multiple means of engagement (e.g., interest, persistence, self-regulation). UDL offers a means to provide opportunities for flexible and deep learning through the design of customizable methods, materials, and assessments (Meyer, Rose, & Gordon, 2014; Rose & Meyer 2002; Rose, Meyer, & Hitchcock, 2005).



In the design process, UDL requires close attention to learners with “disabilities” — the framework posits that these students are “canaries in the coal mine” that can alert designers and educators to problems and barriers in their methods, materials and assessments. When people with disabilities experience difficulty in an educational environment, it is often a sign that others without disabilities may also have difficulty, though it may be less readily apparent. By attending to the challenges faced by individuals in the margins early in the design process, learning environments can be made more accessible, engaging and effective for a wider array of students. Taking this approach results in a profound change in thinking that moves away from the "child as a problem" perspectives that have dominated our view of human diversity (see Dudley-Marling 2004; Albrecht, Seelman, and Bury 2001) and toward social constructivist views of education that recognize that the barriers and limitations of poor design in the environment are the critical problem to address in a democratic society. In this modern, universal design view, it is the "disabilities" and "handicaps" of our learning technologies that must be the first focus of intervention (see Rappolt-Schlichtmann & Daley, 2013; Thaper et al. 2004).

The research base for UDL in practice is growing, with contributions from a wide range of organizations and professionals and includes descriptive, correlational, and experimental studies. A recent review of the research literature suggests that UDL has made significant inroads into a number of educational communities, as measured by journal spread, intended audience, disability categories (including those with no disabilities), describing work affecting students with a wide age range, from early childhood through adulthood (Okolo and Diedrich, 2015). Studies of efficacy have been fewer, but are beginning to provide evidence of the frameworks value in the design of educational tools and environments at scale (for example, see Rappolt-Schlichtmann, et al., 2013 for efficacy trial of UDL science notebook). Further design-based research is needed to explore the many potential approaches (and innovations) to the instantiation of UDL in technology based STEM learning solutions, as well as implementation research that explores and validates the use of UDL approaches in authentic STEM learning settings.

Issues

The **research base on UDL** and the effect on student learning and affect is growing but still emergent, with most of the work done in literacy and inquiry science.

The **impact of the UDL framework** can be difficult to study using traditional research methods because it can be applied in so many different content areas, grade levels, and contexts.

Current approaches to measuring **fidelity of implementation** is an issue for UDL, and personalization generally, because the specific sequence of instructional activities and supports are intended to vary according to student need. They are not expected all be the same for all students. What works for one students might not work for another.

Kitchen sink perception of UDL. There is a perception that UDL covers too much ground, making technology designs too complicated. We view this as a misconception, but a problem that often emerges when designers first attempt to leverage the framework. When designers start with instructional goals and understand what is flexible and not, the application of UDL principles can be applied consistent with of the needs of learners, and in ways that make the technology less and not more complicated from a user-experience design perspective.

Adaptive learning principles have been applied successfully, especially in mathematics. But from a UDL perspective, some of these solutions miss the forest for the trees – they serve academic learning, but do not necessarily meet the broader, key goal of UDL about preparing students to be expert learners. Many questions persist as to how adaptive learning approaches can be used to support UDL goals, like inclusion and independent self-regulation in learning.

Perception that UDL is only for students with disabilities. UDL design benefits from considering the needs of students with disabilities and they often benefit from UDL solutions. It does not mean that they are designed only for that population. Rather, UDL solutions are intended to provide benefit to all students, as the architectural curb-cuts have done for so many.

Projects

Examples of NSF Cyberlearning projects that overlap with topics discussed in this primer (see project tag map).

Accessibility and learning

- CAP: AccessCyberlearning
- DIP: Collaborative Research: Taking Hands-on Experimentation to the Cloud: Comparing Physical and Virtual Models in Biology on a Massive Scale
- EXP: Exploring Augmented Reality to Improve Learning by Deaf Children in Planetariums

- EAGER: Promoting Algebra Learning Through an Accessible Expression System for Students with Visual Impairments and Blindness

More posts: accessibility-and-technology

Personalized learning

- EXP: Attention-Aware Cyberlearning to Detect and Combat Inattentiveness During Learning
- EAGER: Towards Knowledge Curation and Community Building within a Postdigital Textbook
- Badge-Based STEM Assessment: Current Terrain and the Road Ahead
- DIP: EMBRACEing English Language Learners with Technology
- DIP: Collaborative Research: Impact of Adaptive Interventions on Student Affect, Performance, and Learning

More posts: personalized-learning

Resources

National Center for UDL

UDL Guidelines

Implementation Research Metwork for UDL (IRN)

Office of Education Technology: Ed Tech Developers Guide (see Oppertunity 8)

Higher education UDL course design support

NEA Research Spotlight on UDL

AEM Center, accessibility guidence as related to UDL

DO-IT Center, accessibility gudience related to UDL

CAST

Talk by Todd Rose from CAST, at Cyberlearning 2012 Summit

Readings

This section includes references and key readings documenting the thinking behind the concept, important milestones in the work, foundational examples to build from, and summaries along the way.

Meyer, A., Rose, D. H., & Gordon, D. (2014). Universal design for learning: Theory and practice. Wakefield, MA: CAST Professional Publishing.

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The Center for Innovative Research in CyberLearning

CIRCL Primer - circlcenter.org

Games and Virtual Worlds

Contributors: Linda Polin, David Gibson, Shuchi Grover, Cynthia D'Angelo
Questions, or want to add to this topic or to a new topic? Contact CIRCL.

Overview

Computer-based games and virtual worlds provide opportunities for learners to be immersed in situations in which they can experience and get close to phenomena and processes. This immersion helps them develop tacit/implicit understanding and intuitions about such phenomena and processes as they think about choices, take action, and see the impact of their decisions in a meaningful context. These opportunities can be applied to school topics, enabling new genres where school learning becomes "hard fun" or a "serious game." Games are increasingly being seen as an attractive use of technology to enhance learning, and researchers and designers are actively investigating the many ways that games and game-like features can be implemented to motivate and increase student learning. Some genres of games motivate learners to work hard at learning; games can also provide opportunities to interact with phenomena and contexts (e.g. the spread of an infectious disease) that would otherwise not be available in a classroom (Barab & Dede, 2007; Rosenbaum, Klopfer & Perry, 2007).

Although games as a medium of teaching are maturing, more extensive research on deeper learning of concepts beyond simple engagement is needed before it can be conclusively established that games are indeed beneficial in learning contexts. As with all learning technologies that have the potential to engage and engender critical thinking and deeper learning, it depends on the specific game and the design of the learning experience with it. It is difficult to get the integration of games and learning right. Without iterative design improvement which incorporates measurement of learning outcomes in addition to measurement of usability and game play characteristics, impacts on learning are unlikely. Some of the best results in recent years have emerged from virtual worlds through thoughtful design of the learning environment that leveraged what we know about how children learn, especially in collaborative, technology-mediated spaces. These required iterative design-based research studies that helped create the right balance of engaging narratives, roles, and inquiry-based learning that incorporates student agency and choice.

The research literature suggests three different perspectives on designing games for learning. In the design perspective with the longest history, games have been viewed as conduits or vehicles for the delivery of curricular content. This perspective first arose in classroom use of titles such as Oregon Trail, Lemonade Stand, and Where in the World is Carmen Sandiego?These games succeeded in large part due to their interesting storylines and ability to provide learners with engaging opportunities to problem solve in authentic contexts. There were also other successful games such as Math Blaster (and many similar games), where game levels were imposed on unrelated content. These provided extrinsic motivation to increase student engagement in mathematics tasks, however pedagogically they were little more than drill exercises (Bruckman, 1999).

Second, with the growing sophistication of game play and its rise in the general population, educators have looked for game elements or “game mechanics” that can be borrowed and transferred to educational settings to improve engagement. One example is gamification (Deterding et al., 2011), which refers to integrating game methods into content and adding badge systems (the use of achievement markers to motivate continued involvement and development). However there is much debate about using this approach versus embedding learning in more authentic game settings (Tuloch, 2014) where the focus is on the core mechanics of the game and not just on the trivial aspects such as reward systems (Bogost, 2011).

A third perspective on the role of games and virtual worlds in education is organic: looking for and exploiting curricular topics inherent in popular games. Two obvious examples are the opportunity for improving reading that arises in almost every quest-based game, such asWorld of Warcraft, or the use of critical thinking or strategizing required in role-playing and real-time strategy games such as Portal, Civilization IV, Starcraft and Dragon Age, where players’ decisions affect game outcomes. The recent popularity of Minecraft in elementary and middle school classrooms (Duncan, 2011) has underscored the value of well-designed video games to not only engage, but also help children develop life skills such as creative thinking, and perseverance, in addition to visuospatial skills (as described in several articles in mainstream media, e.g. Smith, 2014).

Virtual worlds are sometimes viewed as a sub-genre of games and sometimes seen as just complex simulations with game elements, but the general principles of games hold. Virtual worlds are typically more focused on exploration than a specific game mechanic and they open up other possibilities for learning. Engaging narratives can further motivate students to explore the virtual world and situate themselves in a historical or fictional context that can include specific learning objectives. Virtual worlds support the placement of curricular concepts in the context of their natural or practical use, bringing concepts to practical life and allowing learners to interact and experiment with the changeable elements of the closed system or world. Unlike many purely playful virtual worlds that may offer a thin background of 'lore,' virtual worlds in the service of education make a point of foregrounding the narrative or unifying story element that creates the motive for investigative and exploratory engagement in the world.

Many popular research-based digital games for learning fall into this category, including River City, Quest Atlantis, and Whyville. Research on science learning in these multi-user immersive virtual environments (Barab, et al., 2010; Dede, 2009; Neulight et al., 2007) suggests that authentic designs and contextual narratives around science phenomena are not only engaging but also help learners acquire deep science inquiry skills and conceptual knowledge. Additionally, as Dede (2009) notes of River City, the digital immersion allows low-performing students especially to "build confidence in their academic abilities by stepping out of their real-world identity of poor performer academically, which shifts their frame of self reference to successful scientist in the virtual context."

Issues

Measuring Learning. For many researchers who are designing and using games to teach specific concepts, some of the most pressing issues are related to the assessment (measurement) of learning, and especially, how the kind of learning that happens in games and virtual worlds maps onto curriculum standards. There is, however, a strand of game-based learning research where the game itself is designed to be an assessment: students' choices during gameplay are measures of their higher-order thinking skills and "preparation for future learning" (Schwartz & Arena, 2013).

Balancing Instruction and Game-Play. Another design challenge for educational games is how to embed instruction in the game while still making the game fun and engaging. One way to address this is to use games as an exploratory space that prepares students for better conceptual learning that follows using more traditional means (Arena & Schwartz, 2014). This allows learners to indirectly encounter targeted curricular concepts embedded in the game, that are then reinforced through more direct instruction. Exploration and instruction remains a challenging balancing act in inquiry-based learning, and getting this timing right is important. This balance also may be achieved when a teacher integrates non-game and game elements of instruction while teaching a particular topic.

Avoiding Superficial "Gamification". While most educators agree that sticking a layer of gamification to boring, poorly-designed curricula that emphasize rote learning is ill-advised, it is an easy trap to fall into as it does provide a convenient way to make classroom learning more motivating. Gee (2003) provides an excellent list of design principles that make the best games so compelling for youth. Educators and game designers would find these useful to keep from adding a layer of gamification without deeper thought to the things that make good video games good and could advance learning simultaneously.

Socio-Cultural Issues. Games and virtual worlds sometimes carry sociocultural baggage owing to long-held beliefs in the public mindset that gaming is bad for youth, addicting, violent, and without redeeming social values. Further, in some cases, gaming communities have perpetuated negative stereotypes of women and rejected non-male designers. How do we get past those issues so that educators can bring productive gaming into the classroom? Additionally, how do we design games that appeal to learners who are non-gamers, of different genders, and drawn from diverse sociocultural backgrounds?

Data Analytics, Sharing & Privacy. As big data and game-based analytics become increasingly the go-to means of analyzing student actions and pathways in games, issues of data sharing and privacy become pertinent. There is a need for resolution on these issues as well as cloud-based data sharing protocols for research purposes. There is perhaps a need also for new psychometric models for assessing student learning in such environments as well as models of learning through games and simulations.

Ethical concerns. People can have strong emotional reactions after they leave immersive environments. Unanticipated psychological effects created by the strong illusion of virtual worlds may pose new risks. Researchers (such as Madary and Metzinger) are beginning to raise awarness of possible risks and propose recommendations for reducing them.

Teacher Training and Buy-In. Due in part to the social taboo associated with video games, K-12 teachers have been slow to adopt games for classroom teaching and learning. With the growing pervasiveness of iPads (along with educational games designed specifically for tablets and phones) and the viral popularity of games such as Minecraft among children, educational games are seeing increasing adoption in K-12 classrooms. Just as online resources are now rapidly shifting from being seen as standalone to being a component of a system for learning with strong teacher as well as strong technology roles, games are unlikely to be standalone learning components in the future. As of yet, too little is known about how to blend game-inspired experiences with other instructional genres so as to maximize the opportunities for learning targeted content. Further, understanding how to blend games with other types of instruction is likely to be essential to achieving wider teacher adoption of games into the classroom.

Projects

Examples of NSF Cyberlearning projects that overlap with topics discussed in this primer (seeproject tag map).

Games and Virtual Worlds

- Towards Virtual Worlds that Afford Knowledge Integration Across Project Challenges and Disciplines
- EXP: Learning Parallel Programming Concepts Through an Adaptive Game
- EXP: Teaching Bias Mitigation through Training Games with Application in Credibility Attribution
- DIP: Potential for everyday learning in a virtual community: A design-based investigation
- CAP: Towards Inclusive Design of Serious Games for Learning

More posts: games-and-virtual-worlds

Modeling and Simulation

- DIP: Extending CTSiM: An Adaptive Computational Thinking Environment for Learning Science through Modeling and Simulation in Middle School Classrooms
- DIP: Modeling in Levels
- DIP: Developing Crosscutting Concepts in STEM with Simulation and Embodied Learning
- INDP: Collaborative Research: Coding for All: Interest-Driven Trajectories to Computational Fluency
- DIP: BioSim: Developing a Wearable Toolkit for Teaching Complex Science Through Embodied Play

More posts: modeling-and-simulation

Virtual and Remote Labs

- EXP: Transforming High School Science via Remote Online Labs
- DIP: Collaborative Research: Taking Hands-on Experimentation to the Cloud: Comparing Physical and Virtual Models in Biology on a Massive Scale

- DIP: Using Dynamic Formative Assessment Models to Enhance Learning of the Experimental Process in Biology
- DIP: Collaborative Research: Mixed-Reality Labs: Integrating Sensors and Simulations to Improve Learning
- EAGER: A Prototype WorldWide Telescope Visualization Lab Designed in the Web-based Inquiry Science Environment

More posts: virtual-and-remote-laboratories

Resources

Doug Clark: Designing Games to Help Players Articulate Productive Mental Models
Chris Dede on Cyberlearning and Games
MindShift Guide to Digital Games and Learning
KQED articles on game-based learning

Associations and groups:

- Games+Learning+Society Conference (GLS)
- Digital Games Research Association – General games research and games for learning)
- Game Developers Conference – Education Summit
- TERC''s Educational Gaming Environments Group
- Games+Learnng+Society (GLS) Games
- Higher Ed Video Game Alliance (HEVGA)

Example game collections:

- Learning with Portals and Teach with Portals – A resource for teachers who want to use the game in their classroom, and a good example of a commercial game adapted for use in the classroom.
- NetLogo
- GlassLab games and Research and Evaluation on GlassLab Games and Assessments – an evaluation of the qualities, features, inferential validity, reliability, and effectiveness of the assessments embedded in the Games Learning and Assessment Lab (GlassLab) products
- AAA Lab, Stanford University

- DragonBox games

Readings

This section includes key readings documenting the thinking behind the concept, important milestones in the work, foundational examples to build from, and summaries along the way.

Arena, D. A., & Schwartz, D. L. (2014). Experience and explanation: using videogames to prepare students for formal instruction in statistics. Journal of Science Education and Technology, 23(4), 538-548.

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Neulight, N., Kafai, Y. B., Kao, L., Foley, B., & Galas, C. (2007). Children’s participation in a virtual epidemic in the science classroom: Making connections to natural infectious diseases. Journal of Science Education and Technology,16(1), 47-58.

Rosenbaum, E., Klopfer, E., & Perry, J. (2007). On location learning: Authentic applied science with networked augmented realities. Journal of Science Education and Technology, 16(1), 31-45.

Schank, R., Fano, A., Bell B., Jona M., (1993/1994). The Design of Goal-Based Scenarios. The Journal of Learning Sciences, 3(4), 305-345.

Schwartz, D. L., & Arena, D. (2013). Measuring what matters most: Choice-based assessments for the digital age. MIT Press.

Shaffer, D. L. (2006). Epistemic frames for epistemic games. Computers and education, 46(3), 223-234.

Squire, K., Halverson, R. & J. Gee. (2011). Video games and learning: Teaching and participatory culture in the digital age. NY: Teachers College Press.

Smith, M. (2014). What your kids are learning from Minecraft. Retrieved from https://games.yahoo.com/blogs/plugged-in/what-your-kids-are-learning-from-minecraft-001453153.html.

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Tobias, S., & Fletcher, J. D. F. (2011). Computer Games and Instruction. Information Age Publishing.

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Partnering for Impact: Increasing Cyberlearning's Influence in Education Markets

Contributors: Avron Barr, Jeremy Roschelle, and Lewis Johnson
Questions, or want to add to this topic or to a new topic? Contact CIRCL.

Overview

Many Cyberlearning researchers know that their work could make a significant positive impact on today's educational products and practices, if only there were a way to get it out there. CIRCL's Partnering for Impact activity offers guidance, resources, and workshops to help researchers think through their options and be effective in their outreach efforts.

Partnering for Impact is not new; indeed it has already succeeded. For example, a number of companies sell products based on concepts and technologies developed under the Cyberlearning umbrella. Some, like Carnegie Learning and Alelo, were startup companies launched by the researchers themselves. Other researchers ushered their technology into the marketplace by licensing technology or by consulting for established publishers and technology firms about new product or product feature ideas. And, of course, there are likely many ed tech products that have incorporated the ideas that learning scientists shared openly in their publications and conference presentations.

Terms like commercialization, productization, and tech transfer are often used to describe the process of moving ideas and technology out of the lab and into the marketplace. The education marketplace, however, is special for a number of reasons: state and federal regulations; balkanization (procurement at the state, district, and school level); lagging technology infrastructure in the schools; teachers without the needed time or training; and perennially tight budgets. And the marketplace is now changing rapidly. For example, one major textbook publisher has increased its software development staff from 5 to 500 people in the last year and converted all of its 1500 titles into digital offerings of some type. Thus, approaches to bring consumer, healthcare, or military innovations to market do not always smoothly apply in education.

Because of the special expertise and capabilities involved in bringing educational products to market, arranging to work with people who already have the needed expertise — entrepreneurs, investors, educational publishers, marketing consultants, educators — will expedite the transition from research to broad adoption: partnering for impact.

> Cyberlearning researchers can envision the possibilities afforded by learning science. Ed tech companies work with educators every day, and have insights into the critical needs and major opportunities in education. Partnering can lead to scalable learning solutions that address these critical needs, and which are infused with insights into how people learn.
> – W. Lewis Johnson, Ph.D., Co-Founder and CEO, Alelo

Learning scientists' and Cyberlearning researchers' technical inventions and findings about how technology is best used in the classroom are extremely relevant to the current ed tech boom — the multi-year surge of investment in new products from startups and established companies that target education at all levels. There are now hundreds of startups, incubators, accelerators, and hackathons focused on the education market.

> In 2014 alone, US ed tech companies raised $1.36B in 201 rounds from more than 386 unique investors. (EdSurge, Dec. 23, 2014).

Despite the fact that tech entrepreneurs are the celebrities of our day, there are often more effective and efficient ways to move scientific research into products and practice. Researchers who want to invest their time in outreach activities should consider the alternatives to entrepreneurship, think about their own personal motivations, and take a fresh look at the potential impact of their work from the perspective of market demand.

- Often there is little incentive for, or accommodation of, entrepreneurial efforts in academic career planning or in the funding of scientific research.
- While Cyberlearning researchers (and NSF) often envision their work applied in K-12 classrooms in the US, that's probably the hardest market to penetrate. Could the innovation be a game changer for community colleges, private schools, foreign universities, or enterprise training departments?
- What problem gets solved? Who will buy the product or service featuring your innovation, and why? Do these future customers need relief badly enough to change "the way things have always been done"?

- Typically, not every element of one's work has commercial potential. What's the gem? What insight or innovation will capture the interest of product developers and their customers? Is there some way (patent, copyright) to protect inventions so as to assure that a commercial venture can profit from the work before it is copied by competitors?
- What work is left to do, besides "hardening the software," before the innovation is packaged in a product that can be sold and used effectively?
- Does it make more sense, based on personal goals, to forego entrepreneurship and license the technology or consult for a while with an established firm, and let them bring a product into the world?

There are many areas of opportunity within the corpus of Cyberlearning research. Some researchers may indeed be appropriate candidates for the venture funded startup route. But for those not ready to devote their energy to a startup company, there are alternatives.

The subsequent tabs in this article highlight some of the issues and options to be considered by researchers who are interested in seeing their work move into products and into the schools. We also list some recommended first steps and useful resources, including non-academic conferences that offer excellent opportunities for exposure and for finding partners as one's plans mature.

Issues in Reaching the Ed Tech Marketplace

In 2014, CIRCL hosted a Partnering for Impact Workshop in California to identify and address the barriers that must be overcome in the community's efforts to bring learning science research results to bear on ed tech products and on their use in schools. We've summarized here some of the issues that researchers should be aware of as they consider how their work might find its way into the hands of teachers and learners.

Cross-cultural communication. Since academic researchers, commercial product developers, and educational adopters operate in substantially different worlds, extra effort is required to achieve effective communication. Each community has its own goals, priorities, schedules, and deadlines, not to mention terminology and communication styles. With a little effort and a bit of empathy, researchers can effectively communicate our ideas, results, and vision to investors, publishers, and educators, but it might feel like an unnatural act at first.

For example, we tend to leave out some steps, assumptions, or facts that are taken for granted among researchers, but that must be explicitly laid out for practitioners. We like our jargon and acronyms, vs. theirs. Our communication style tends toward lecturing — it's an occupational hazard. We think research and scientific truth are what's really important, whereas a classroom teacher, even one who loves science, might have other day-to-day requirements for selecting and adopting products. Bottom line, we need to know whom we're talking to, and be able to describe benefits and costs from their perspective in their language.

The press and media can help create awareness of the potential impact of Cyberlearning on people's lives. Getting the story out right can be tricky, and may require a few learning trials. It is, however, important that teachers, parents and learners see the point, from their perspective. Ultimately, there must be public demand for better products that incorporate what Cyberlearning has learned about learning. See for example this piece from the Huffington Post (April 2015)

Alternative paths. Besides starting one's own company to bring a product to market, there are alternative paths with very different requirements and outcome. These options are not necessarily exclusive. It's advisable to consider all the options in the context of your personal values, lifestyle, expectations, and ambitions.

- Startups. These days, starting a company, getting venture financing, and selling out for billions shortly thereafter is a meme that's hard to avoid. There are all sorts of incubators, hackathons, and VC pitch sessions organized to help get your startup started. While entrepreneurship can be challenging and rewarding, it can also be disappointing and hugely time consuming. That said, once you've got a solid business plan, pitching your company/product idea to seasoned investors who know the ed tech space can be enlightening, even if you don't get funded. And if you are offered financing from an established venture firm, it's a good sign that your team is qualified and that you're starting out in a good direction.
- Licensing intellectual property. A much less time-consuming and life-altering path to commercial success is possible if your research has resulted in an invention that might be patented or in learning materials that might be copyrighted, for instance. Often universities will help researchers protect their intellectual property, which can then be licensed, productized, and taken to market by an existing firm with an established reputation and marketing organization. Once the IP protection is in place, you would then pitch your ideas to educational

publishers, platform and device providers, and even well-financed startup companies, and negotiate a fee structure for the (exclusive or non-exclusive) license.

- If you and your employer are not concerned with seeing additional revenue from your inventions and ideas, you might expedite the impact of your work by just talking to educators, publishers, investors, entrepreneurs, policy makers, or the public about the potential impact of your work. Choosing the right audience, the right venue, and the right wording is important, as discussed below. This path is a relatively low-revenue one, but not necessarily zero revenue. For instance, you might:
    - Get hired as a consultant to help product developers understand, implement, and extend your research results
    - Secure a summer internship for you or one of your students at an ed tech firm or at a school that's making an effort to adopt and integrate technology
    - Hold a workshop (or a MOOC) of interest to industry players
    - Form a university-industry consortium or a Github community
    - Supply a piece of the needed infrastructure, like a database or ontology
    - Partner with other research teams to create a more complete offering
    - Write a bestseller about the future of education targeted at a non-academic audience

What's a product? No matter what path you follow, it's important to understand the difference between research results and products. Sometimes, just a small part of your research work is a gem that could be directly turned into a viable product. On the other hand, creating a product from where you're at now could require ten times more work and money than you've already invested.
People buy products because they solve a problem they're having — hit a pain point. Your idea is not actually a product idea until you have a notion of who will buy it, why they'll buy it, and how they'll use it to solve their problem. And once you have an initial notion of what you'd be selling to whom, it's a really good idea to go talk to some of those "customers." And listen.

Understanding the market generally — who's buying what from whom — is key to refining the product concept; describing it in the best way; and positioning it relative to competitors and alternatives. Working with people who have been active in the market (investors, entrepreneurs, school superintendents, consultants) is the best way to learn, because the ed tech market is complicated and changing rapidly.

Its important to understand the idea of the "whole product." If you're introducing a new software app, for instance, there may be a lot of work to do, besides "scaling up the code," before you have a viable product. You might need to: build additional software components; populate your skeletal content framework; create a user interface acceptable to today's learners; integrate your system with databases and other systems; collect money from buyers or users; write an implementation guide; or offer online support or teacher training. No matter how much efficacy data you have accumulated, if the teachers don't like it or the students don't use it, it doesn't work.

Two additional issues related to productization are especially relevant to researchers: myopia and inflexibility. After spending years developing a system or approach and demonstrating its effectiveness, it's natural to remain focussed on what you've been working on and even expect that additional funding would be best spent perfecting your algorithm, for instance. Entrepreneurs and investors often focus on what's called the Minimal Viable Product, because speed to market can sometimes determine success more that functionality, and additional features can always be added in Version 2. Similarly, as the process of productization proceeds, it is often happens that the eventual product offering differs substantially from the system or approach you perfected and demonstrated. (Sticky Notes was a failed adhesive product). Flexibility is a key trait of successful entrepreneurs.

Technical Issues. "Scaling up" is probably the wrong way to think about moving an academic software system that has been used to collect data into a commercial product. First of all, professional software development and product management are different from the work of even the most talented amateurs. Commercial software teams address issues like architecture, platforms (tablets, publishers, analytics, schools), performance, usability, time to market, flexibility, understandability, and maintainability.

Whether in a school or in a publishing house, there are an increasing number of systems and apps that your system or app might need to interface with, to retrieve data about the student, monitor and alert a teacher, or record activity and performance. You can't ask a teacher or student for information that your system should already know, and you can't expect your system to collect and store all of the learners' data. Systematic instrumentation and independent data analytics are increasingly expected in the marketplace.

Academia. You might not at first think of academia as a barrier to your efforts to broaden the impact of your research. There are, in fact, several issues.

First, your academic career is typically not advanced by your success in “spreading the word” or by the number of students who are using products based on your work. The time involved in pursuing these outreach goals does not count towards your obligations to the university. Similarly, while there are certainly exceptions, most funders of scientific research expect you to make progress on the science, not necessarily on any related engineering or application.

Most universities nowadays would like to get a piece of the action on any profits derived from inventions or advances made by their faculty and students. You should be familiar with your employer’s policies about intellectual property, consulting, and sabbatical leave. Schools often have tech transfer offices staffed with lawyers. Your research funders may also have commercialization policies you should be aware of.

Research plans are laid out and funded in advance — often you’re proposing work that you will not get funded to do for a year or more. The research horizon makes it difficult sometimes for academics to be responsive to businesses on their time scale, which is driven by the changing competitive landscape. Getting a product out the door can require planning through several stages, each depending on the previous one. Missing deadlines at any stage can be catastrophic. University and government accounting and reporting requirements can also interfere with the flexibility businesses need.

The game in business is solving customers’ problems — exactly the inverse of academia. In other words, your research funders, the folks who give you money, succeed if you succeed — if you do good science, get published, get recognized, etc. In business, you succeed only if the folks who give you money, your customers, succeed. Scientific simplification is an important technique for identifying studiable phenomena and solvable problems. In the real world, friction is not 0 — the nuances and variability of the learning context, for example, can be critical to product design.

Finally, entrepreneurship often involves “sweat equity.” Months or even years of unfunded, unrewarded, unrecognized work before investor or publishers will buy into what you’re doing. Furthermore, success often depends on building a team of people who have expertise in areas you’re not expert in (software development, product management, marketing, finance, …). For a salaried university researcher, the transition to entrepreneurial status can be difficult.

The education marketplace. There are a lot of new educational products targeted at schools, universities, parents, and students. There are many more in the pipeline, and future saturation of the market is potentially problematic in itself. But there are many other issues in the educational marketplace that have been around for a quite a while.

The U.S. K-12 market, where many learning scientists hope to see the impact of their work, is notoriously hard to penetrate for several reasons, besides perennially tight budgets:

- Balkanization (procurement at the state, district, and school level) makes efforts to market new products very expensive. The textbook publishers and some platform vendors have developed large sales and marketing organizations to address this reality. Similarly, there are numerous regulations and requirements from multiple jurisdictions that impact educational products in the various market segments.
- The technology infrastructure in the schools is not typically what you'd find in the university research environment. The computing and communication situation in students' homes may also be suboptimal.
- While the situation is changing, classroom teachers have not had a lot of technology training and often struggle to find time to learn to use new products. If Cyberlearning doesn't fit into the way classrooms operate, it won't make a difference. There are schools and teachers that are changing the way their classrooms are used, but that is not the case in most of the K-12 market and won't be for many years.

A similarly fractured market structure exists in higher education, where publishers often sell new products directly to individual professors. Economic and social pressures are causing many colleges to rethink their business models, and many are trying to use technology to cut costs, differentiate themselves, or find new markets.

Finally, you might be thinking about selling an app or other products directly to teachers, parents, and learners online. While it does avoid some of the market structure problems, it's hard to get the attention of busy teachers and learners. That's a problem you will share with many ed tech entrepreneurs.

Next Steps and Useful Resources

We've listed here some suggested first steps and selected resources that might be useful in your initial explorations of ways to broaden the impact of your work.

- Look for local experts and resources. University and regional incubators, consultants familiar with the ed tech market, veteran ed tech entrepreneurs, and even meetup.com groups could shorten your learning curve and help in deciding on a path forward.
- Read EdSurge, a weekly newsletter that covers the ed tech landscape, including announcements about startups and VC funding, ed tech conferences, workshops, hackathons, prize competitions, and just about every new product that hits the market. Understanding a bit about what else is going on in the marketplace will help you refine your ideas and communicate more effectively with potential partners. Some other interesting resources:
    - The Office of Educational Technology's Ed Tech Developer's Guide
    - Ed Table Talk, Michael Jay's monthly webcast about issues in ed tech
    - Stanford's Patent Law and Strategy for Innovators and Entrepreneurs (iTunes)
    - 51 Questions Any Edtech Entrepreneur Must Answer (Edsurge)
    - NewSchools Entrepreneur Resources (New Schools Venture Fund)
    - Ed-Tech Guide (Audrey Waters, Hack Education)
    - 10 Startup Lessons From Kaplan's EdTech Accelerator Demo Day (Entrepreneur Magazine)
    - Ed Tech Magazine
    - Building Strong Public/Private Partnerships in Information Technology: A Cross Cultural Primer
- NSF's Innovation Corps is a public-private partnership program that teaches grantees to identify valuable product opportunities that can emerge from academic research, and offers entrepreneurship training to student participants. I-Corps Teams — composed of academic researchers, student entrepreneurs and business mentors — participate in the I-Corps curriculum. The curriculum is administered via online instruction and on-site activities through one of several I-Corps Nodes. Also, there are Small Business Innovation Research (SBIR) programs from NSF, Department of Education, and other federal and state agencies that are sources of information, funding, and potential partners.
- Attending conferences and showcases might be a good idea early on, to get an up-to-date picture of today's ed tech marketplace; make some connections with people and companies; and learn what will be expected when you are ready to seek funding and partners. Eventually, you should plan to be speaking at these non-academic conferences to educators, publishers, and investors. Edsurge maintains a list of ed tech conferences and events. Some

recommendations (note that deadlines for speaking proposals are often 6-12 months before the program):

- TransformingEDU, Consumer Electronics Show, Las Vegas, January
- SXSWedu, Austin, Texas, March
- ASU+GSV Education Innovation Summit, Scottsdale, Arizona, April
- SIIA Ed Tech Industry Summit, San Francisco, May
- Assoc. of American Publishers: Content in Context, Washington, June
- ISTE Conference and Expo (educators), Philadelphia, June
- Edsurge: Digital Innovation in Learning Awards, Silicon Valley, November
- Masie Learning Conference (enterprise training), November, Orlando
- I/ITSEC (the military training conference), Orlando, December
- SIIA Education Business Forum, New York, December
- Online Educa (Europe's biggest event), Berlin, December

- Practice explaining your work and its potential impact to non-scientists. Family members will do, especially if they're inclined to ask hard questions. Potential team members with business backgrounds are even better. Eventually, whatever path you take, you will be talking to intelligent non-scientists: investors, publishers, educators, policy makers, software vendors, and the press. Practice will help you answer their questions within their framework of understanding and action.
- If you're targeting classroom adoption, talk to teachers about what technology they use; what they have not been able to integrate into their workday; and what products they'd like to see in the future.
- Write articles that will be read and understand by educators and business people, and get them published in non-academic trade or consumer publications. Or write a book that is published by someone other than Elsevier or Springer. Creating demand among educators, parents, and students for the innovations you envision will drive the market and eventually resolve the business and classroom issues. When you speak or write about your work, don't focus only on efficacy as demonstrated in your pilot studies. Think about how the product will be sold and how it will be used by teachers. Who will buy it? How will they deploy it? How will teachers or learners use it?
- If you decide to start a company, put together a team with expertise in marketing (preferably in education), finance (preferably in raising capital), and product management. Top-tier venture capitalists say that the team is more critical in their evaluations than the technology or the business plan.
- There are a wide variety of incubators, hackathons, and advisors that focus on ed tech startups. They are a good place to find team members and advisors in the very early stages of your explorations. Later on, when you have a business plan, a pitch, and maybe a demo, there

The Cutting Edge of Informal Learning: Makers, Mobile, and More!

Contributors: Sherry Hsi, Shuchi Grover
Questions, or want to add to this topic or to a new topic? Contact CIRCL.

Overview

Cyberlearning spans in-school and out-of-school learning — and these days, a lot of meaningful learning is taking place outside of classrooms. Amateur designers, students, and artists are teaching themselves and each how to make their own electronic toys, program flying robots, or manufacture custom-designed parts with 3D printers and desktop milling machines. Families are doing science together through making backyard instruments to collect local environmental data and share their data online with other global citizen scientists (Anastopoulou et al., 2011; see Cornell Lab of Ornithology). Kindergarteners to senior citizens are combining traditional physical materials like paper, yarn and fabric, together with digital materials like electronics and sensors to create new homespun fashions, to design useful products, and to pursue their interests. (Buechley, Peppler, Eisenberg, & Kafai, 2013; Peppler & Glosson, 2013.) Important learning is also taking place in public libraries where librarians invite youth to author digital stories, produce new media, and publish personally-relevant stories while museums are hosting workshops to reach different audiences (IMLS, 2014; NYSCI, 2013). These learning experiences prove to be highly influential in the choices that youth make about further education, career pathways, and participation as citizens.
In contrast to traditional classroom learning, informal learning is often:

- interest-driven: learners engage based on their interests, not an externally mandated curriculum.
- learner-centric: adults help as guides, facilitators, coaches, and mentors, but the role is to support the learner, rather than to regulate the content, pace, and progress
- playful in approaches: informal experiences tend to engage participant's imagination, encourage exploration, allow tinkering, celebrate teamwork, and take failure in stride, unlike traditional didactic school experiences
- multigenerational: participants often include be children, parents, and senior citizens learning side by side

- intrinsically assessed: outcomes tend to be tangible and readily appreciated by the participants, with less reliance on formal, standardized tests as outcomes

Informal learning institutions like museums with both structured and unstructured activities by themselves don't guarantee a meaningful learning experience. Today's informal learning more often also emphasizes:

- active engagement: the physical space provides unique affordances for doing, not just collections to be viewed
- building materials: the glass between the learner and the artifact is gone, learners are expected to construct not just appreciate
- multiple representations: learners are encouraged to engage with an idea through multiple media, such as storytelling, sketching, constructing, simulating, visualizing, role-playing, discussing socially
- learning trajectories: the informal experience is less contained to a specific space and time, but may span multiple visits or connect to home, to community, or to school.

The movement among "Makers" is one prominent example of today's approach to informal learning and an important arena for cyberlearning advances. Making is "a class of activities focused on designing, building, modifying, and/or repurposing material objects, for playful or useful ends, oriented toward making a ''product'' of some sort that can be used, interacted with, or demonstrated. Making often involves traditional craft and hobby techniques (e.g., sewing, woodworking, etc.), and it often involves the use of digital technologies, either for manufacture (e.g., laser cutters, CNC machines, 3D printers) or within the design (e.g., microcontrollers, LEDs)" (Martin, 2015). Makers are people who openly share tools, knowledge, and materials who value learning and creativity over profit and social capital (Kuznetsov & Paulos, 2010). From creating new artifacts, hacking software, or repurposing objects, makers are highly motivated, interest-driven learners that seek out new experiences and actively share what they learn in a community. Informal settings, such as science museums, increasingly host making experiences and digital technology is frequently used to enhance the opportunities for learning in these experiences. Martin (2015) provides a comprehensive synthesis of making and argues against a tool-centric approach to bringing making into classrooms. He contends that in order to understand the promise of making in education, educators need to appreciate all three interconnected elements of making-"(1) *digital tools*, including rapid prototyping tools and low-cost microcontroller platforms, that characterize many making projects, 2) *community infrastructure*, including online resources and in-person spaces and events, and 3) *the maker mindset*, values, beliefs, and dispositions that are commonplace within the community" (p. 31).

This kind of informal learning aligns well with educational research about authentic, active education that happens in a social community. Education research has shown that meaningful learning is situated in authentic practices using inquiry-based approaches to solve relevant problems, sharing skills in a community of others, and making meaning through activity and action (Wenger, 1998). Whether using physical or digital materials, learning is mediated by multiple media representations and facilitated through direct experiences and interactions mentored by disciplinary experts, more expert peers and novices in a social community of practice (Lave, 1991). Episodic and distributed, learning is interest-driven, serendipitous, sometimes sustained with access to a network of human and technical resources in their community.

Technology is playing a big role in the maker community to enhance informal learning and to better connect informal with formal learning. The maker community leverages online information extensively from using tutorials, online forums, open shared code libraries, social media, and digital video platforms that connect different aged learners to contribute, discuss ideas, share tips, and self-publish instructional videos. Maker communities also use digital fabrication and a network of physical spaces like community workshops, FabLabs, and tech shops, that allow use of shared manufacturing tools to realize their digital imagined and physically implemented projects. These spaces host novice friendly software for programming, computer-aided design, and digital media production. These same tools and software enable control of microprocessors that are used by robotics clubs to get more fluent in coding and learn computer science concepts and computational thinking. Within blended learning environments, smart phones offer digital access to content and limitless knowledge via ubiquitous, wireless access to the Internet while makers meet in physical communities, festivals, and faires to build, experiment, and test their designs. Physical computing devices ranging from programmable maker technologies like Arduino, servo motors, 3D printers, to computer-controlled milling machines help foster new ways to learn through collaborative computer-aided design, online research, and documentation (Halverson & Sheridan, 2014; MakerEd, 2014; Martinez & Stager, 2013).

However, for technology use to reflect cyberlearning ideals, technology must be more than resource in a learning activity: it must enable the design of activities that connect to what we know about how people learn and thus enhance learning. Thus, a cyberlearning approach to maker activities does not over-emphasize the materials used or the thing made. A focus on the materials or things can sometimes lead to cookbook recipes, narrow instruction, and standardized expectations, ending up in an experience not much different from poor schooling. A cyberlearning view emphasizes the transactions among students, materials, and the social setting — and how those transactions provide students opportunities to explore, investigate, test, and refine their knowledge and abilities. Technologies provide more than a resource for building when they enable students to better represent concepts, to gather data and analyze it, to share knowledge with peers, to discuss theories and construct explanations, to critique and suggest improvements, and to reflect on their own learning.

Cyberlearning projects in informal learning can also go beyond maker experiences, too:

- Mobile devices can provide a layer of augmented reality as learners explore an important physical space
- Museum exhibits can invite visitors to learn via new modes of interacting with the setting and visualizing phenomena
- Sensors and cameras can enable citizen science investigations

Several aspects of learning theory are particularly useful to cyberlearning in informal settings for studying and understanding individual learning and learning that happens in a shared, public environment or social community. More specifically:

- **Constructivism and constructionism** provide long-standing ways to conceptualize learning through doing.
- **Identity** is concerned with how learners' sense of who they are and who they can become is shaped through opportunities to explore their interests, values, commitments, and convictions in relation to their participation and engagement with others, new ideas, activities, and phenomena. Further, youth are drawn to expressing identity through new, social media.
- **Embodied cognition** considers how doing and experiencing in a bodily way leads to learning and connects with learning that may later become more de-contextualized and abstract, and can often involve **tangible interfaces**.
- **Collaborative learning** or more broadly, social learning, provides traditions for designing effective learning experiences for groups and for analyzing social interactions for insights about learning

Cyberlearning is poised to contribute to transforming STEM education by using learning theory and technology to enhance powerful grassroots movements in informal learning and develop entirely new informal experiences. Cyberlearning research is needed both to contribute to design, but also to document how people learn in these new experiences and how learning is improved. Further, cyberlearning is well-positioned to connect these informal advances to issues in school learning. For example, schools are looking to the maker community for ideas about how to teach science and design solutions to problem-based challenges. Teachers see making as way as to support inquiry, project-based learning, authentic problem-solving, and deeper discussions (Honey & Kanter, 2013). Educational leaders see the potential to engage greater numbers of underrepresented groups in STEM-related activities including encouraging more girls and women to pursue computer science to help develop a more diverse technological workforce (Fried & Wetsone, 2014).

Issues

Design and theory development. Because making is both a highly collaborative and mobile activity, making opens up new possibilities for exploring how different mobile technologies and apps can be used to support design work and documentation of individual and group projects. Using digital cameras, smart phones, and tablet computers, students self-document their work, monitor their progress, and contribute to online portfolios. New challenges and research opportunities arise in the assessment of design-oriented projects that are collaborative in nature, multi-disciplinary, and process-driven, accomplished intermittently or intensely over weeks and months with the help from multiple peers and educators.

Connections to other Contexts. A great promise of cyberlearning is that learning will be more connected across informal and formal spaces, such as science museums and schools. Much design research is needed to make this promise a reality, as the culture of school and the cultures of informal learning do not easily mix. It is unlikely to be a good idea to require informal spaces into produce standardized outcomes like achieving a particular curricular goal but also unrealistic to expect that schools can become as interest-driven as informal environments are. Considerable challenges of describing and documenting the learning that occurs in each setting in useful ways for other settings are likely to emerge.

Research Methods. Making is also driving changes to what is being researched and how research is accomplished. Researchers are exploring new ways to advance theories of social learning, interest, and motivation. The objects and artifacts created by learners serve as a reflection of their different selves, providing rich avenues for researchers to study identity formation and identities in practice (Ching & Foley, 2013; Tan, Calabrese-Barton, Kang, & O'Neill, 2013). With learning happening in physical, online, and blended learning environments, new research methods are being created to study these complex STEM-rich environments to examine new literacies, representations, dialogue, design-based learning, and collaborative teaming (Halversen, 2013; Ito, 2009; Litts, 2015).

Measurement and Assessment. Making akin to design-based learning is spurring new embedded assessment tools and cyber-enabled research tools to capture moment-to-moment, emergent learning in out-of-school settings. Rather than using high-stakes tests as measures of learning or teacher-graded work, teachers use digital portfolios, scaffolded peer critique, and documentation support to assess project-based learning from collaborative teaming, solving design challenges, and learner-centered making. Learning analytics and online traces are being used to capture multi-modal interactions, online behaviors, participation, and activity over long periods beyond school hours. Digital videos with high storage capabilities archive months and years of video data empowering researchers to conduct longitudinal, ethnographic studies to analyze-in-depth collaborative inquiry, learning conversations, and teaching practices (see Gutwill, Hido, & Sindorf, 2015). Individuals are not only evaluated for changes to their understanding of STEM disciplinary knowledge, but their inquiry processes, empowerment, and resourcefulness (Dixon & Martin, 2014; Brahms, 2014). Other researchers and their developers are exploring how to design better instructional supports, physical computing materials, programming languages, and design tools to support the development of computational thinking, data literacy, and modeling expertise (Blikstein, 2013.)

Professional Development. New models of professional development are needed to prepare peers, coaches, mentors, tutors, facilitators and other adults who support learners in informal spaces — and may be working with cyberlearning technologies in doing their work. Similarly, new approaches to professional development are also needed to meet the needs of teachers who want to learn how to better facilitate maker activities and to assess maker-style projects. For example, MOOCs and web-based video chats can offer mentors and/or teachers a way to join professional learning communities to discuss issues of practice, and learn ways to assess learning that happens in blended learning environments.

Lack of Diversity in the Maker Movement. Making is meant to bring playful designing and fabrication quite literally in the hands of the learner and is believed to be a democratizing force. However, it suffers from a serious lack of diversity, and underrepresentation of women in minorities. While Kneese & Rosenblat (2014) think this issue simply mirrors general Silicon Valley disparities, Lilypad inventor Leah Buechley believes that MAKE magazine has propagated an exclusionary culture in their choice of featured projects (mostly robots and vehicles) and makers (white men/boys). Clearly taking making into all schools and classrooms will help level the playing field.

Challenges Shared with Other Cyberlearning Areas. As learner engagement in spaces is captured digitally, issues about privacy and data security arise, along with new IRB issues. Likewise, as students create their maker artefacts, issues of copyrights, attribution, etc. can arise. Technological barriers to the flow of information across settings can arise (incompatibility between informal settings and school learning management systems, for example). As institutions tend to reflect societal issues, gaps in equity across gender, race, and other demographic characteristics may persist if not addressed.

Projects

Examples of NSF Cyberlearning projects that overlap with topics discussed in this primer (see project tag map).

Making learning tangible

- EXP: BodyVis: Advancing New Science Learning and Inquiry Experiences via Custom Designed Wearable On-Body Sensing and Visualization
- EAGER: Engineering Inquiry for All at Nedlam's Workshop
- EAGER: Paper Mechatronics: Creating High-Low Tech Design Kits to Promote Engineering Education
- RAPID: Learning in the Making: Leveraging Technologies for Impact
- EAGER: Infusing Learning Sciences Research into Digital Fabrication and Making in Education

More posts: making-learning-tangible

Citizen science

- DIP: Next Generation WeatherBlur: Expanding Non-Hierarchical Online Learning Community Models for Citizen Science
- DIP: Collaborative Research: STEM Literacy through Infographics

- DIP: ScienceKit for ScienceEverywhere - A Seamless Scientizing Ecosystem for Raising Scientifically-Minded Children
- DIP: Potential for everyday learning in a virtual community: A design-based investigation
- CAP: Towards Inclusive Design of Serious Games for Learning

More posts: citizen-science

Informal learning

- EAGER: Collaborative Research: Virtual STEM Buddies for Personalized Learning Experiences in Free Choice Informal Learning Settings
- EAGER: Collaborative Research: Designing Digital Rails to Foster Scientific Curiosity around Museum Collections
- CAP: Innovating Data-driven Methodologies for Documenting and Studying Informal Learning
- RAPID: Learning in the Making: Leveraging Technologies for Impact
- Badge-Based STEM Assessment: Current Terrain and the Road Ahead

More posts: informal-learning

Resources

Martin, L. (2015). The Promise of the Maker Movement for Education. Journal of Pre-College Engineering Education Research (J-PEER), 5(1).

Informalscience.org web site, run by the Center for Advancement of Informal Science Education (CAISE)

Maker Ed (The Maker Education Initiative) – Every Child a Maker

Make: Do-it-yourself projects, how-tos, and inspiration.

Exploratorium Tinkering Studio blog

FabLearn conference web site

Community Science Workshop Network

Readings

This section includes references and key readings documenting the thinking behind the concept, important milestones in the work, foundational examples to build from, and summaries along the way.

Anastopoulou, S., Sharples, M., Ainsworth, S., Crook, C., O'Malley, C., & Wright, M. (2011) Creating personal meaning through technology-supported science inquiry learning across formal and informal settings. International Journal of Science Education.

Bevan, B., Bell, P., Stevens, R., Razfar, A. (Eds.) 2013, XIV. LOST Opportunities: Learning in Out-of-School Time. Explorations of Educational Purpose, Vol. 23. Springer-Verlag.

Blikstein, P. (2013). Digital fabrication and 'making' in education: The democratization of invention. FabLabs: Of Machines, Makers and Inventors, 1-21.

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are showcases that specialize in ed tech startups. EdSurge keeps a list of all of the ed tech incubators.

If you come across useful resources for learning scientists who would like to see their research results in the hands of teachers and learners, please send CIRCL a note.

Technology Enabled Formative Assessment

Contributors: Mingyu Feng, Janice Gobert, Patti Schank
Questions, or want to add to this topic or to a new topic? Contact CIRCL.

Overview

Formative assessment occurs when teachers check student understanding and guide decision making to improve learning. Formative assessment is a powerful way to improve student achievement, particularly when teachers use data to adjust instruction (Black & Wiliam, 1998a, 1998b; Boston, 2002; Roediger & Karpicke, 2006; Speece, Molloy, & Case, 2003). Formative assessment can provide critical information about whether students understand the targeted concepts and skills, and if not, what problematic or partial understandings are present instead. Teachers can use the evidence about student understanding to guide students from partial or incorrect understandings toward targeted learning goals.

Black and Wiliam's (1998a) review of 250 studies found effect sizes for formative assessment to be larger than those seen for any other instructional intervention tested. Formative assessment has also been shown to have beneficial effects for student motivation: feedback to students about progress and performance can increase student persistence, sense of self-efficacy, and self-regulated learning (Black and Wiliam, 1998; Brookhart, 1997, 2001; Stiggins, 2001b). Still, teachers often feel they don't have time to assess students due to tight schedules for covering new content (Dodge, 2009).

Technology enabled formative assessment has the potential to bring formative assessment and the associated benefits to more teachers, students, and classrooms in a timely, usable fashion (Bennett, 1999; Pellegrino, Chudowsky, & Glaser, 2001). Technology can help educators effectively implement formative assessment by enabling more immediate feedback, displaying feedback in readily usable ways, and by providing new possibilities for assessing student understanding of scientific phenomena in dynamic, interactive ways (Gobert et al., 2013). Technology-based systems, which log students' actions in a non-intrusive way , can react on the basis of formative data to scaffold student learning in real time–even on open-ended, higher-order thinking skill tasks (Pellegrino, et al., 2001). (See, for example, the CIRCL Spotlight on dynamic formative assessment to enhance learning in virtual biology labs.) When carefully designed to align with the curriculum, standards, and large-scale tests, technology-supported classroom assessment further has the potential to generate data that are usable not only in guiding classroom instruction, but also in informing accountability programs (e.g., Wilson & Draney, 2004) and in improving program implementation.

Interest in technology-enabled assessment in K-12 Education is accelerating (Olson, 2004). Important drivers of growth include the ongoing shift of assessment from paper to digial media, educational policies that promote formative assessment, and the desire of actors at all levels of the educational system to improve their performance. Today, many online testing companies (such as Renaissance Learning, www.renlearn.com) automatically grade students and provide reports. Classroom response systems (e.g., clickers) have been widely used to pose multiple-choice questions and collect responses from students instantly; students' responses can be aggregated visually and shared immediately with the class for discussion (Bransford, Brophy, & Williams, 2000; Roschelle, Penuel, & Abrahamson, 2004; Zurita, Nussbaum, & Salinas, 2005).

Commercially-available formative assessments, however, tend to focus on the most conventional aspects of school topics. Available assessments are more likely to measure student understanding of facts and procedures than concepts and strategies. They are more likely to be informed by classical test theory than by learning science methods, such as evidence-centered design (ECD; Mislevy, Steinberg, & Almond, 2003; Mislevy & Haertel, 2006). Formative assessments which are aligned to the ambitious elements of today's standards are rare. Thus, important opportunities for advancing the field await research-based initiatives that integrate learning science-based views of content and learning with technology and with modern assessment frameworks such as evidence-centered design.

Indeed, NSF-funded dynamic assessment systems such as ASSISTments, Science Learning by Inquiry,Diagnoser.com, and Simbio are going beyond commonplace formative assessments. For example, they combine formative assessments with real-time scaffolding of student learning. When students respond to problems in these systems, they receive hints and tutoring to the extent they need them, based on a student model that is developed and constantly updated by the system. Research-based systems are exploring the use of games, visualizations, and simulations in formative assessment, as well as more complex tasks and scenarios. These systems also provide teachers with detailed diagnostic reports to help them adjust their instruction accordingly.

Issues

While the positive role of formative assessment has been widely accepted in the educational field, challenges persist for the implementation of formative assessment practice and technology-enabled formative assessment in schools.

Data Mining. A key issue is the complexity of the log data from technology-enabled learning environments, and the difficulty of meaningfully distilling, parsing, and aggregating the large amounts of log data generated by students as they work in such environments (Quellmalz & Pellegrino, 2009; Gobert et al., 2013). See the Educational Data Mining and Learning Analytics synthesis for more discussion of this issue.

Professional Development. The most effective formative assessments are embedded within the classroom and happen on a moment to moment basis. An implementation challenge is developing formative assessment practices in teachers and integrating these with instruction (including what concretely, they should do next). Technology-enabled formative assessment practices have the potential to increase student learning, but only where the teachers are prepared to adjust instruction and learning activities quickly and responsively while learning is in practice. Professional development needs to be provided to help teachers understand the output of formative assessment systems and respond to the results appropriately.

Design and Accessibility. The user experience (for both student and teacher views) needs to be well designed and highly accessible to lower the demands for teachers and students. For example, the ease of collecting data in technology-enabled assessment systems can lead to reports that could be overwhelming.The technology, ideally, should provide clear opportunities and resources for intervention. Careful design is required so that assessment feedback and reporting is informative and understandable and can be immediately acted upon by teachers and students.

Technology cost and support. The cost of introducing technology (clicker systems, laptop or desktop computers, touch pads, smart boards or other types of display stations, etc.) in the classroom can be high. When a project introduces technology into a classroom, how will the technology be maintained? What technology support is provided by the project vs. the school? Who pays for repairs? Can the school IT staff understand and support the technology?

Projects

Examples of NSF Cyberlearning projects that overlap with topics discussed in this primer (see project tag map).

Cyber-enhanced/computer-assisted assessments

- Badge-Based STEM Assessment: Current Terrain and the Road Ahead
- EXP: Enabling Pedagogical Communication Between Learning and Programming Environments
- EXP: Collaborative Research: Fostering Ecologies of Online Learners through Technology Augmented Human Facilitation
- EXP: Collaborative Research: A cyber-ensemble of inversion, immersion, collaborative workspaces, query and media-making in mathematics classrooms
- BCC-SBE/EHR: Developing Community & Capacity to Measure Noncognitive Factors in Digital Learning Environments

More posts: cyber-enhancedcomputer-assisted-assessments

Formative assessment

- Badge-Based STEM Assessment: Current Terrain and the Road Ahead
- EXP: Enabling Pedagogical Communication Between Learning and Programming Environments
- EXP: RUI: Exploring Spatial-Temporal Anchored Collaboration in Asynchronous Learning Experiences
- EXP: Learning Lens: An Evidence-Centered Tool for 21st Century Assessment
- EXP: Building a Learning Analytics System to Improve Student Learning and Promote Adaptive Teaching Across Multiple Domains

More posts: formative-assessment

Resources

Exemplary web sites and examples:

Technology to Support Next-Generation Classroom Formative Assessment for Learning

ASSISTments mathematics tutoring system

Diagnoser.com instructional tools for science and mathematics

Simbio virtual biology experiments

Science Learning by Inquiry microworlds for inquiry

SimScientists science learning and assessment projects

Virtual Performance Assessment Project to assess students' science inquiry skills

Situated Assessments Using Virtual Environments (SAVE) Science

Crystal Island intelligent game-based learning environment

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AI Applications in Education

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Questions, or want to add to this topic or to a new topic? Contact CIRCL.

Overview

AI pioneer Marvin Minsky and his colleagues highlighted key aspects of vision for Artificial Intelligence in Education (AI in Ed):

> '…we could try to build a personalized teaching machine that would adapt itself to someone's particular circumstances, difficulties, and needs. The system would carry out a conversation with you, to help you understand a problem or achieve some goal. You could discuss with it such subjects as how to choose a house or car, how to learn to play a game or get better at some subject, how to decide whether to go to the doctor, and so forth. It would help you by telling you what to read, stepping you through solutions, and teaching you about the subject in other ways it found to be effective for you. Textbooks then could be replaced by systems that know how to explain ideas to you in particular, because they would know your background, your skills, and how you best learn." (Minsky et al., 2004, p. 122)

Similar visions can be found in Pressey's teaching machines (1924), the "Illustrated Primer" of Neal Stephenson's science fiction novel The Diamond Age (1995), and many other contemporary sources. Although, the vision of a conversational tutor which can help anyone to learn any topic more quickly or easily has not yet been achieved, researchers have made many advances on aspects of this vision.

For example, researchers have developed applications of AI in Ed that can:

- track the "mental steps" of the learner and underlying goal structure of problem solving tasks (Anderson et al., 1995)
- diagnose misconceptions and estimate the learner's understanding of the domain (VanLehn, 1988)
- provide timely guidance, feedback and explanations (Shute, 2008)
- promote productive learning behaviors, such as self-regulation, self-monitoring, and self-explanation (Azevedo & Hadwin, 2005)

- prescribe learning activities at the right level of difficulty and with the most appropriate content (VanLehn, 2006)

Indeed, over the course of different investigations, nearly every AI technique – natural language processing, uncertain reasoning, planning, cognitive modeling, case-based reasoning, machine learning and more – has been applied to challenges of learning (Woolf, 2009).

In particular, AI techniques can enable educational technologies to better track, adapt to, and support individual learners. For example, AI technologies can track learners by building a model of what a students knows based on their successes and errors in solving problems. AI technologies can adapt to students by changing the sequence of problems presented to students and by changing the interactions of the computer with the student on specific steps of a problem. AI technologies can give students help within well-defined and carefully limited domains in the style of a conversational agent, sometimes even with a virtual avatar.

Many AI in Ed systems have aimed to mimic the benefits of one-to-one tutoring shown in Bloom (1984); some of these systems now outperform untrained tutors in specific topics and can approach the effectiveness of expert tutors (VanLehn, 2011). Close analyses have found that much of the benefit of both human and AI tutors arises from intervening at the specific step where a student makes a mistake, rather than giving feedback only on the correctness of the entire problem solution (Corbett & Anderson, 2001; Shute, 2008). Implementing step-based feedback on a computer requires representing how problems are solved step-by-step; AI technologies are a good choice for specifying these step-by-step processes. In general, however, building an expert model that is suitable for use in education is a difficult and slow undertaking, requiring highly skilled labor and access to expertise. Therefore, a key difference between the Minsky's vision and practical accomplishments of AI in Ed is the careful selection of a constrained and well-specified domain of knowledge.

One particularly well-known and fruitful line of work began with development of John Anderson's ACT-R theory (Anderson, 1983, 1993). This theory models how people learn to solve problems in terms of if-then rules, called "productions." ACT-R implements the theory in a kind of programming language, which can be programmed to solve information processing tasks in the way people do. This line of work gave birth to a type of Intelligent Tutor System (ITS) called the Cognitive Tutor. The cognitive tutor can simulate how an expert would solve the same problem that a student is currently working on. This simulation is used to trace differences between student and expert problem solving, and when the steps diverge, to provide feedback. This approach has led to commercial products from Carnegie Learning such as the Algebra Tutor, and these products have been used with hundreds of thousands of students. Some careful analyses of these products have found positive results, although results in other cases have been mixed (What Works Clearinghouse [WWC], 2010). A meta-analysis that compared outcomes of learners using an ITS to outcomes of learners using other instructional methods found that over a wide array of conditions, learning from ITS was associated with higher outcome scores (Ma et al, 2014).

AI in Ed today is not limited to simulating expert human tutors and teachers. For example, the use of physiological monitoring technologies (e.g., skin conductance, posture) is helping researchers understand the role of emotions in learning and develop new models of pedagogical intervention. Further, work on teachable agents leverages the idea of reciprocal teaching by having the (human) student take on the role of teacher. Here, AI techniques are used in a variety of ways, such as simulating human communication, learning, and emotions. A final example is the use of narrative learning environments and educational games that can be designed to provide customized experiential learning opportunities and better maintain learner motivation and engagement.

AI is poised to play a pivotal role in growing the field of learning analytics and personalized learning. There is also potential for the use of AI to create unique learning pathways in MOOCs and adaptive systems for use blended and online learning, however this vision is yet to be fully realized. In a recent special double issue of AI Magazine (Chaudhry, et al., 2013), these topics were addressed in some detail.

AI techniques can thus continue to provide deeper insights into human learning, inspire curiosity and interest in the world around us, and ultimately help keep educational technologies caught up with the rest of the world – if they can be made smart enough.

Issues

A series of AI Grand Challenges for Education were proposed (Woolf, et al., 2013):

1. **Virtual mentors for every learner**: omnipresent educational support; brings together knowledge representation, user modeling, social simulation, and many more.

2. **Addressing 21st Century skills**: our educational technologies must go beyond conveying knowledge and support learners with self-direction, self-assessment, teamwork, and more.
3. **Analysis of interaction data**: the vast amounts of data about learning, social contexts, learning contexts, personal interests, and more is a key source of information that must be leveraged in future educational technology research.
4. **Universal access to global classrooms**: ensuring that the classrooms of tomorrow are interconnected, accessible, and personalized requires a great deal of computational and automated reasoning power.
5. **Lifelong and lifewide technologies**: understanding, modeling, and guiding learning in the context of a learner's life outside of school is critical if we are to improve education. Persistent models, interoperable systems, intelligent search, and more all contribute to the vision of technology that stays with you and helps you learn throughout a lifetime.

Projects

Examples of NSF Cyberlearning projects that overlap with topics discussed in this primer (see project tag map).

Speech recognition:

- CAP: Building Partnerships for Education and Speech Research

Intelligent tutors and tools:

- EAGER: Exploiting Keystroke Logging and Eye-Tracking to Support the Learning of Writing
- EAGER: Collaborative Research: Virtual STEM Buddies for Personalized Learning Experiences in Free Choice Informal Learning Settings
- EXP: Helping Teachers Help Their Students: Teachers' Use of Intelligent Tutoring Software Analytics to Improve Student Learning.
- EAGER: Computational Models of Essay Rewritings
- EXP: Partners in Learning: Building Rapport with a Virtual Peer Tutor

More posts: intelligent-tutors

Resources

AAAI topics page on education (from the Association for the Advancement of Artificial Intelligence)

Ken Koedinger Podcast on Intelligent Tutoring

International Artificial Intelligence in Education Society, which organizes the biennial AIED Conference.

International Journal of Artificial Intelligence in Education

Full text of The Handbook of artificial intelligence, Volume 2

A Roadmap for Learning Technology (from the CCC, CRA, and NSF)

Readings

Key readings documenting the thinking behind the concept, important milestones in the work, foundational examples to build from, and summaries along the way.

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Educational Data Mining and Learning Analytics

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Questions, or want to add to this topic or to a new topic? Contact CIRCL.

Overview

Educational data mining (EDM) is the use of multiple analytical techniques to better understand relationships, structure, patterns, and causal pathways within complex datasets. Learning Analytics (LA) is a closely related endeavor, with somewhat more emphasis on simultaneously investigating automatically collected data along with human observation of the teaching and learning context. Overall, cyberlearning emphasizes the integration of learning sciences theories with these techniques in order to improve the design of learning systems and to better understand how people learn within them.

Educational systems are increasingly engineered to capture and store data on users' interactions with a system. These data (e.g., big data, system log data, trace data) can be analyzed using statistical, machine learning, and data mining techniques. The development of computational tools for data analysis, standardization of data logging formats, and increased computation/processing power is enabling learning scientists to investigate research questions using this data (Baker & Siemens, in press).

Research goals which EDM/LA can address include:

1. Predicting students' future learning by creating models that incorporate information such as students' knowledge, behavior, motivation, and attitudes.
2. Discovering or improving models that characterize the subject matter to be learned (e.g. math, science, etc.), identify fruitful pedagogical sequences, and suggest how these sequences might be adapted to students' needs.
3. Studying the effects of varied pedagogical enhancements on student learning.
4. Advancing scientific knowledge about learning and learners through building models of learning processes that incorporate data about students, teachers, understanding of subject matter, pedagogies, and principles from learning sciences.

5. Supporting learning for all students by adapting learning resources to fit the particular needs identified, including adaptations for individual students when warranted.

In addition, researchers are expanding EDM/LA to new frontiers, such as studying learning in constructionist research where the lack of formal structure in learning environments (such as games and maker spaces) make traditional assessments difficult to implement. Another new frontier for EDM/LA is understanding collaboration in formal and informal learning environments.

Large scale use of learning management systems, games, virtual worlds, augmented reality, simulations, and constructionist spaces in learning, as well as the emergence of online open learning materials (such as Khan Academy) and courseware (including MOOCs) has fueled research in EDM/LA. The NSF-funded Pittsburgh Science of Learning Center (PSLC) or 'LearnLab' has spearheaded key research in this field in the past decade. The PSLC Datashop is an important resource serving as a central repository to secure and store research data and provide a set of analysis and reporting tools. Early work in EDM/LA by the PLSC team (Koedinger, Corbett, and others) was conducted in the context of Intelligent Tutoring Systems. The cognitive models of learning they used and developed (drawing on earlier work by John Anderson) have contributed to understanding the design of adaptive, data-rich learning systems, especially in STEM subjects. Other noteworthy efforts include (among others) the development of tools and techniques for mining data and making inferences about non-cognitive aspects of learning (Ryan Baker and colleagues); growing an understanding of conversation analytics (Carolyn Rose's group at CMU); analytics in games (Constance Steinkuehler and Kurt Squire; Taylor Martin and colleagues); LA to serve teacher needs (Mimi Recker et al.); studying collaborative processes and social learning analytics (Dan Suthers; Simon Buckingham Shum; and others); and multi-model learning analytics in constructionist spaces (Paulo Blikstein and colleagues).

Issues

As practiced in cyberlearning, EDM is often deeply interdisciplinary. Thus in planning EDM efforts, a critical question is how to support multiple disciplinary specialists work together in order to (1) address the most pressing problems of practice, (2) collect useful data both online and through more traditional techniques, (3) analyze data using appropriate techniques to rigorously answer the question at hand, (4) interpret results and elicit feedback from multiple stakeholders to generate appropriate implications for action, and

(5) continue to represent and display data in ways that support valuable uses of the data by researchers and practitioners.

Issues of privacy and ethics of data use are yet to be resolved. Standards that balance the need for data privacy with the need to link student and teacher data across distributed systems need to be established as also mechanisms for informing users about what data are collected in addition to providing users a means to control access, anonymize, and opt-in or out.

An important trend in research, amplified by EDM/LA, is to take products to scale first, and then begin conducting research. (In contrast, a traditional pathway involves slowly scaling research on educational technology over a decade or more.) The Evidence Framework (Barbara/Bakia et al.) provides valuable guidance for research approaches when working in the scale first/then study paradigm.

Overall, EDM draws on traditional statistical techniques and shares further challenges with other analytic uses of research data, such as:

1. Combining needed data from different systems, which can be difficult.
2. Achieving construct validity and interpretability of results.
3. Understanding consequential validity and use of results to drive decisions.
4. Deciding whether use of data to drive high-stakes and/or low-stakes decisions is warranted.
5. Establishing safeguards for privacy and ethics of data use.

Several other key issues have been identified by the Learning Analytics Workgroup report (Pea, 2014). These include foregrounding the needs of learners and challenges of educators, defining success metrics for personalized learning while recognizing that different outcomes of the learning process are relevant for different stakeholders, and creating the necessary infrastructure for supporting research in learning analytics.

Projects

Examples of NSF Cyberlearning projects that overlap with topics discussed in this primer (see project tag map).

Analytics/data mining

- Doctoral Consortium for the 2016 Learning Analytics and Knowledge Conference
- CAP: Data Consortium Fellows: A Mentorship Program to Expand the Cyberlearning Data Analytics Community
- CAP: Doctoral Consortium for the 2015 Learning Analytics and Knowledge Conference
- CAP: Advancing Technology and Practice for Learning Reading and Writing Skills in Secondary Science Education
- EAGER: Automatic Classification of Programming Difficulties by Mining Programming Events
- Badge-Based STEM Assessment: Current Terrain and the Road Ahead
- EXP: Transforming High School Science via Remote Online Labs
- EXP: Collaborative Research: Fostering Ecologies of Online Learners through Technology Augmented Human Facilitation
- EXP: Learning Lens: An Evidence-Centered Tool for 21st Century Assessment
- DIP: Collaborative Research: Taking Hands-on Experimentation to the Cloud: Comparing Physical and Virtual Models in Biology on a Massive Scale

More posts: analyticsdata mining

Readings

Key readings documenting the thinking behind the concept, important milestones in the work, foundational examples to build from, and summaries along the way.

The Learning Analytics WorkGroup Report (Pea, 2014) is a great synthesis of the issues and current state of the field of Educational Data Mining and Learning Analytics.

A new report, Accelerating Science: A Computing Research Agenda by Honavar, Hill, and Yelick (2016) seeks to articulate a research agenda for developing cognitive tools and leveraging big data to augment human intellect and enable new modes of discovery — and may inspire some interesting ways to think about smart and connected communities of learners.

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U.S. Department of Education, Office of Educational Technology (2012). Enhancing Teaching and Learning Through Educational Data Mining and Learning Analytics: An Issue Brief. Washington, D.C., 2012.

Executive Office of President (2014). Big Data: Seizing Opportunities, Preserving Values. The White House, Washington, DC.

Resources

Organizations:

- International Educational Data Mining Society (publishes Journal of Educational Data Mining and convenes the International Conference on Educational Data Mining)
- Society for Learning Analytics Research, which sponsors LAK conferences
- Learning Analytics Community Exchange (LACE), an EU funded project involving nine partners from across Europe

Online courses and video:

- Big Data in Education MOOC
- Big Data in Education MOOC (archive)

Tutorials:

- LearnLab 2013 (PSLC) Resource Archive
- Introduction to Data Mining for Educational Researchers

Online Data and Analytic Sharing

LearnSphere integrates existing and new educational data infrastructures–including MOOC data, discourse data, and the LearnLab DataShop–to offer a world class repository of education data. Funded by the NSF Data Structure Building Blocks (DIBBS) program, it is the first education-focused DIBBs project. LearnSphere is led by Ken Koedinger at CMU in collaboration with MIT, Stanford, and U Memphis.

The LearnLab DataShop has 100s data sets on student learning from educational technology and associated analytics.

The KDD Cup 2010 competition has large student data sets available and will evaluate submitted prediction models.

Other potentially relevant repositories the Linguistic Data Consortium at UPenn and the DataBrary.

Learning Sciences

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Questions, or want to add to this topic or to a new topic? Contact CIRCL.

Overview

The Learning Sciences is a field of scientific research that developed in the 1980s, from influences which include cognitive science, computer science, information processing psychology, child development, anthropology, and linguistics. The International Society of the Learning Sciences (ISLS) hosts conferences, organizes journals and provide ongoing forums which bring learning scientists together, worldwide. The two ISLS journals, Journal of the Learning Sciences and the International Journal of Computer-Supported Collaborative Learning, consistently rank among the top 10 educational research journals. The number of university-based Learning Sciences programs has expanded greatly since 2000, signifying institutional recognition of the importance of this field of inquiry.

Whereas traditional educational research sometimes determines what to study by looking at education as an institution (e.g. with policies, practices, organizational structures, etc.), learning science research more often starts with a **focus on learning**: how do people learn, what resources and supports enable learning, and how do features of settings and contexts interact with the learning process. Also, whereas traditional educational research focuses primarily on students' test scores or attainment of credentials, learning scientists are often concerned with knowledge, skills, and abilities that are not yet measured well by commonplace test scores nor yet signified by established credentials — for example, their knowledge of an emerging scientific topic like nanoscience, their skills in participating in a scientific discussion, or their ability to work with others to build knowledge. Learning science is willing to be future-directed, imaginative and risky — to explore how learners could develop in ways that are clearly valuable, but presently hard to learn. Learning scientists also investigate how people develop identity, as well as other social and emotional outcomes. Overall, learning scientists focus on learners and their needs.

Although learning scientists actively use a wide range of methods in order to conduct rigorous investigations of learning in these and other areas, two particular methods are much more common in learning sciences than in related fields. First, learning scientists often engage in ***design*** of new ways to facilitate learning in order to study whether issues in learning are constrained by existing resources or pedagogies and whether new technologies or approaches might overcome these limits and advance learning. Learning scientists tend to believe that technology can promote learning, but only if carefully designed and integrated into the life of the learner in a learning environment. Often, design is pursued by teams with multiple sources of authority and expertise, which can include teachers and other participants.

The need for contextual inquiry and the focus on design in the learning sciences prompted the birth of the design-based research (DBR). Second, learning scientists almost always seek to **capture details of how learning processes unfold** over time in interaction with people and materials and a setting — not just inputs and outputs, and not just discrete snapshots of learning at particular times. Methods to capture these interactions are therefore prominent, such as use of video and audio records, system log data, and observation. Presentations, reports, and journal articles often show examples of new designs and also display transcribed conversations and other interactions which would allow the reader to closely follow the process of learning as it unfolded over time.

Learning scientists study learning in specific ways. Learning scientists study learning in natural environments or in designed environments which could fit into realistic settings — and engage with the messiness of learning in realistic settings, rather than controlling variation precisely. For example, the learning sciences is strongly focused on studying human learning (rather than learning of other animals or machine learning). Most learning sciences work is deeply concerned with subject matter, such as mathematics, science, or history. When learning scientist study learning in a subject matter, they examine constructs and process which are important to the specific subject, and not just issues of memory and attention which apply similarly to all subjects. Topics can include how students can learn to engage in scientific inquiry, to understand fundamental but difficult math concepts, can participate in disciplinary practices of argumentation and explanations, and how students can learn subjects which are not ordinarily taught in schools in authentic ways, such as data science, nanoscience, or robotics. Learning scientists are also deeply engaged in how to measure and assess student learning, particularly when the target knowledge or skill is important to measure and not easily captured by conventional tests. Learning Scientists most often conduct studies in naturalistic settings (schools, museums, homes, community centers, etc.) rather than in highly controlled laboratories.

Learning sciences research is often concerned with designing environments, tools, materials and practices for optimal learning and tends to accumulate around design principles which interlink with empirical findings. Four exemplary areas include:

1. **Modeling learning progressions** and adapting learning experiences, resources and feedback to support learners' progress. Design principles in this area relate to how to to design learning environments, sequence instruction and optimize feedback both to learners and to teachers. These have been realized in intelligent tutoring systems, for example.
2. **Collaborative learning** and scaffolding, scripting, and orchestrating social interaction. Design principles in this area relate to how to organize social learning (often in small groups) to overcome known challenges and to increase the opportunities to learn deeply and may include designing particular structures, conversational supports, or ways for teachers to modulate the setting.
3. **Simulations, visualization, modeling, and representation**. Design principles in this area link new possibilities for displaying information to cognitive processes involved in making sense of scientific models or phenomena and/or mathematical constructs and notations — often with an emphasis on real-time, dynamic presentations which could not be easily portrayed on paper or in books, and with an emphasis on engaging students in an inquiry or investigative stance.
4. **Opportunities to engage in hands-on constructive activities**, when carefully designed to include well-designed materials, challenges, and allow for playful interactions, interest-driven learning, and sufficient mentoring or guidance, as a way to developing students' identity as a participant in challenging domains of expertise.

Learning scientists tend to be less enthusiastic about black box experiments, in which only inputs and outcomes are reported, with little empirical documentation of how the inputs contributed to the outcomes. Learning scientists want to go beyond only studying users' perceptions of how much they enjoyed a particular learning experiences or found it useful, unless this data is triangulated with other data that tracks the quality of the learning process. Learning scientists also tend to be less involved in large-scale survey methods or secondary analysis of existing data sets, as these methods tend to only have snapshots in time. While learning scientists value self-reflections about a learning experience, they work to move from insights to empirical accounts, which can be more easily verified by others.

Learning Sciences research is particularly important as a key vector of cyberlearning investigations. The presence of a potentially transformative learning technology, alone, is not sufficient for a cyberlearning investigation. Rather, cyberlearning is realized through the interweaving of technology with learning science and other methods that illuminate processes of learning with theoretical depth and empirical precision. This interweaving requires research in computation, STEM or other fields to intersect with principles of how people learn as informed by the learning sciences.

Issues

Learning scientists are looking for ways to add rigor both to the theoretical basis of design and the empirical claims about efficacy, especially as educational technology surges in the marketplace but often lacks depth in theory and rigor in empirical evidence.

Learning sciences intersects with other emerging fields, such as learning analytics. As an example, see Roy Pea's address at the ELI 2013 annual meeting – Learning Sciences and Learning Analytics: Time for a Marriage).

Historically, learning sciences research has examined smaller populations of learners in great depth, often revealing insights that would not be apparent in larger populations and aggregate data. However, to maintain relevance, learning sciences has to evolve to interpolate between larger-scale and smaller-scale studies, and slower and more agile research methods.

Learning sciences has had a healthy mix of public and policy engagement along with the mechanisms for growing a strong internal research community through a society, journals, conferences, and other efforts. Continued effort to address broad, important policy issues while conducting high quality research is important to the health of the field.

Readings

Key readings documenting the thinking behind the concept, important milestones in the work, foundational examples to build from, and summaries along the way.

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Sawyer, R. K. (2006). Introduction: The New Science of Learning. In R.K. Sawyer (Ed.), The Cambridge handbook of the learning sciences (1-16). Cambridge: Cambridge University Press.

Kelly, A. & Lesh, R. (2000). Handbook of research design in mathematics and science education. Dordrecht, Netherlands: Kluwer.

Resources

To learn more about the learning sciences visit The International Society of the Learning Sciences (ISLS) web site, as well as the Journal of the Learning Sciences (JLS) and the International Journal of Computer-Supported Collaborative Learning (ijCSCL).

The International Society of the Learning Sciences Network of Academic Programs in the Learning Sciences (ISLS Naples).

A brief history of the learning sciences by Chris Hoadley (ISLS Naples webinar recording).