Contemporary Technologies in Education

Maximizing Student Engagement, Motivation, and Learning

Edited by

Olusola O. Adesope and A. G. Rud

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macmillan

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ISBN 978-3-319-89679-3 ISBN 978-3-319-89680-9 (eBook)
https://doi.org/10.1007/978-3-319-89680-9

Library of Congress Control Number: 2018953346

This Palgrave Macmillan imprint is published by the registered company Springer Nature Switzerland AG
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

Foreword: Maximizing the Effectiveness of Learning with Media

Learning with Media

The field of education is confronted by a revolution in potentially useful computer-based technologies, ranging from digital games to wikis to online courses. The educational potential of these kinds of computer-based technologies is explored in the ten content chapters of *Contemporary Technologies in Education: Maximizing Student Engagement, Motivation, and Learning* edited by Olusola O. Adesope and A. G. Rud. In short, the guiding question addressed in this book is, "How can we best use technology to help students learn?" To answer this question, rigorous experimental research is needed to identify instructional features in technology-rich environments that maximize learning outcomes and promote appropriate learning processes.

Historical Context of Educational Technology

This certainly is not a new question, as is reflected in the history of research on educational technology (Cuban 1986; Saettler 1990/2004). However, a worthwhile lesson to be drawn from this history is that the educational technologies of the twentieth century were sometimes oversold, which should temper our enthusiasm for claims about the educational value of today's technologies. For example, Cuban (1986) documents the rise and fall of educational technologies throughout the twentieth century such as motion pictures in the 1920s, radio in the 1930s, television in the 1950s, and programmed instruction in the 1960s. In the present book focusing on the twenty-first-century technologies, Glazewski (2019) adds *Second Life* to the list of highly touted technologies that have failed to live up to expectations. In short, an important message reflected in this book is that the use of educational technology should be based on research evidence and grounded in scientific theory rather than follow from grand promises and rosy predictions by visionaries.

What is new about the question of how to use technology is the array of technologies being made available in the twenty-first century, such as wikis (Reich 2019), digital games (Annetta et al. 2019; Virk and Clark 2019), MOOCs (Waks 2019), virtual reality (Kessler, this volume), cognitive tools (Nesbit et al. 2019), and learning analytics (Winne 2019; Wise 2019). Yet, ways must be devised to adapt these technologies to the human mind, including how we learn, and research evidence is needed to determine which instructional features are most effective.

Overall, this book reflects three themes for research in educational technology: (i) shifting from media comparison studies to value-added studies, (ii) broadening research in educational technology to include dependent measures of learning and motivation, and (iii) deepening research on educational technology to connect instructional design principles with theories of learning and motivation.

Theme 1: Shifting from Media Comparison Studies to Value-Added Studies

First, this book reflects a shift in research paradigm in the field of educational technology from media comparison studies to value-added studies (Mayer 2014a). In media comparison studies, researchers compare the learning outcomes of students who learn with one medium versus the learning outcomes of students who learn with another medium. For example, we can ask whether students learn better about electromagnetic devices when they play an interactive, desktop game called *Cache 17* or when they receive the material in the form of a slideshow presentation (Adams et al. 2012). This research paradigm is relevant to the classic debate of the effects of instructional media versus instructional method in education (Clark 2001; Clark and Feldon 2014; Kozma 1991, 1994). Furthermore, the media comparison paradigm is problematic to the extent that learning is caused by instructional method rather than instructional media (Clark 2001; Clark and Feldon 2014) or even to the extent that learning is caused by the instructional method afforded by instructional media (Kozma 1991, 1994). Finally, it is challenging to conduct media comparison research because of difficulties in ensuring that the two groups are equivalent in instructional content and instructional method, and differ only in instructional medium.

In value-added studies, researchers compare the learning outcomes of students who learn with a base version of a learning situation involving technology with the learning outcomes of students who learn with the same version with one feature added. For example, we can ask whether students learn better about environmental science when they play a version of an interactive, desktop computer game called *Design-a-Plant* in which an on-screen agent, Herman-the-Bug, communicates by using text printed on the screen versus when he presents the same words in the form of narration or what can be called spoken text (Moreno et al. 2001; Moreno and Mayer 2002). This approach explores the instructional impact of using the affordances of a computer-based technology, which in this case involves using spoken text. Value-added studies can be useful in pinpointing instructional design principles for maximizing the effectiveness of computer-based learning situations. Consistent with the growing consensus favoring value-added studies, the chapters of this book include value-added studies and this appears to be a reasonable strategy for future research.

Theme 2: Including Dependent Measures of Learning and Motivation

The editors of this book call for expanding the measurement of outcomes to include not only changes in learning outcomes, such as knowledge and skills, but also changes in learning processes involving motivation and engagement during learning. Several chapters examine how learning analytics—analysis of detailed computer-recorded data on what students do during learning—can be useful in understanding the underlying learning process for each learner and ultimately in adapting instruction accordingly (Winne 2019; Wise 2019). For example, metrics based on persistence on a task before asking to see the correct answer or time spent looking at feedback can be used to assess motivational processes during learning with an online tutor.

As an example of the potential of learning analytics, in a recent study, Rawson, Stahovich and Mayer (2017) used smart pen technology to record every pen stroke of engineering students as they solved assigned homework problems. Course grade was predicted by metrics based on these pen strokes, such as the total number of pen strokes, and proportion of pen strokes produced more than 24 hours before the deadline. Future work is needed to determine whether this technology can be used as an early warning system to alert students when they are engaging in strategies that are likely to lead to or hinder success in a class they are taking.

Theme 3: Connecting Instructional Design Principles to Theories of Learning and Motivation

This book also highlights the need to ground design principles in research-based theories of learning and motivation, which I refer to as applying the science of learning to education (Mayer 2011). For example, the cognitive theory of multimedia learning is based on the idea that people have separate channels for processing verbal and visual material, only a limited amount of processing can occur in each channel at any one time, and deep learning occurs when the learner mentally selects relevant information, organizes it into a coherent structure, and relates it to relevant prior knowledge (Mayer 2009, 2014b). Instructional methods used with educational technology should be understood in terms of the underlying cognitive processes they are intended to foster.

Similarly, a potential benefit of various educational technologies is their positive effect on student motivation and engagement, so they should be interpreted in terms of current theories of academic motivation (Wentzel and Miele 2016). Relevant motivational theories include interest theory (Alexander and Grossnickle 2016) which holds that people try harder to learn when they are interested; expectancy-value theory (Wigfield et al. 2016) which holds that people try harder to learn when they value what they are learning; self-efficacy theory (Schunk and DiBenedetto 2016) which holds that people try harder to learn when they feel confident about their competence to learn the material; and self-determination theory (Rigby and Ryan 2011; Ryan and Deci 2016) which holds that people try harder to learn in situations where they feel competent, autonomous, and related to others.

Conclusion

What is new in the field of educational technology is the availability of a new suite of computer-based technologies, some of which are explored in this book. What is not new is the human learning and motivation systems that are responsible for promoting valued outcomes. What also is not new in the field of educational technology is the instructional goal of improving learning and motivation through appropriate use of effective instructional methods. The challenge of applying computer-based technology in education is to identify evidence-based and theory-grounded principles for how best to adapt the affordances of technology to help people learn rather than to expect people to adapt to every new learning technology that comes along. This effort will benefit from value-added studies using measures of learning outcomes and learning processes, as exemplified in this book.

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Acknowledgments

The editors would like to thank the following people and organizations. Caroline Ojeme provided capable editing and proofing of manuscripts. The American Educational Research Association awarded a grant to our team that included the editors as well as Professors Joy Egbert and Richard Lamb to design and run TechEd conferences at Washington State University where the drafts of these chapters were first presented. Additional support was provided by the Office of the Provost at Washington State University and its College of Education. We thank Provost Daniel J. Bernardo and Dean of the College of Education, Michael S. Trevisan for their support for the TechEd conferences. We would like to thank our spouses, Tolulope Adesope and Rita Rud, for their love and support for our research endeavors. Finally, Sola would like to thank his kids, Florence Adesope, Felicia Adesope, and Josiah Adesope, for allowing him time to work on this book.

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Olusola O. Adesope is a Boeing Distinguished Professor of STEM Education in the College of Education at Washington State University. His research is at the intersection of educational psychology, learning sciences, instructional design, and technology. His recent research focuses on the cognitive and pedagogical underpinnings of learning with computer-based multimedia resources; meta-analysis of empirical research, knowledge representation through interactive concept maps and diagrams, learning analytics, social programming, and investigation of instructional principles and assessments in Science, Technology, Engineering, and Mathematics (STEM) domains. He has served as Principal Investigator or co-PI on more than 12 external grants, mostly from the National Science Foundation. More recently, he is a co-PI on a $3 million grant for mass dissemination and investigation of the effects of desktop learning modules for learning engineering concepts, and another NSF computer science education grant that is exploring the use of social programming environments to foster both technical as well as soft skills development. He is currently a senior associate editor of the *Journal of Engineering Education*, and serves on the editorial boards of several other top-ranking journals such as the *Review of Educational Research*, *Journal of Educational Psychology*, *Educational Technology Research & Development*, etc. He has delivered numerous conference presentations and is the author of more than 100 publications including 3 books.

Leonard A. Annetta is Taft Distinguished Professor of Science Education at East Carolina University. Before joining the faculty at ECU, Len was a professor at George Mason University and an associate professor of Science Education at North Carolina State University where his research focused on distance learning and the effect of instructional technology on science learning of teachers and students in rural and underserved populations. Although there is considerable research on distance learning, he has focused on the untapped analyses of learning science through various distance delivery strategies. His research has cascaded from his dissertation on comparing three different distance delivery strategies on science teacher professional development to his current focus on evaluating video games as a teaching and learning tool and as a vehicle for synchronous online instruction. The results of his dissertation research suggested that synchronous interaction proved most effective on learning science in a distance-learning environment. Achieving synchronous interaction in distance learning was possible only through videoconferencing technology until recent years. As technology continues to emerge and the push to be connected through the web becomes more and more critical, it became obvious that there needed to be a strategy to deliver science content, synchronously, over the Internet. Upon accepting a position at North Carolina State University, he vigorously began to parlay the results of his dissertation into a pursuit of how synchronous interaction could come to fruition over the Web. Understanding the popularity of online, multiuser video game play, he began to use his past programming knowledge to build a virtual environment that became the platform for his current research. Through two separate internally funded grants, he designed and created a synchronous, online 3D virtual environment for distance-learning courses offered at North Carolina State.

Douglas B. Clark completed his MA at Stanford University and PhD at the University of California at Berkeley in Math, Science, and Technology Education. Prior to joining the University of Calgary in 2017, he was a professor at Vanderbilt University in the United States. He loves playing digital games and imported board games of all kinds. His research investigates the design of digital-learning environments and the learning processes through which people, particularly middle school and high school students, come to understand core science and computer science concepts in the context of those digital-learning environments. This work focuses primarily on conceptual change, inquiry, modeling, digital games, explanation, collaboration, and argumentation. His research is now also extending into the exploration of people's own design processes and supporting those design processes. Dr. Clark has served as an associate editor of the *Journal of the Learning Sciences*. He has also served on the editorial boards of several of the most prestigious journals in science education and the learning sciences including *Journal of the Learning Sciences*, *Journal of Research in Science Teaching*, and *Science Education*. He is a Survey Assessment Innovations Lab Network advisor to the National Assessment of Educational Progress (NAEP) in the United States and was one of the original 20 members of the Academic Consortium on Games for Impact that was initially commissioned by the US White House Office of Science and Technology Policy. In addition, he is active with his local schools and runs a weekly role-playing club for middle school and high school students at one of the schools.

Krista Glazewski is a former middle school science teacher and is an Associate Professor of Instructional Systems Technology at Indiana University exploring means of supporting teachers as they adopt new technological and curricular innovations. Her partnership work has spanned multiple regions in the USA to investigate how and under what conditions teachers might adopt and adapt to new practices. She currently serves as editor of the *Interdisciplinary Journal of Problem-Based Learning*, an open-access journal that publishes peer-reviewed articles of research, analysis, or promising practice related to all aspects of problem- or inquiry-based learning.

Greg Kessler is a professor of Computer Assisted Language Learning (CALL) in the Department of Linguistics and Director of the Language Resource Center at Ohio University. He teaches courses in CALL teacher preparation and research methods. His research addresses CALL teacher preparation, student language use in collaborative language learning, the role of students and teachers in innovative pedagogical contexts, student and teacher autonomy, and the relationship between technology and change in the English language. He has overseen the development of numerous technology-enhanced language programs and has spoken, consulted, and published widely in the area of CALL. He has served the teachers of English to speakers of other languages (TESOL) through a number of roles and was president of Ohio TESOL from 2007 to 2008. He co-authored the TESOL Technology Standards Framework as well as the full volume, *TESOL Technology Standards: Description, Implementation,* *Integration*. He is currently the interim co-director of the computer assisted language instruction consortium (CALICO). He has taught CALL teacher preparation courses and programs across the United States as well as in Burma, China, Croatia, Czech Republic, Egypt, Greece, Hong Kong, Hungary, Japan, Kazakhstan, Korea, Mexico, Montenegro, Saudi Arabia, Serbia, and Turkey.

Diane Jass Ketelhut interests center on improving student learning and engagement with science through increasing access, particularly in urban contexts, to scientific inquiry experiences and through raising self-efficacy in science. She looks specifically at the use of virtual environments to deliver scientific inquiry curricula and science assessments to students in the classroom and at professional development to help teachers integrate scientific inquiry into their curricula. Most recently, I am exploring the integration of computational thinking learning into preservice elementary science teacher education. She holds certification in secondary school science and was a science curriculum specialist and teacher (science and math) for grades 5–12 for 15 years. Prior to that, she conducted immunology basic research for 2 years. She received a BS in Bio-Medical Sciences from Brown University, an MEd in Curriculum and Instruction from the University of Virginia, and her doctorate in Learning and Teaching from Harvard University. She was an Assistant Professor of Curriculum, Instruction, and Technology in Education at Temple University for 5 years prior to coming to the University of Maryland in 2011. She is currently an associate professor in the Department of Teaching and Learning, Policy and Leadership at the University of Maryland.

Richard Lamb is an associate professor and director of the Neurocognition Science Laboratory University at Buffalo Graduate School of Education. His research focuses broadly on the use of educational technology, neuropsychology, neuroscience, and psychometric theory to examine some of the factors that may impede or enable learning in science. His tools include computational modeling of student cognitive processes, measurement of affective dispositions, and identification of physiological systems that are associated with learning via neuroimaging technologies. Recently, he has been exploring the use of educational technology, specifically virtual reality in pre-kindergarten through college level educational environments to study learning.

Qing Liu joined the Teaching and Learning Centre as a learning technology specialist. Since 2008, Qing has engaged in various research projects investigating the use of educational technologies as instructional tools to support teaching and learning, such as Intelligent Tutoring Systems (ITS), online peer evaluation systems, and argumentation visualization tools. She has extensive experience in designing and teaching online courses. She holds an MA and is currently a PhD candidate in educational technology and learning design. She is skilled in conducting systematic reviews and meta-analyses of empirical studies. Qing is working on a project that investigates the use of Microsoft Office 365 in school contexts, teaming with researchers from SFU, Microsoft, and the Coquitlam School Board.

Richard E. Mayer is Distinguished Professor of Psychology at the University of California, Santa Barbara. His research interests are in applying the science of learning to education, with current projects on multimedia learning, computer-supported learning, and computer games for learning. His research is at the intersection of cognition, instruction, and technology, with a focus on how to help people learn in ways, so they can transfer what they have learned to new situations. He served as President of Division 15 (Educational Psychology) of the American Psychological Association and Vice President of the American Educational Research Association for Division C (Learning and Instruction). He is the winner of the Thorndike Award for career achievement in educational psychology, the Scribner Award for outstanding research in learning and instruction, and the American Psychological Association's Distinguished Contribution of Applications of Psychology to Education and Training Award. He is ranked #1 as the most productive educational psychologist in the world in *Contemporary Educational Psychology*. He has served as the Principal Investigator or co-PI on more than 30 grants, including recent grants from the Office of Naval Research to investigate how to improve the effectiveness of educational games, from the Institute of Education Sciences to investigate the effectiveness of features of an online tutoring system, and from the National Science Foundation to study students' learning and problem-solving strategies. He is the former editor of the *Educational Psychologist* and former co-editor of *Instructional Science*, and he serves on the editorial boards of 12 journals mainly in educational psychology. He is the author of more than 500 publications including 30 books, such as *Learning as a Generative Activity* (with L. Fiorella), *Computer Games for*

Learning, *Applying the Science of Learning*, *e-Learning and the Science of Instruction: Fourth Edition* (with R. Clark), *Multimedia Learning: Second Edition*, *Learning and Instruction: Second Edition*, *Handbook of Research on Learning and Instruction: Second Edition* (co-editor with P. Alexander), and *the Cambridge Handbook of Multimedia Learning: Second Edition* (editor).

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Hui Niu finished her PhD in educational technology at Simon Fraser University (SFU), Canada. She was one of SFU's most outstanding graduate students from the Faculty of Education and was awarded the Dean of Graduate Studies Convocation Medal. For her dissertation entitled "Pedagogical Efficacy of Argument Visualization Tools", Dr Niu developed a new online argumentation visualization tool called the dialectical map. Students create dialectical maps by identifying and composing claims, evidence, and warrants and filling them in an online map. They then draw an integrated conclusion by evaluating arguments and counterarguments in a visually hierarchical structure. Findings from her empirical research showed that the dialectical map fostered learning and comprehension from text and increased the quality of writing about the topic in a post-test. Between 2006 and 2010, she worked as a research analyst at the Canadian Council on Learning she developed grant proposal, wrote reports for various audiences and educational stakeholders, and managed research projects and provided leadership and research consultation for clients.

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A. G. Rud is Distinguished Professor, Cultural Studies and Social Thought, at Washington State University. Nationally known for his expertise in the philosophical dimensions of education, Rud's research focuses on the cultural foundations of education, with particular emphasis on the moral dimensions of teaching, learning, and leading, P-20. He is the president of the John Dewey Society 2017–2019 and edited its peer-reviewed international journal, *Education and Culture*, 2004–2010. Rud is widely published in his field. He has three books that are due to appear in 2018, two co-edited and one co-authored. He teaches graduate courses in the cultural studies and social thought in education doctoral program in philosophy of education, history of education, John Dewey and progressive education, and social theories of education. He is a past chair of the WSU Faculty Senate and chaired the WSU Presidential Commission on Campus Climate.

Marina Shapiro holds her BS and MS from Towson University and a PhD from George Mason University. Her background is in Science Education Research (Chemistry) and Learning Technologies. Her research interests are implementing game-based learning environments into undergraduate college chemistry curricula in order to facilitate methods for active and experiential learning, particularly in the context of lecture settings where students are often passive learners. The focus of her dissertation research was on evaluating the implementation of a chemistry video game into an undergraduate General Chemistry course where she concentrated on evaluating knowledge gains of chemistry content and attitudinal increase toward chemistry. The results of the dissertation showed that the chemistry serious educational game (SEG) led to a significant increase in students' knowledge of chemistry concepts, thereby indicating the potential for implementing SEGs into undergraduate college chemistry curricula. Additional research interests include investigating how SEGs can be used to increase motivation, engagement, and how they can be implemented as tools for measurement of assessment as research shows that

SEGs can serve as tools for assessment and that there is a link between engagement, motivation, attitude, and knowledge gains in science class. By increasing attitude toward chemistry the goal is to also see an increase in engagement and motivation to learn chemistry. She teaches General Chemistry, Foundations of Analytical Chemistry, Biochemistry, and Food Science lecture and laboratory courses.

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CHAPTER 1

Maximizing the Affordances of Contemporary Technologies in Education: Promises and Possibilities

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For several decades, extensive instructional research comparing the effects of different media on learning has been conducted, albeit with mixed results (Broadbent 1956; Clark 1983; Kinchla 1974; Kozma 1991; Mayer 2009; McLuhan 1964; Severin 1967). Researchers have debated whether educational technology (media) use is actually effective for improving student learning (Clark 1983; Kozma 1994; Tamin et al. 2011). Research in educational technology has moved past the classic debates that pervaded the educational literature between the 1980s and 90s. Rather than continuing the debates on media versus pedagogy, researchers have called for efforts to maximize the affordances of new technologies based on sound pedagogical principles (Kozma 1994). Hence, a plethora of studies have been published over the last two decades on multimedia learning and the use of learning technologies (Clark et al. 2016; Guri-Rosenblit and Gore 2011; Mayer 2009, 2014). However, development of new technologies continues to outpace research efforts on best practices for effectively using

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O. O. Adesope, A. G. Rud (eds.), *Contemporary Technologies in Education*, https://doi.org/10.1007/978-3-319-89680-9_1

such technologies for learning. For example, the last few years have witnessed the emergence and extensive use of contemporary technologies such as the Flipped Classroom (FC), Massive Open Online Course (MOOC), Social Media, Serious Educational Games (SEG) and Mobile Learning (ML). While some of these new learning environments have been touted as panaceas, researchers and developers have been faced with enormous challenges in enhancing the use of these technologies to arouse student attention and improve persistent motivation, engagement, and learning (Annetta 2008; Hamlen 2011; Waks 2013; Yarbro et al. 2014). Broadly speaking, educational technologies have brought about developments and challenges in theory, methods, and practice. In the next section, we discuss theoretical, methodological, and practical developments and challenges with educational technologies. We caution that our review of these developments and challenges is not exhaustive, as such endeavor is beyond the scope of this chapter.

Theoretical Developments and Challenges with Educational Technologies

Because human learning, motivation, and engagement are highly complex, researchers have constructed several theories of human learning and instruction to explain these constructs (e.g., Jonassen and Land 2012; Mayer 2014; Reigeluth 2012). Among the more important recent theoretical advances relevant to emerging educational technologies are theories on multimedia learning, cognitive load, machine learning, data mining, learning analytics, and knowledge representation, and how they can be used to model human learning (Bottou 2014; Kirschner 2002; Markauskaite 2010; Martin and Sherin 2013; Mayer 2014; Plass et al. 2010). More recently, Michelle Chi and her team developed the ICAP framework (Chi and Wylie 2014). This framework provides theoretical underpinnings for the effects of educational technologies on different forms of cognitive engagement and the resulting learning outcomes. Other theoretical advances in the field of educational technologies are refinements or applications of long-standing psychological theories, including the social cognitive theory (Bandura 1989), its concomitant model of self-regulation (Zimmerman and Schunk 2001), and situated learning theory (Dawley and Dede 2013), especially legitimate peripheral participation and communities of practice (Lave and Wenger 1991) to explain student learning and engagement. For example, some contemporary educational technologies have incorporated online collaborative learning environments that facilitate learning with the help of others. Today's students increasingly use social, intelligent, and online learning environments to share ideas, get feedback, refine ideas, and publish information (e.g., Carter et al. 2017; Hundhausen et al. 2015; Kaufer et al. 2011; Ma et al. 2014; Maloney et al. 2010; Myneniet al. 2013). Hence, these long-standing psychological theories of learning have advanced the design of contemporary educational technologies and provided theoretical explanations for their benefits and challenges.

Although theoretical developments in educational technologies are advancing, new technologies are being developed at a rapid pace. This gives rise to the need for new theories to help researchers understand learning processes and outcomes. Some argue that existing theories of learning cannot sufficiently explain the fundamentally changed contextual conditions for learning brought about by advances in the technological landscape (Siemens 2005). More than ever before, new learning technologies help track and log learners' traces of their learning activity across different contexts—in school, at home, indoors, and outdoors (Martin and Sherin 2013). This generates rich, *big data* and a new wave of research questions (Greenhow et al. 2009; Reich et al. 2012).

Today's educational technologies provide fine-grained, process-oriented data at every click of the mouse. Tracking time spent online reading or working on a unit, notes taken, common errors, and other details can open up new pathways for understanding how people learn (Feng et al. 2009; Kramer and Benson 2013). SEG, intelligent tutors that provide formative feedback, MOOC courses or FCs, and posting reflections on electronic boards and blogs is part of daily life for many students. Such affordances of contemporary educational technologies require development of new learning theories and reconceptualization of research (DeBoer et al. 2014). The chapters in this book showcase affordances of contemporary and emerging educational technologies thus presenting a rich space for robust discussions on the role of existing theories and development of new theories to conceptualize and understand anticipated findings related to contemporary and emerging educational technologies.

Methodological Developments and Challenges with Educational Technologies

The field of educational technology has made great methodological strides. Methodological advances through the development of machine learning, data mining, and learning analytics have significantly expanded the research that can be carried out with contemporary educational technologies (Bottou 2014; Markauskaite 2010; Martin and Sherin 2013). More than ever, the use of technologies allows teachers, researchers, and instructional designers to track students' interaction with learning resources and offer more real-time support for students. The nature of these technologies and the ability to ask rich research questions provide new opportunities to collect, analyze, and synthesize data in ways that were previously considered impractical. Based on this influx of data from rich research questions on both the process and outcomes of learning, educational researchers now harness statistical techniques such as hierarchical linear modeling, growth curve analysis, and latent profile analysis (Lee 2010) to advance our knowledge of human learning, engagement, and motivation.

Despite these methodological advances, several methodological challenges require immediate attention. For example DeBoer et al. (2014) argued for a reconceptualization by way of creating new educational variables or providing different interpretations of existing variables to more accurately understand the nature of MOOC data. They demonstrated the inadequacy of conventional interpretations of four variables for quantitative analysis (enrollment, participation, curriculum, and achievement). Although their research exclusively focused on MOOCs, similar issues may be found with some educational technologies that generate big data (e.g., logs of class interaction with SEG, instructional materials in a FC, etc.). There is a need to reconcile the changing nature of variables generated or afforded by several new technologies with entrenched practices, particularly curriculum-based learning with fixed learning objectives evaluated by standardized exams. Although methods for analyzing big data to understand student learning are evolving, this evolution is slow. The need to keep pace by developing effective methods at a brisker pace is vital.

Another area of educational technology requiring methodological consideration is the use of conversational agents and interactive technologies (Graesser et al. 2008; Rus et al. 2013; Spector 2010). Conversational agents and interactive technologies on the internet can collect detailed information from students in log files that track learning, emotions, and achievement with a fine-grained focus. The agents can precisely manipulate what is said and how it is said. However, using agents is often challenging, particularly where online delivery is necessary. There is a need for researchers to discuss and explore viable scalable approaches for delivering agents over the web.

Perhaps one of the great methodological challenges in educational technology is a dearth of rigorous experimental research that will examine the effects of different features of contemporary technologies. There is clearly a need for more robust research efforts supported by a national agenda to rigorously examine the effects of technology-rich environments through experimental work. There is clearly a need to engage in robust discussions around these methodological challenges, as well as others, posed by advances in educational technologies.

Practical Developments and Challenges with Educational Technologies

One practical example of educational technology is the use of Khan Academy videos and problem sets as learning resources both in the classroom and at home. Indeed, the Khan Academy video library is associated with the FC model, where teachers assign videos on concepts to be learned for students to watch at home and then use the class time to engage students in discussion and interactive activities (Murphy et al. 2014). The evaluation report by Murphy et al. (2014) suggests that the use of Khan Academy and similar resources and models may facilitate both cognitive and noncognitive outcomes, including student learning, engagement, perseverance, motivation, and self-regulation. However, current implementation of such resources precludes researchers from making causal claims about their effectiveness. The promise of FCs, immersive environments, and machine learning are not yet fully realized (Calders and Pechenizkiy 2012; Bienkowski et al. 2012; Yarbro et al. 2014). For example, although classroom lectures are problematic for today's students in terms of engagement, MOOCs and FCs have not yet leveraged the affordances of immersion and motivation offered by the technologies people use in daily life. Practical applications of educational technologies must move beyond the classroom and static experience to incorporate innovative approaches.

One of the educational technologies of the future will be intelligent systems that incorporate sophisticated learner and teacher models (Ma et al. 2014). They will monitor and model the emotional, metacognitive, and cognitive states of learners and will interact with them through avatars that function as pedagogical agents. The systems will support collaborative learning and simulate peer agents with whom the learner can practice to improve cooperative learning skills. Applying adaptive models of assessment to each learning activity allows for continuous assessment and increases accuracy, although challenges abound in embedding those diagnostic, dynamic assessments in multimedia learning environments (Dede 2013).

Summaries of Each Chapter

This section focuses on the road ahead that each chapter delineated. More specifically, we summarize where current trends lie to predict affordances of the technologies and how the technologies might be able to advance student engagement, motivation, and learning in the future.

Annetta, Lamb, Vallett, and Shapiro-Eney

Annetta, Shapiro, Luh, and Berkeley focus on learning progressions and project-based learning in STEM fields, and how these become a powerful learning technology when used in the construction of SEG. The authors state that learning progressions and project-based learning have had increased attention in the past decade, as educators endeavor to improve STEM learning. These activity-based modes of learning show higher results than other, older, and more passive means used in science education. The emphasis on agency and activity by the student learner is taken a further step if she engages in the construction of a serious educational game. The authors show how the construction and playing of a serious educational game develops the understanding of science required by current science assessments, specifically the Next Generation Science Standards (NGSS). The joining of learning progressions and project-based learning provides a powerful tool for learning within the inviting format of a serious educational game, as the authors explain:

> The use of project-based learning, as discussed above, fosters the development of science and engineering practices including making observations, making determinations regarding data, and the construction of explanations and arguments. Likewise, well-identified learning progressions would prove

useful not only in creating the deeper conceptual understandings that the NGSS purports to target but in vertical planning for the spiraling aspects of the content in the standards.

Reich

Wikis are characterized as collaborative websites where users comment, amend, and further develop content. Wikis seem like ideal environments to further goals of progressive education, and to realize a democratic form of learning advocated by John Dewey 100 years ago. Reich wants to know if this is the case: "Is the wiki-inspired 'revolution in education' underway or do these thousands of new learning environments show little sign of nurturing Dewey-inspired forms of collaborative learning?" After studying the behavior of participants in a large sample of wikis, Reich concludes that students engage in sparse collaborative behavior when contributing to a wiki. Such collaborative activity is present only 11% of the time on wikis. Wikis are more accurately characterized as venues where individual accomplishment is evident. Reich discusses the optimistic view of wikis as a technology of furthering progressive, Deweyan education discussed by Glassman and Kang:

> My reading of Glassman and Kang, however, is that they argue that knowledge-building, content co-creation, and communities of investigation are not merely made theoretically possible by wikis, but that educators should understand wikis as places where these advanced learning behaviors can emerge with some regularity, indeed, enough regularity to inspire a revolution. The evidence presented here suggests that these particular arguments should be tempered with the caveat that, in practice, most wikis are individually-produced platforms for content delivery, more often created by teachers than by students.

Nesbit, Niu, and Liu

Cogently advancing a position is an important skill for all students. Traditionally this skill is learned in presenting reasons orally for a position or writing a paper, and, importantly, getting feedback from others and a teacher. John Nesbit, Hui Niu, and Qing Liu focus on the goal of learners to argue as well as the instructional strategy of "argue to learn" by utilizing the developing technology of cognitive tools. Argument is notoriously difficult to teach but of vital importance to a democracy. The future of argumentation in education for these authors is instructional software that utilizes tools such as cognitive schemas, cognitive tools, argument tagging, and argument maps, and how these may be refined and further developed. Of even greater importance to future development in this area is how to spread and deepen this practice in all subject matter. The authors see that the technology of cognitive tools aid this endeavor:

> If arguing about subject knowledge has the dual effect of developing students' subject knowledge and developing their argumentation abilities, we propose that using appropriately designed cognitive tools in such learning activities can boost that effect.

The authors present evidence from studies of how they have accomplished an increase of argumentation and subject knowledge through the use of cognitive tools. These tools are highly interactive and take advantage of visualization of evidence, reasons, and argument paths to further enhance a student's ability. Though the authors do not discuss the need for cooperation among instructors to enable cross over, this is certainly assumed here.

Winne

It is well-known that computers permit analysis of much larger data sets than was previously feasible with pen and paper. If we study large data sets on learner behavior, we can begin to see how we can enhance learning. Philip Winne uses nStudy software to gather big data in both ipsative (within an individual over time) and normative (comparing an individual to a group) means, all in an effort to support learning analytics that will enhance self-regulated learning and problem-solving. Recording each action by a learner provides a powerful ipsative feedback loop to the learner, while comparing individual learners across the collected data points gives a picture of how effective a learning task is, how engaged the learners are with the task, and what gaps in learning may be addressed. nStudy permits fine-grained analysis of trace data. One gets a sense from Winne's chapter that we are at the very beginning of this kind of robust learning analytics that allows researchers, teachers, and learners to drill down, to compare, and to draw up plans for further learning that was not possible even a few decades ago. Big data allow these kinds of comparisons that both provide ipsative and normative feedback useful to designers of learning activities.

Kessler

Certainly one aspect of the innovative environment for learning today are the many opportunities for the collaborative construction of a learning environment. Elsewhere in this volume, Justin Reich examines critically claims that wikis promote collaboration among learners. In his chapter, Greg Kessler reviews a wide range of social learning experiences enhanced by technological development. He sees that these practices are still nascent, but promising. Kessler acknowledges that schooling is for the most part still conducted as it was a century ago, when John Dewey tried to alter the instructor-centric model of content delivery to a learner-centric, participative model where the instructor facilitated student-driven learning. Kessler believes that the new social learning experiences being developed now in such arenas as augmented reality and virtual reality draw students in to be agents of their own learning, and in the case of big data coupled with artificial intelligence and bots, come to conclusions that would be impossible for humans to do unaided. Kessler mentions the IBM artificial intelligence agent Watson, which is able to examine the 8000 medical papers published each day to sort out salient information, and asks how education might be transformed if we utilized such a process. A particular strength of Kessler's chapter is his focus on the future of teacher preparation in light of rapid development and implementation of learning technologies. He believes teachers should not be apprehensive about these technologies, such as the widespread fear that robots will replace teachers, but should embrace opportunities to enhance social learning through technologies.

Virk and Clark

It is important to acknowledge the limitations of new learning technologies, and endeavor to overcome them, as that will help optimize what helps learners best. This is a lesson that helps learning technologies progress, and will be central to their adoption in the future. Virk and Clark's chapter discusses the use of signaling in a Disciplinarily Integrated Game (DIG). Signaling is a well-known procedure where cues direct learners toward particular features or content. A DIG uses game technology to support the development of scientific modeling in K-12 classrooms. The DIG examined in this chapter, SURGE Symbolic, is on Newtonian physics concepts, and signals were embedded with one group and not another in the authors' study. While signaling should improve the efficacy of learning by coaxing and encouraging learners toward relevant parts of the game, Virk and Clark found that learners who did not have signaling performed better than those who had signaling embedded in the game. Signaling, as a proven cognitive tool, provides the leverage to improve and refine the SURGE Symbolic DIG. This process of iterative and dialectical testing and improvement must remain robust as development and assessment practices as games, a burgeoning area of learning technologies, are developed in the future.

Glazewski

Krista Glazewski advocates for skepticism about the claims of technologies for educational transformation. Her chapter goes back to the early proponents and skeptics of how transformative technology would be to teaching and learning, and states many of us are still allured by the promises of such. She cites how Second Life was widely adopted and then abandoned, and proposes using it as a cautionary "yardstick" example of what she calls the "enthusiasm-interest-investment-expiration-desertion cycle." Her chapter sets out policy direction for the future of educational technology as "innovative and pedagogically coherent."

> In short, I am arguing that educational technology should not be cast as both the *goal* of the learning environment and the *actor* for catalyzing change in higher education. However, if we decouple technology from the revolutionary role to place emphasis on understanding robust pedagogical uses, we can inform practices and potential in higher education. In this context, educational technology can be broadly defined as the ways in which we make pedagogical decisions to support a wide range of teaching or learning actions in our classes.

Here the emphasis is first upon pedagogy, and she gives three examples in university instruction, in history, biology, and medical education, where pedagogy guided the choice and use of technology, and where technology afforded transformative teaching and learning.

Ketelhut

The science educator Diane Ketelhut builds upon Lee Shulman's concept of "pedagogical content knowledge" by considering how technology can become an added layer of pedagogy in how content is tailored for learning. Students are already steeped in computer and especially now smart phone technology—she notes that high school seniors were in second grade when the iPhone was released—but schools and especially teacher education programs have not kept up with these innovations. In teacher education students, there are wide variations in knowledge of science and the integration of technology into pedagogy is inchoate. Ketelhut, like Glazewski, stresses that technology is not an end in itself, but a means to focus on strong pedagogical uses of technology. Teachers should acquire "technological pedagogical content knowledge" (TPACK) and having such "means knowing what tools to use for what purposes to achieve what learning." Thus the road ahead for the uses of technology is all about integration and choice of appropriate means to tailor content for learning. There is much to achieve here in preservice and inservice teacher education; science content must be mastered and technologies must be appropriately integrated for the particular purpose of the learning.

Waks

Leonard Waks recounts the quick rise and early maturity of an innovation in the delivery of online education. Starting ten years ago and developed at a rapid pace in the last five years, MOOCs "promised to bring free university courses by global super-star professors at top-ranked universities to any student with Internet access, anywhere in the world."

Here rather simple information technology helped to facilitate a leveling of the educational playing field and a greater degree of participation, much as the earlier technology of the printing press did centuries ago. Waks sees MOOCs as an early development in what he calls Education 2.0, where learners will take more fully charge of their learning by customizing their education to fit their needs, taking short courses to gain a skill for employment or learn about a topic for pleasure. Waks predicts that such education, uncoupled from degrees and credit hours, will enable workers to move around nimbly in the "gig" economy, retooling qualifications as needed:

> As firms shift from full time 'professional workers' to short-term, low obligation contract workers, they search for those who can perform specific tasks at high competence levels without further training. In the process, university degrees and transcripts become less important, searchable credentials of capabilities essential. This has created pressure to break apart or rearrange the elements of college education.

Wise

Alyssa Wise discusses how advances in digital technologies allow the collection and analysis of large numbers of various and finely grained data provided by learning activities. This endeavor, called learning analytics, is still nascent, but its practices should help us improve teaching and learning:

> Learning Analytics is the development and application of data science methods to the distinct characteristics, needs, and concerns of educational contexts and the data streams they generate. The goal is to better understanding and supporting learning processes and outcomes through both short-cycles improvements to educational practice and long-cycle improvements to the underlying knowledge base.

There are technical and policy issues that need to be addressed before such practices can become effective. Wise notes that infrastructure enhancement is crucial for learning analytics to be robust and widespread, but just as important is attending to the policy and ethical issues surrounding such data uses. It is crucial that stakeholders understand why certain data are gathered and analyzed. It is up to researchers and practitioners to make plainly clear how the collection and analysis of certain data are linked to enhanced learning in ways that would not have been possible otherwise. Collecting large amounts of data could also be used in surveillance and control, so the ethics of learning analytics promises to be a burgeoning subfield.

Advances in learning science are highly dependent on technological developments. This book will create a unique opportunity for robust discussions among expert researchers in the fields of educational technology, educational psychology, learning sciences, computer science, instructional design, educational game development, social media for learning, and other relevant areas to inspire new thinking and lay out bold research ideas that will significantly advance the field theoretically, methodologically, and practically.

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CHAPTER 2

Improving Science Education Through Developing Technological Pedagogical Content Knowledge in Teachers

Diane Jass Ketelhut

Digital technologies are ubiquitous. Their uses are myriad and include gaming, social media, organizational tasks, and even learning. Indeed, they have impacted how we live, learn, and even think. One has only to watch the television show *Jeopardy* to see the stark difference in what we value as knowledge between the twentieth and twenty-first centuries. Few today would see any value in memorizing a plethora of information that can be searched for very quickly on a smart phone. Instead, our children need to learn how to evaluate that information, how to problem-solve, and importantly, how to collaborate.

The children in our K-12 schools today only know this technologically enhanced world. Today's high school seniors were in second grade when the iPhone was first released. Even before that as digital technologies began to take hold, the seminal thinker, John Seely Brown, said that "Today's digital kids think of information and communications technology (ICT) as something akin to oxygen: they expect it, it's what they breathe, and it's

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O. O. Adesope, A. G. Rud (eds.), *Contemporary Technologies in Education*, https://doi.org/10.1007/978-3-319-89680-9_2

how they live. They use ICT to meet, play, date, and learn. It's an integral part of their social life; it's how they acknowledge each other and form their personal identities" (2002, p. 70).

Unfortunately, schools have not kept up with this digital revolution. Curriculum materials and pedagogies still remain eerily similar to those from the mid-1900s. Not only does this not match how children interact with the world, it also does not prepare them for the modern working world. To try and change this, multiple organizations have called for the integration of technological tools into curricula and pedagogy. For example, the Next Generation Science Standards list computational thinking as one of the eight science and engineering practices in which students should engage (NGSS Lead States 2013).

One digital technology that is showing promise in classroom settings is that of computer gaming. The Federation of American Scientists held a summit on digital gaming in 2006 in which they concluded that gaming might help improve training and education for twenty-first century jobs: "game players exercise a skill set closely matching the thinking, planning, learning, and technical skills increasingly demanded by employers in a wide range of industries" (FAS 2006, p. 4).

While these recommendations are impacting curricula design, and even schools' willingness to try new approaches, little has been done to impact teacher knowledge of how to use digital technologies, like computer games, in their practice. Higher education is slow to change and, lagging farther behind are teacher education programs. This chapter will focus on science teacher education programs, and the need to improve them to create technology-savvy teachers. Results from pilot studies of helping preservice teacher education students understand digital computer games as well as from an in-service professional development program will be shared to illustrate a possible approach for creating teachers competent to integrate technology into their practice.

Theoretical Foundation

Pedagogical Content Knowledge

Since seminal work 20 years ago by Shulman (1986, 1987), educators have recognized the importance of pedagogical content knowledge (PCK) as a distinct area from subject content and pedagogical knowledge. PCK includes understanding areas of student misconceptions, preconceptions, instructional strategies, curriculum, and assessment. Gess-Newsome (1999) describes PCK as when an expert teacher "has well-organized individual knowledge bases [of subject matter, pedagogy and context] that are easily accessed and can be flexibly drawn upon during the act of teaching" (p. 11). For science teachers, this means making decisions on what to teach—content or process—as well as how for each teaching moment. In the best of all worlds, science teachers would flexibly draw upon a strong scientific knowledge base that consisted of what science is known and how science works as well as a strong pedagogical understanding of how children learn science.

Exploring the use of scientific inquiry is a good example of PCK. The 1996 National Science Education Standards (as well as many current state standards) identified scientific inquiry as both a key pedagogical tool and scientific process to be learned, explored, and used in the classroom (National Research Council 1996). It is at the intersection of science content and pedagogy. However, research indicates that as science teachers' personal science content knowledge and scientific inquiry experiences decrease, so does their use of scientific inquiry in their classrooms (Windschitl 2004; Roehrig and Luft 2004). In other words, as Gess-Newsome indicated, an expert teacher needs "well-organized individual knowledge bases." Without having a strong understanding of science content and pedagogy, a teacher refrains from creating an environment for learning real science.

These two knowledge bases are in play differently for those certified in elementary education versus those certified in secondary science based on certification requirements. Secondary teachers typically are required to have a major in a science discipline. Thus, not only do they then have a strong content background, but upper-level science courses in higher education tend to include opportunities for research—that is scientific inquiry. Unfortunately, elementary education certification programs rarely require more than two or three science classes. More often than not, students draw these from a collection of introductory college courses. These courses, unlike the higher-level ones, generally are taught didactically and are content-heavy (Alberts 2009). Thus, these budding teachers end up with minimal knowledge and little to no experience in scientific inquiry. It is, therefore, not surprising that some reviews indicate that up to 80% of K-8 teachers do not teach with inquiry methods (Jorgnenson and Vanosdall 2002). Thus (as would seem obvious), deficiencies in content impact Gess-Newsomes "easily accessed … flexibly drawn upon" PCK.

Technological Pedagogical Content Knowledge

Despite the fact that we are still struggling to achieve this expert teaching in science, we are now faced with an additional need. Koehler and Mishra (2008) have expanded our thinking of important teaching domains by adding a new one: technology. In their model, they view a successful teacher as one that can draw from content, pedagogy, and technology in a similar manner to that described by Gess-Newsome, forming a technological pedagogical content knowledge (TPACK) framework (Fig. 2.1; http://tpack.org). Koehler and Mishra claim that effective teaching with technology requires TPACK, or an ability to draw on and integrate content, pedagogy, and technology flexibly during the act of teaching, to paraphrase Gess-Newsome. Koehler and Mishra see TPACK as understanding the use

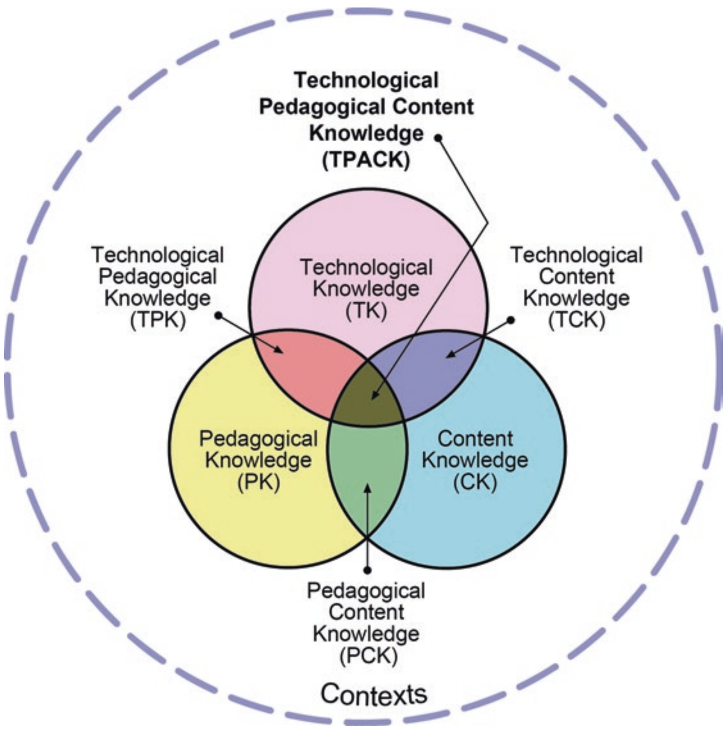

Fig. 2.1 Koehler and Mishra's TPACK framework. (Reproduced by permission of the publisher, © 2012 by tpack.org)

of technology to improve pedagogy, to facilitate learning of content, and to build on student technological literacies as content.

But how do teachers achieve this TPACK? Koehler and Mishra view the relationship between these knowledge bases as an equilibrium that is in constant flux, responding to learning in a manner similar to Piaget's theory of assimilation and accommodation (Rathus 2004). As new information, for example, a new technology, is encountered, this information must either be assimilated into the existing mental frameworks or those frameworks must be forced into disequilibrium until accommodation is reached, creating a new TPACK for that teacher.

University-Based Teacher Education Programs and TPACK

Similar to PCK, TPACK for science teachers requires knowledge in science content and pedagogy. However, it adds a third base: technology. We have already seen that typical university-based teacher education programs produce elementary teachers with a deficit in science content, although this is a strength for secondary science education programs. Both programs do a good job of teaching pedagogy, with secondary science education students being far more likely to be exposed, as discussed previously, to scientific inquiry than elementary ones. What is the impact of these programs on developing technology knowledge?

How teacher education programs approach teaching about technology is widely varied. Traditionally, all students regardless of certification pathway would take a single stand-alone course that is focused on technology knowledge. For example, such a course might teach students how to design a web page to interface with parents and students. Far more rarely is this course connected to a specific content area. So for example, for science teachers, there would be little about how to use digital tools, such as scientific inquiry-based virtual environments, to teach higher-order concepts. Those topics are typically relegated to an already dense science methods course, often taught by a professor without a strong TPACK themselves.

Thus, in a traditionally designed, university-based, teacher education program, graduating teachers would have a strong background in general pedagogical methods, knowledge of technology tools, mixed experiences in scientific inquiry depending on whether they are in the elementary or secondary track, and an uncertain knowledge of how technology tools can help them teach science (Abdal-Haqq 1995). Given that background,

Table 2.1 Aspects of the TPACK framework achieved by graduates of traditional teacher education programs

Knowledge aspects of the TPACK framework	*Elementary certification graduates*	*Secondary certification graduates*
Content knowledge	Weak	Strong
PCK	Weakened by content deficiency	√
Pedagogical knowledge	√	√
Technological pedagogical knowledge	Weak in traditional program	Weak in traditional program
Technological knowledge	√	√
Technological content knowledge	Weak in traditional program	Weak in traditional program

Table 2.1 shows how a teacher graduate might fare on six of the seven different knowledge areas of TPACK. The row for TPACK is left off as it cannot be attained without adequate knowledge in the other bases. As can be seen, both programs have their weaknesses preventing a teacher from achieving TPACK.

While this chart looks relatively dire, it is less so for secondary certification graduates. While their technology knowledge relative to science-specific pedagogy and content is lacking, they typically have strong knowledge of science content and pedagogical methods. The importance of these two knowledge bases for developing TPACK can be seen in a study by Hofer and Swan (2008). They followed two experienced social studies and literacy teachers while they attempted to design and incorporate a middle school digital documentary project. Hofer and Swan concluded that the teachers' strong content and pedagogical backgrounds pulled them through difficulties relating to TPACK. With secondary teachers being protected by their strong content knowledge, elementary certified teachers are most at risk for a low TPACK, just as they are for a low PCK.

Investigating TPACK in a Preservice Elementary Science Methods Course

Working in an elementary certification program that only required a single stand-alone technology content course, I sought to uncover my students' understanding of integrating technology into their science teaching.

As their science methods teacher, I required my preservice elementary teachers to explore a scientific inquiry-based virtual environment designed for upper elementary-aged students. These preservice teachers were in a master's certification program, and thus had varying levels of scientific knowledge depending on where they had received their undergraduate education and in what they had majored. They were asked to explore the virtual environment for several hours, discuss their experience with their peers in an online forum, and then read published articles about how elementary teachers used it with their students. This was followed by an all-class discussion of their experience. To be clear, my primary goal as their instructor was to expose them to digital tools they could integrate into their future practice. However, their conversations shed light on their motivation and confidence to use such tools. Qualitative data from class and asynchronous discussions were analyzed in order to understand the impact prior technology experience and science content expertise had on teacher perceptions of the usability of these virtual environments to facilitate science learning.

These elementary preservice teachers' conversations about the value of the virtual world covered aspects of engagement, collaboration, and pedagogy. Less clear was their understanding of how it might be used to teach science, which was not unexpected. On engagement, their conversations indicated their own discomfort with technology (in TPACK terms: a technology knowledge weakness); the preservice teachers, regardless of their own backgrounds, found the site somewhat confusing but all thought that students would find the site engaging. For example, Jane (all names used are pseudonyms) stated, "*I think that children adapt to these skills quickly as if it were instinctual.*"

Their conversations were more diverse on topics of pedagogy, an area that they clearly felt more comfortable with (the pedagogy knowledge area of TPACK). Interestingly, the preservice teachers split along lines of science content knowledge on their views of using the virtual world for collaboration. The students with a great amount of science expertise did not mention collaboration at all, while several of the less scientifically trained students did applaud the abilities of the site to promote real collaboration. They pointed out that in several places in this virtual environment, it would be impossible to succeed at tasks on your own, but participants could be successful if they teamed up with another participant. It is possible that this difference in observation is an artifact of the particular students involved (this was a small sample of only 20 students), but the TPACK framework might offer another interpretation. Koehler and Mishra indicate that the three knowledge bases are in equilibrium. But for those students with a very strong academic science background, their equilibrium might have been pushed toward content and away from pedagogy. On the other hand, those students who had only taken a couple of science classes in college and were steeped in pedagogy courses had the opposite push on their equilibrium toward instructional strategies. It is another indication of the difficulties that preservice teachers have in developing TPACK.

Of most interest to this study is how these preservice teachers viewed the potential for using virtual worlds in the science classroom. Their reactions to this were varied and showed a spectrum of knowledge across the TPACK framework. For example, Marie concluded, "*interactive technology is a great way to use visual and auditory learning styles*[1] *to reach students with different learning abilities.*" In this statement, she is showing a beginning understanding of technological pedagogical knowledge but is not yet including science content ideas.

Only a few students made comments that seemed to indicate some TPACK. Interestingly, similar to Hofer's study of social studies and literacy teachers, those students either had a strong knowledge base in content or in pedagogy. For example, Steve who had a strong science background thought that "*using interactive technologies is essential in these times and as with anything there are different qualities to the different technologies. Our task is to identify and use the better interactive technologies that engage and educate.*" Vicky was a preservice elementary teacher without a strong background in science, but who, as a result of having an emergency teaching certificate, had in-depth experience in teaching. She felt equally strongly that technology should have a role, "*We are currently living in an age where video games, iPods, laptops and cell phones rule. In order to compete schools must find ways to engage and maintain our students' attention. We have to incorporate more computer based research and activities into our lessons.*" Both Steve and Vicky show a beginning awareness of TPACK.

Contrarily, Jane did not agree. Jane professed to loving science although she had not majored in it and was not in the classroom yet. She felt very strongly that virtual science experiments had no place in the science classroom: "*Most kids are too engrossed in the techno world. They have forgotten what it is like to use their hands, get dirty, discuss with a peer face to face,*

[1] Please note that 'learning styles' was her term. These students were taught that the research does not support this concept.

write with pencil and paper." She goes on to state, "*We didn't have the resources kids have now but are we any less educated? I don't think that I will do all that much with technology when I get into my classroom … If we can provide entertainment without the computer how cool are we*?" She was unable to see—despite her own experiences, the readings and her peers' conversations—that it does not have to be one or the other. Having TPACK means knowing what tools to use for what purposes to achieve what learning. Sometimes those tools are hands in the dirt; other times, they are scientific inquiry-based virtual environments.

Thus, the preservice teachers, as hypothesized, are grouping together in their views of technology based on their expertise levels in one or more of the domains of the TPACK framework. Those with either content or pedagogy experience and knowledge seem to understand the role that technology could and should play. While none of them have demonstrated TPACK in their teaching, they understand and support it. The preservice teachers without strong content or pedagogy backgrounds, such as Jane, have not even reached an understanding of its value.

However, understanding the value of technology is only the first step. Helping teachers know how to seamlessly integrate it into their classroom, the heart of TPACK, is much more difficult. Vicky stated, "*I am a teacher who has two computers at home, I occasionally use my daughter's iPod, I play video games with my son and who doesn't have a cell phone. I have all of these devices at the tip of my hand and yet I rarely use technology in my classroom.*" She puzzled over why this was and went on to say,

> *It is simply my unwillingness to think out of the box when it comes to technology. I'll try the latest teaching strategy or do something out of the norm that my colleagues won't do and yet I refuse to give technology a try. Here I go with the excuses: lack of working computers, time, the curriculum, standardized testing, students' behavior, school walkthroughs, etc, etc, etc. In spite of these I know I have to do better by my students. Hopefully, this summer I'll be able to create some lessons and reformat some activities that will incorporate more interactive technology. Sadly, this statement sounds familiar. Oh yeah, I think I said it last spring.*

This reflection illustrates the difficulties inherent in the TPACK framework. At one level, the difficulties stem from weaknesses in one or more of the three domains of the TPACK framework. However, Vicky's reflection makes it clear that having domain knowledge in content, pedagogy, and technology is not enough on its own. In order to achieve TPACK, something else is needed.

Today's teacher of science, whether that is in elementary or secondary grades, requires a strong foundation in science, pedagogy, and technology. However, as the TPACK framework theorizes and my small study indicates, simply learning about science, pedagogy, and technology in isolated courses is not sufficient. Teachers need to know how to integrate and embed technology into their practice to improve student learning. They need to be exposed consistently to models in their coursework of professors using technology tools beyond PowerPoint.

Implications for In-Service Teacher Education

Up to this point, I have been discussing preservice teacher education, but even if all teacher education programs changed tomorrow, we do not have the luxury of waiting for these new technological pedagogical content knowledgeable teachers to permeate our schools. Instead, while we rethink preservice teacher education, we simultaneously need to be helping in-service teachers develop TPACK. From conversations such as these, I have designed a professional development model that integrates learning on all three of Koehler and Mishra's framework categories. In this model, teachers would learn about a science topic, explore PCK related to it and learn about associated technologies that could facilitate student learning about it. However, while this helps strengthen the domains, we saw that in and of itself it is not enough, so two more elements have been incorporated: seeing instructors model the authentic use of various tools, and, spending time with expert help in designing and practicing lesson plans showing evidence of science PCK and TPACK.

The first instantiation of this model was held with ten in-service teachers attending a one-week institute (the sessions were called an institute). None of these teachers had strong backgrounds in science; however, they did vary in their experiences quite significantly. During this institute, the teachers explored an interactive whiteboard (Detailed case studies of these teachers are described elsewhere: Ketelhut et al. 2009). The final products of the week were team-designed mini-units or single lesson plans using at a minimum the interactive whiteboard. These lesson plans were presented to peers and all instructors.

One teacher team consisted of two teachers with little technology or science expertise at the start. They persisted throughout the institute despite their deficiencies and by the end, these preschool/kindergarten teachers had created an interactive flipchart that included dragging images of foods into category boxes integrated with using examples of real foods. Using their PCK, these teachers justified their design by stating that having their students interact directly with the board and real food would help them learn and remember the content (Ketelhut et al. 2009).

A second group initially sounded very much like Jane in their discussion of why and how to use the interactive whiteboard. The more experienced teachers were having trouble seeing how to use it to improve their pedagogy. However, by the end of the institute, they had figured out how to integrate scientific tools with the whiteboard, using the whiteboard as an extension of their other tools. Thus, while they collected data with more traditional instruments, they used the newer technology (the whiteboards) to synthesize and analyze the data—an area on which their typical lesson plans needed improving. Thus it would seem that these teachers made definite strides toward achieving TPACK in this institute.

As further evidence, I asked the teachers to highlight the most important things they would take with them from the institute. Of the 25 items listed by the 10 teachers, 5 of them were clearly on PCK, such as learning how to make science more relevant to the children and how to engage them with real world examples; 5 were about the science content they had learned. Of interest here, however, is that in this institute three of the 25 items listed were clear evidence of TPACK. One teacher specifically stated that she would take with her the understanding of using new technology with a purpose of improving her science teaching.

Conclusions

I hypothesized at the beginning of this study that beginning teachers would have more trouble seeing the benefits of integrating technology into their practice as they were already struggling with developing PCK. However, initial results indicate that having some area of expertise (science or teaching experience) helps them begin to see the value of integrating technology into their pedagogy. Further, controlled exposure to the technologies helped one preservice teacher (Vicky) confront her own preconceptions about TPACK. Thus, creating a professional development model that integrated instruction on content, PCK and TPACK authentically helped teachers move closer to developing TPACK.

While the motivation for this has been primarily student-centered, teacher practice has changed over the last ten years to require that teachers not only be comfortable with using technological tools in their practice, but schools are requiring that teachers interact with parents and students virtually and that they analyze vast streams of data from assessments. As in most professions, technological tools are changing teacher practice faster than universities can keep up. It is incumbent on those of us in higher education to help teachers develop the skills and understandings they need to be successful throughout their careers.

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CHAPTER 3

Toward Understanding the Practice and Potential of Educational Technologies on Our Campuses: Should We Be Skeptics First?

Krista Glazewski

A Brief History of Educational Technology's Conscription into a Revolutionary Role

When educators envisioned the potential of educational technologies five or more decades ago, they regularly considered ideas that seemed to place technology in a transformative, if not revolutionary, role. In the early 1960s, Patrick Suppes, director of Stanford's *Institute for Mathematical Studies in the Social Sciences*, pioneered some of the earliest computer-based experiments in numeracy and mathematical fluency with young children, and proposed wide-ranging potential for the role of technology:

> One can predict that in a few more years millions of school children will have access to what Philip of Macedon's son Alexander enjoyed as a royal prerogative: the personal services of a tutor as well-informed and responsive

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O. O. Adesope, A. G. Rud (eds.), *Contemporary Technologies in Education*, https://doi.org/10.1007/978-3-319-89680-9_3

> as Aristotle…The role of the computer is scarcely implemented as of yet, but, assuming the continuation of the present pace of technological development, it cannot fail to have profound effects in the near future. (Suppes 1966, p. 207)

The following year, the *San Francisco Sunday Examiner and Chronicle* published an op-ed by Robert Hutchins titled "The Machines Run Education," in which he asserted that the changes originating with educational technology might render educational institutions unrecognizable, potentially dissolving them (Hutchins 1967). In 1968, a report prepared by the National School Public Relations Association summarized an individualized math and reading program at Oakleaf Elementary outside Philadelphia after the fifth year of implementation as they were preparing to scale to multiple sites. They detailed a litany of potential benefits, which they attributed to individualization, and characterized the approaching revolution as historic in scale and significance (Neill 1968). Neill and his team were excessively optimistic about the list of potential benefits, which included greater longitudinal learning capacities and achievement, increased motivation, decreased discipline problems, greater retention rates, extra flexibility of learning, and more robust service to underserved learners. Research had not been done to test or capture any of these effects, and there was little other than enthusiasm to support such optimism.

More Expansive Optimism

A similarly optimistic, yet even more expansive, vision of a future for education was advanced by Seymour Papert in the pioneering days of LOGO, a children's computer programming language developed with a team of researchers out of MIT's *Artificial Intelligence Laboratory.* His team was the first to flip the pedagogical model: rather than the computer offering programs to children, they should be programming the computer (Papert 1972). He reported his observations of children's work in LOGO, asserting that their efforts with programming built important intellectual habits:

> Many children are held back in their learning because they have a model of learning in which you have either "got it" or "got it wrong." But when you program a computer you almost never get it right the first time. Learning to be a master programmer is learning to become highly skilled at isolating and correcting bugs … The question to ask about the program is not whether it

> is right or wrong, but if it is fixable. If this way of looking at intellectual products were generalized to how the larger culture thinks about knowledge and its acquisition we might all be less intimidated by our fears of "being wrong." This potential influence of the computer on changing our notion of a black and white version of our successes and failures is an example of using the computer as an "object to think with." (Papert 1981, p. 84)

Papert's impact spanned half a century, and his influence reached schools, commercial ventures (e.g., Lego Mindstorms), and international initiatives (e.g., One Laptop per Child). In 1995, he testified before a US House of Representatives hearing on educational technology and stated,

> The question at stake is no longer whether technology can change education or even whether this is desirable. The presence of technology in society is a major factor in changing the entire learning environment. School is lagging further and further behind the society it is intended to serve. Eventually it will transform itself deeply or breakdown and be replaced by new social structures. The open question is not whether but how. Will the transformation of schooling take place in an orderly, constructive manner or will we see aggravated versions of the breakdown already happening in some cities? Will public schooling survive? Will the needs of the economy be well served? … [But] it is impossible to think sensibly about change and resistance to change in education unless one recognizes that the Education Establishment will not easily depart from the [current] view. (Educational Technology in the 21st Century 1995, pp. 38–9)

Today we might invoke the term "disruptive technology." While Papert, Suppes, Hutchins, and their contemporaries never used this phrase, they invoked a comparable sentiment when discussing the potential educational revolution. Which is not to say they collectively embraced the disruption. Whereas Papert supported an absolute educational transformation, it is fair to clarify that his ideas were never fully mainstreamed. Suppes (1969) forecasted a more measured, incremental approach and advanced the idea that the teacher would be more crucial given new learning complexities and curricular demands. Hutchins (1967) warned that we should resist the appeal that computer-based learning could make things easy, implying this view would obstruct, rather than expand, education:

> In principle, the computer will eventually be able to supply any kind of education that is desired. But I am afraid we may come to desire the kind of

> education that is easiest for the computer to provide. In fact we desire that kind of education already. When Americans think of education, they think of information and training. Machines can do a better job of this kind than people…Mass education is a repellent term. It involves a contradiction. A mass can be trained or informed, but it cannot be educated. (p. 3)

Educational Technology in Higher Education Is Not Immune from Revolutionary Conscription

While the introductory examples above reflect patterns primarily across K-12 public education, it is important to recognize that educational technology has been similarly cast into a revolutionary role in higher education. Typically, educational technology leaders foreground technology solutions when discussing challenges facing higher education. In the early 2000s, online learning was forecasted as possessing the transformative potential to address achievement, cost, retention, and engagement in higher education, and some suggested that educational technology investment would separate great from mediocre institutions (Garrison and Kanuka 2004). The 1998 *National Survey of Information Technology in Higher Education* promoted technology as a catalyst for a paradigm shift coupled with a focus on learning rather than teaching (Rogers 2000). Furthermore, the promotion of technology toward a catalyst role remains a pattern to this day, as is typically foregrounded in the annual New Media Consortium's *Horizon Report* (Higher Education Edition) (e.g. New Media Consortium 2017).

However, it is important to note that I am not endorsing a move away from technology in education, but, rather, advocating for deepening understanding predictable patterns. Veletsianos and Moe (2017) described one concerning pattern that shifts value away from instructional expertise toward the similar K-12 phenomenon of personalized learning through packaging content, delivering it to learners, and automating the process:

> Its very idea is predicated on defining discrete learning objectives; identifying content to address those objectives; *packaging* content into discrete chunks; *delivering* it to individual learners according to various behavioral, emotional, or cognitive measures; and *automating* the process so that it can be repeated for many different learners in many different contexts. (p. 17)

The authors' critique is not altogether different from what Hutchins cautioned over a half century ago:

> We shall now have the opportunity at last to apply our favorite standards to mechanized electronic education. We shall have the enthusiastic support of the large, rich and powerful commercial organizations that are interested in selling their equipment to educational institutions. The danger is that the technology of education will in effect determine its methods and its aim, though in principle there is no reason why this should be so. Forebodings in this regard are justified by the fact that mankind has so far been unable to control technology…. (1967, p. 3)

Thus, I argue that a dose of skepticism is necessary given our considerations of educational technology and its role on our campuses.

Chapter Purpose

Given the historic background and patterns, it is important to persistently reconsider the role of technology within our educational institutions. The current landscape suggests that our investments represent not just expenditures of devices and infrastructure, but also values and visions of what does and should matter in education. At times, leadership rhetoric may stand in conflict with classroom goals and pedagogy. Thus, my central focus reflects an attempt to contribute a deeper understanding of contextual practice and potential with regard to our technologies, doing so in the context of three examples drawn from history, biology, and medical education. From there, I will highlight distinctive and intersecting features about each example in order to convey how we might consider priorities and goals regarding our technology investments. However, it is critical to first acknowledge that not all of our educational technology investments are good.

Whatever Happened to [Second Life] (and Why Do We Make Bad Investments)?

In 2003, the entertainment company Linden Lab launched *Second Life,* a 3D virtual world where users pay real money for the exchange of goods and services, including virtual property—"islands"—on which they can create buildings. Users can establish customizable avatars that can fly or teleport, and navigation in the 3D virtual world resembles playing a 3D video game; however, there is no defined goal or objective, unlike a game. Because of its real-world sense, the community captivated attention from many different institutions and industries, including education.

By 2007, more than 6.4 million people had created a *Second Life* account, and it was adopted by various companies such as IBM, Dell, and Toyota as a new multi-feed channel for everything from meetings to marketing (Joly 2007). Over 160 universities and 450 K-12 schools invested in islands and other projects within the platform (L'Amoreaux and Lester 2007). Most universities invested thousands, if not tens of thousands, of dollars in island purchase and maintenance (Wecker 2014). In-world activities included marketing, recruitment, tours, lectures, orientations, and even full courses. But in 2010, Second Life announced it would revoke an existing educational discount in 2011, and *The Chronicle of Higher Education* reported on a mass migration out of *Second Life* (Young 2010). Where did institutions go? Some found open source platforms; others realized they did not simultaneously require both virtual and brick-and-mortar homes (Wecker 2014). And by 2012, we were all talking about Massive Open Online Courses (MOOCs).

From Enthusiasm to Desertion: A Second Life Yardstick To the extent that we have observed a predictable cycle of a technological innovation, we may be able to draw parallels to other educational technology initiatives in higher education—a type of *Second Life* measuring stick, if you will, that might inform how we can avoid common consequences. That is, by acknowledging that the enthusiasm-interest-investment-expiration-desertion cycle is fairly predictable, we might avoid a type of afterlife hangover that follows the abandonment of our initiatives. And while enthusiasm-to-desertion may occur for any number of idiosyncratic and distinctive reasons, I argue that it is the cycle itself that might be transferable beyond individual examples. From Suppes' computer mathematics programs with children to Oakleaf's isolating individualization to *Second Life*, there may be any number of reasons that an initiative cannot be sustained, including cost, context, feasibility, commitment elsewhere, natural end, or just generally a bad fit. As one result, we tend to be good at fostering enthusiasm and making initial investments, while not really working to understand why an initiative fails to meaningfully take hold. In short, we typically let desertion happen without interrogating or learning from it (Selwyn 2011).

Which is not to say that our educational technologies or our intentions are bad, nor is it to suggest that our initiatives should be sustained indefinitely. But well-intentioned initiatives are generally not enough to overcome the momentum of existing norms and practices, particularly if conditions do not reflect an understanding of those norms and practices. For example, a university may decide to replace an existing Learning Management System (LMS) with one that has been determined to offer higher quality features. Conventional understanding might suggest that a better LMS should be well received, practice tells us this is not generally the case and there are numerous variables that will determine acceptance of the new system. While we would assume that the new system is selected for its high-quality features, rarely does it hinge on the quality of the system. Rather, acceptance may depend on any combination of contextual or system features: comparative ease of use, user affinity for the existing system, user goals, user skills, overall strategy, system limitations, support services, accessibility, time to phase out, time to phase in, data management, date reporting, and the list goes on. The new LMS adoption could be relatively smooth or it could be a disaster, but either outcome does not primarily inform the quality of the technology as much as it exposes the level of understanding of prevailing norms and practices. It is the difference between asking, "What's the best LMS?" versus "What do *our* users need from an LMS?"

Toward Understanding What Works

Despite numerous examples that reflect the enthusiasm-to-desertion cycle, a half century of research that informs a deeper understanding of educational technology suggests a wide range of associated positive effects. One relatively recent second-order meta-analysis reviewed 25 studies that captured student achievement across technology-enhanced classrooms versus similarly matched technology-free classrooms (Tamim et al. 2011). The authors reported a low to moderate effect size (0.30 fixed effect and 0.33 random effect), explained by the authors that a student at the mean level of performance would experience a 12-point percentile gain with technology use rather than without. Further analyses of moderator variables, namely the primary purpose of the technology use, found differing impacts. More specifically, technologies that supported instruction reflected a significantly higher average effect size compared to technologies that provided direct instruction (Tamim et al.). In other words, the greatest achievement impacts were realized when technology was used to support student cognition as opposed to the presentation of content, though the authors also indicated a greater need to understand more about the contexts of our initiatives: goals, pedagogy, teacher characteristics, student characteristics, and the like.

It is important to acknowledge that Tamim et al.'s (2011) findings toward supporting student cognition reflect a widely held judgment of the potential for technology to enhance learning in robust and meaningful ways. In the early 2000s, as technology and connectivity reached a pivotal point on our campuses, Gerjets and Hesse (2004) suggested that some of the biggest impacts for technology use could be found in the contexts where technology meets a legitimate need in a well-designed, environment that can foster learners' experiences of authenticity in the domain. Herrington and Oliver (2000) also coupled the potential of educational technology with authenticity and emphasized the numerous ways this could be enacted in the classroom, including interactive media, collaboration, simulation, and scaffolding. However, coupling technology and pedagogy may not be compatible with the reform goals many educators foreground when they promote educational technology in higher education.

Decoupling Technology from the Revolution In short, I am arguing that educational technology should not be cast as both the *goal* of the learning environment and the *actor* for catalyzing change in higher education. However, if we decouple technology from the revolutionary role to place emphasis on understanding robust pedagogical uses, we can inform practices and potential in higher education. In this context, educational technology can be broadly defined as the ways in which we make pedagogical decisions to support a wide range of teaching or learning actions in our classes. For this, I will borrow a framework from Ross, Morrison and Lowther (2010): "Educational technology is not a homogeneous 'intervention' but a broad variety of modalities, tools, and strategies for learning. Its effectiveness, therefore, depends on how well it helps teachers and students achieve the desired instructional goals" (p. 19). In other words, when we try to understand successful implementations, we should do so with the recognition that the examples reflect complex pedagogical action. Given this lens, how do our practices take shape and what is the potential?

What Can This Look Like on Our Campuses? Three Campus Snapshots

Snapshot #1: Representational Tools in History

In one undergraduate history course, a scholar of medieval studies combined analog and digital tools to support students learning from and with mapping (Craig 2017). Specific goals included spacial history, text analysis, and network analysis toward an overarching understanding that agency is impacted by geographic context. In one activity, students read the biography of Ibn Shaddad, a Third Crusade Middle Eastern military leader. They were divided into three groups and created one of three maps based on text and document analysis: estimated travel times using medieval travel methods, scale or importance of location based on the frequency of mention, or geographic space that reflected emotional experience. Students could use any digital tools they chose for building understanding, but final maps had to be analog and all were the same size. The analog and digital blending for the maps fostered critical learning experiences for the students. The digital tools provided resources and visualizations not accessible without technology. For example, students could leverage the resources in ORBIS (http://orbis.stanford.edu), a dynamic geospatial model of the ancient Roman world that allows users to calculate travel distances based on season, mode of transportation, and other contextual priorities. Users can enable also or disable specific features (e.g., terrain or city names). Such tools enable opportunity for students to ask deep questions of a context and receive reliable information as a result. In Craig's study, students used tools like ORBIS to plan their representations and depictions. Each resultant team map held significance for the individual teams, but it was the act of comparing the representations across the three depictions that fostered rich reflections and discussions.

Craig (2017) noted that tasks involved decoding text, considering narrative authority, making large texts consumable by dividing them into smaller pieces, addressing cultural values, and engaging rich discussions with other teams. The instructor also highlighted the diversity of learning strategies employed by each team and proposed tremendous value for such work that fosters authentic historical practices. As she stated, "The broader examination of activity that began this study addresses some of the general concerns historians have as they seek to move students from memorization of facts to use of evidence, context, perspective, and corroboration in a historical argument" (p. 12).

One outcome was that student maps reflected a reduced role and importance of Jerusalem in the Middle East, representing a significant departure from modern geopolitical relationships. The instructor recapped this experience as follows:

> Prior to reading the text, [two students] assumed that Jerusalem would figure heavily in the Third Crusade. As they were reading the text, the students said, they began to revise their assumption and give Jerusalem slightly less weight, but it still held a place of honor. Given media emphasis on Jerusalem in coverage of the Israeli/Palestinian conflict, this is hardly surprising, since students tend to import familiar knowledge into their historical understanding of events taking place in geographies with which they have little personal experience. After the mapping exercise, however, both students described their surprise that Jerusalem was far less dominant than Acre, a tiny fortress on the Mediterranean coast, which figured far more heavily in Ibn Shaddad's narrative than their unstructured reading and notes suggested. At this point, a student from the GIS/travel map added support for this shift away from Jerusalem by pointing out that Acre was the only city connected to two separate travel routes that figured highly in Ibn Shaddad's narrative. (Craig 2017, p. 7)

The researcher attributed much of student success to the ways in which technological resources blended with pedagogy to foster perspective shifts and the ability to explain such shifts using the language of the discipline. She also noted the importance of establishing tasks that did not rely on students having continuous access to technology, an important viewpoint given that it is not reliable to assume all of our students have prevalent access given the wide range of students we serve. Her recommendations included making more explicit the connection between the digital tools and learning tasks. Finally, the instructor recommended that the structured pre-reading and prompting tasks might make the in-team mapping activities more robust and durable.

Snapshot #2: Scaling Pedagogical Shifts and Interactive Technologies Across Introductory Biology

Context At New Mexico State University (NMSU), a Hispanic Serving Institution, faculty serve a wide range of diverse learners. NMSU is classified as an access institution, meaning that students who meet one of the minimum requirements will be offered admission as follows:

- 2.75 high school GPA, or
- Top 20 percent of their graduating class, or
- ACT composite score of 21 or SAT score of 990 (New Mexico State University Student Affairs 2017).

NMSU's service as a land-grant institution is critical to providing economic and educational opportunity for the region and the state. A recent report by the Brookings Institute titled *Labs, Ladders, or Laggards?* characterized the extent to which state institutions made contributions to missions that serve a public good: research (*labs*), upward social mobility (*ladders*), or neither (*laggards*) (Halikias and Reeves 2017). In their report, 72 institutions were classified as *leaders* for achieving a dual contribution high research and high upward mobility contributions. They ranked NMSU second as a leader when it comes to contributing a combination of valuable research and educational opportunity to low income, underserved communities (Halikias and Reeves). Furthermore, it is relevant to note that the top-ranked institution, University of Texas at El Paso, serves roughly the same region as NMSU. In contrast, most selective state institutions, such as Indiana University, ranked high for critical research contributions, but low when it comes to making contributions for upward social mobility.

Biology Education Initiatives at NMSU For the last decade, faculty in biology at NMSU have made a strong commitment to understanding the strengths and requirements for the wide range of learners that they serve. Learning in biology involves handling complex concepts, processes, cycles, and systems that intersect with our environmental, physical, and even political worlds. In addition, the biology education is composed of numerous subdomains, broadly including plant, animal, cell, and molecular. Furthermore, the field is growing with the addition of bioinformatics and genomics in the last three to four decades. In short, foundational courses in biology are complex and demanding for most learners, and the burden is greater for learners who tend to arrive with less science exposure and who may also be working more than part-time.

After observing a consistent pattern of lower pass rates among underrepresented minorities (URM) compared to non-URM students, the faculty decided to transform the introductory courses beginning in 2004 (Shuster and Preszler 2014). With concomitant support from NMSU and the Howard Hughes Medical Institute (HHMI), the pedagogical transformation was gradual and multifaceted. The first step within Biology 111 involved replacing one of the three weekly lectures with a small discussion group facilitated by advanced undergraduate peer instructors (i.e., Biology Learning Catalysts, or BioCats). Each weekly discussion group was faculty-developed, and the instructor worked with the BioCats to learn methods and strategies for facilitation. One immediate outcome was an increase in the number of students making As and Bs, and a decrease in the number of failing students (Preszler 2009).

The next phase involved expansion to more courses (Biology 211) with a continuation of the BioCats program, the addition of inquiry case studies in the lecture courses, and the use of interactive technologies (i.e., individual student response clickers). Between 2006 and 2011, faculty systematically taught versions of the course with variations of case studies, interactive technologies, and discussion group format in order to understand the forms of pedagogy that seemed to make the strongest positive impact on (a) student learning overall and (b) closing the achievement gap between URMs and non-URMs.

The study spanned five years with multiple variations over the two introductory Biology courses and is worth reading in its entirety. However, one interesting result is that the narrowing of the achievement gap was most profound during a format that incorporated instructor-plus-BioCat facilitated discussion sessions in the lectures. Interaction in this format consisted of structured and small discussion groups combined with large lecture case overviews/questions handled with knowledge and concept questions using the student response systems. The revised pedagogical approaches have not fully closed the achievement gap, but it has narrowed significantly from the pre-transformation course model.

Presently, faculty at NMSU are sustaining their refinement efforts within their introductory courses, and sections are now taught in a new Technology Enhanced Active Learning (TEAL) classroom. This involves a configuration of students at tables with the instructor in the middle—rather than the traditional lecture hall arrangement—and the capacity to display student work or discussion products on any number of the screens mounted around the circular room. Their most recent results suggest that the TEAL configuration coupled with the associated pedagogical approaches that enable even greater interaction that demonstrates the most successful narrowing of the achievement gap thus far (M. Shuster, personal communication, July 16, 2017). To be sure, achievement gaps are not eliminated within one semester, but in this case, the pedagogical transformations supported by the technological resources make an appreciable difference.

Snapshot #3: Building Cross-Cultural Understanding Through Video in Medical Education

Few have doubts that high-quality medical education represents an important investment. The result has been not only tremendous medical advancements but also deep understanding based on research regarding medical education practice. One medical program in Canada has partnered with another in Hong Kong for a number of years in order to share ideas and achieve mutual educational goals. In one project, instructors in each country facilitated a joint online workshop for students to help students consider issues surrounding delivering bad news to patients (Lajoie et al. 2014). Students first encountered a video trigger to introducing the learning issues: a video case (acted with trained standardized patients) of scripted patient/doctor interactions that involved the doctor delivering bad news to the patient. Mixed teams from each country engaged the online workshop across three different sessions through online video conferencing and chat. Medical educators facilitated each session. Basic activities involved observation of a modeled session in which a doctor delivered bad news, online discussion regarding the doctor's strengths and weaknesses, the opportunity to practice giving bad news, and, finally, a structured reflection. The primary goal of the workshop included building skills for physician-patient interaction that might be informed by culturally relevant issues in a setting that involved cross-cultural interaction.

One finding for their research included some gains with regard to social and cognitive outcomes that they coded for (Lajoie et al. 2014). Another finding informs how we leverage affordances of technology to foster building cross-cultural understandings among learners. The successful experiences were not without challenges, namely with regard to some connectivity complications, time-zone complexities, and other associated technology issues. Nonetheless, students found tremendous value in the experience overall. One student spoke directly to this:

> What really surprised me about these sessions this week, I was thinking was that everybody comes to any session with their own culture…So each of us bring [sic] our own culture to our medical work. But there is another culture that we all have and which I thought was very well demonstrated during this entire week: Medical culture… that physicians share that seems to me to be universal…[Y]ou have rather different backgrounds in terms of medical education and each of you are not even perfectly matched in terms of where you are in respective medical schools. Yet, when we got together around these patients there was an understanding that we had of what was important and what wasn't. (pp. 66–67)

In their interpretations, the researchers considered the value for the learners and remarked,

> Online digital technology, as it was used in this study, may provide opportunities for developing intercultural competence that one cannot learn through lectures. Providing individuals with authentic intercultural experiences in which working with other cultures in meaningful contexts such as patient care is relevant and important may lead to better appreciation of differences by listening to the multiple perspectives shared online. This was particularly relevant to these participants as they were all working towards their shared goal of becoming physicians. At the same time, the goal of this research was not to train intercultural competence but to describe how culture may influence understanding and communication about emotionally sensitive issues. (p. 72)

Overall, the video cases and the video interactions afford unique forms of participation and collaboration toward deeper cultural and process understandings.

What Stands Out?

Each of the three examples reflects robust and meaningful technology integration to meet a wide range of pedagogical needs. In the history course, the instructor used technology to help students gain a sense of real time representations and cultural experiences. Furthermore, her use conveyed geographic prominence and the variances across time. In the biology course, instructors transformed (and are still transforming) the course to incorporate interactive technologies that target a documented achievement gap between URM and their peers. Finally, the medical education team leveraged video conferencing and video cases to immerse students in evocative, cross-cultural participation that enabled a unique form of perspective taking. Yet the settings do not on the surface have very much in common, particularly with regard to scale, features, goals, resources, or instructional actions.

However, I argue that what these inform together is unique as a specific result of their distinctive, uncommon features. The history teacher imagined the potential for her students to conceive the world differently, and she facilitated a collaborative experience supported by a set of blended analog and digital tools. The biology faculty imagined the potential for their students to handle complex content in ways that delivered equitable opportunity to each individual. The medical faculty imagined the importance of fostering physicians' ability to build cross-cultural understanding facilitated within a cross-national setting. What they inform overall is not only a wide range of technologies that can be used but also great variation in context, audience, and scale.

Which is not to say that the examples have nothing in common. In fact, I would argue that they have at least three things in common.

1. *These are not initiatives about technology.* One critical feature about each research project is that they do not reflect efforts in which the goal was to use technology in the classroom. Rather, the examples represent complex classroom narratives with unique features, characteristics, and pedagogical goals. In other words, these efforts diminished questions of technological possibility and prioritized questions of pedagogical possibility.
2. *Targeted is better than more.* At the same time, while these are not initiatives about technology, it is difficult to decouple the pedagogical innovation from the technological one. More specifically, the technology could not be swapped out for analog resources and still be recognized for the features that make it successful. However, as a result of the technology following the pedagogy, each instructor made targeted, informed decisions about where technology achieves potential to make a difference (and in the case of biology, research variations, and refinements over the course of five years).
3. *We can help populate students' imaginations.* Each presented initiative began with the idea that we can help students to assume new perspectives about the world. In the example from history, the faculty, literally, wanted students to see the world differently. Or put another way, she did not want students to see the world in the same

ways that had been. In the case of biology, faculty wanted students to see themselves differently, as capable students of biology. And in the case of medicine, faculty wanted both. They wanted students to view both themselves and the world differently.

Recommendations

My recommendations are aimed at two sets of audiences: scholars and leaders because these are often two very different groups of people who are not always in conversation with each other about educational technologies.

To Our Scholars

To the scholars, my primary recommendation is that we enlist our technologies into service of pedagogy and not the other way around. Some of these resources such as virtual reality or digital fabrication are exciting and might provide new and different learning opportunities. We should seize those opportunities, but place the pedagogy first.

After we have acquired a resource that serves us well, my second recommendation is that we document the coupling of our pedagogy and our resources with contextually rich and detailed descriptions so that readers can understand our design moves. Furthermore, numerous journals have begun to value such work as its own form of scholarship, and many offer outlets for publication. For example, a journal I co-edit, *The Interdisciplinary Journal of Problem-Based Learning*, has a "Voices from the Field" section committed to presenting the stories of classroom implementations. The journal *Cell Biology Education* has a similar section. In addition, there are stand-alone journals dedicated to capturing how we design our learning environments, such as *The International Journal of Designs for Learning* and *International Journal for the Scholarship of Teaching and Learning*. We should all document and publish our implementations.

To Our Educational Technology Leaders

In my first academic position at Purdue University from 2003 to 2006, students registered for classes with paper forms that had to be physically signed and submitted to the registrar. This was a decade or so beyond the point at which most universities began to transition to electronic registration, and I suspect Purdue was among the last of the last holdout campuses in the United States. The reason behind this practice was storied and mythological. Then president Martin Jischke, highly respected by the university community for his vision and leadership, had formerly served as president of Iowa State and he enjoyed telling others he had been able to avoid the transition to electronic services in student affairs. He came to Purdue and made it known he would rather spend time in public service than overseeing the transition to IT in student affairs. Whether or not this is true, who can blame him? Leaders of educational technologies have one of those unenviable jobs of receiving blame when initiatives fail and little recognition when they succeed because the labor in those instances is not always visible. Furthermore, when projects succeed, the resultant outcomes tend to be that another faculty member or administrator looks good.

I have never been a campus technology leader, and am not in the position to make recommendations based on experience. But it strikes me that if I ever became one, there is one question I might continually want to ask: *How and where does this serve our campus mission?* An idea or a resource may represent a fantastic investment, but that does not universally mean that it is fantastic for our campus at this time. I might keep a secret *Second Life* ruler by which I measure everything. In short, this is another way of saying that we should be skeptics, possibly our leaders the most.

I am promoting skepticism because, ultimately, what I want to be is optimistic. I want to imagine my classes differently. I want to read more studies that inform how I might help my students see the world differently, interact with others differently, and see themselves differently.

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CHAPTER 4

Promoting Engagement Through Participatory Social Practices in Next Generation Social Media Contexts

Greg Kessler

Technology as a Disruptive Force in Education

In recent years we have witnessed a dramatic shift across many sectors of society as a result of the ubiquitous social interaction taking place through new and social media. These disruptions have influenced politics, commerce, and other domains while largely leaving education unchanged. There have been suggestions that online education, MOOCs, flipped classrooms, or mobile learning would dramatically alter the educational landscape, but these movements have not had as dramatic an influence as some anticipated. In fact, much of the formal educational world still operates as it did decades ago. Although there are exceptions, education is still far too commonly delivered in the same teacher centered, lecture-based, factory model context that scholars like Dewey sought to change nearly a century ago (1938). As our society has changed so dramatically in response to the socially networked world we live in, it is high time for our educational models to change as well.

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O. O. Adesope, A. G. Rud (eds.), *Contemporary Technologies in Education*, https://doi.org/10.1007/978-3-319-89680-9_4

We are surrounded by compelling and authentic opportunities to engage in social practices that can support virtually any academic discipline or topic. We are also surrounded by an overwhelming amount of information that can be manipulated, conceptualized and visually represented in varied ways. This quantity of information is a great asset, but to truly benefit from it, we need to work collaboratively in these social contexts toward shared goals (Weinberger 2012). This understanding allows us to construct wholly new authentic learning experiences that encourage participation from all members of an educational community. These social contexts have the potential to engage participants by involving them directly in the co-construction of knowledge as then navigate and negotiate their learning (Kessler 2013). In fact, the participatory culture that is pervasive across social media contexts compels participants to be active contributors (Jenkins 2006). At the same time, we have new opportunities to provide participants with immediate and salient feedback that can guide them as they co-construct knowledge with other members of these social communities. Throughout this co-construction of knowledge, participants share ideas and negotiate the nature of the construction itself. Such negotiation of community behavior allows participants to contribute across a spectrum of roles allowing an individual to take the lead on one topic or aspect of a topic while another participant assumes control over another topic. This shared responsibility can motivate participants to continue to be involved. By contextualizing our instruction within the constructs of these tools and social practices, we can promote student engagement in ways that we have attempted but failed for years. Situating learning within participatory social co-construction of knowledge allows us to approach group work tasks from an authentic, compelling, and engaging perspective. Further, as trends such as big data, artificial intelligence (AI), and virtual reality (VR) expand and converge, we will certainly see greater potential for customizing intelligent social media practices that engage and compel students around educational topics. It is important to note that the point of leverage in these future educational contexts will continue to be instructors and instructional designers. While some have predicted or feared that instructors will be replaced by robots or some similar entity, tomorrow's instructors will need to be well versed in the abilities of these various technologies and will know when, how and why to introduce a particular technology at a moment in instruction when it may be most valuable and salient. Consequently, it will be necessary for teacher preparation to adapt to these demands. Rather than focusing on a single technology, or even a category of technology, this chapter addresses the opportunities for creating varied engaging experiences upon current social media communication practices. The author anticipates developments that embrace a diversity of interconnected technologies to dramatically alter these practices, making them even more engaging and expanding their potential for instruction.

I am interested in the convergence of social and new media and the opportunities for compelling social engagement that result from the co-constructed participatory culture they promote. These practices are relatively nascent and require us to collectively negotiate as we learn to use them to their full potential. As they evolve, we will certainly need to learn to adapt. Developments in big data, AI, and virtual/AR will not only expand the potential for our engagement, they will also obligate us to engage in new ways. With the advent of texting and internet-based communication, we developed new forms of literacy that Crystal (2004) referred to as Textspeak and Netspeak, respectively. Similarly, we will develop new forms of literacy to communicate in these emerging social contexts. The influence that these combined forces will have across all social contexts is likely to be very dramatic. The communicative practices that are pervasive across social media contexts provide opportunities for varied engaging and compelling educational experiences. The ability to construct such experiences upon customized rich data creates wholly new opportunities for learning. Other opportunities to build wholly new educational experiences include the use of augmented and VR. Both of these experiential enhancements benefit greatly from AI and social media practices. AR allows us to embed various collections of extant or customized information upon the physical world around us. As a result, learners can be immersed in environments that represent authentic locales in otherwise inaccessible geographic locations as well as fully artificial contexts. These environments provide instructors and instructional designers with new opportunities to construct engaging experiences in which learners can gather information and interact with other learners, cultural and instructional informants and automated avatars toward some meaningful goal. We can anticipate virtually immersive experiences that are individualized for each of us based upon our own interests, abilities, and previous performance. We already have some early examples of these potential experiences, modest as they may be. This chapter will present some of these examples while discussing future directions that we are likely to encounter.

Where to Begin?

The increasing variety of technologies that are interconnected with social media are likely to be overwhelming for casual observers. Maintaining awareness of these rapidly changing domains may be even more challenging. To aid the reader, I have selected some of the most obvious developments that readers are likely to understand and encounter in the near future, but these should not be considered to be exhaustive.

Augmented Reality

Augmented reality (AR) is an interesting development that is already quite common in some educational contexts. AR presents opportunities for us to interact with one another and the physical world around us in wholly new ways. Readers will likely be familiar with the Pokemon Go craze that swept the globe recently. This experience of playfully collecting characters in the real world certainly captured the attention of many and motivated them to participate. We should strive to create similarly engaging experiences for our students. There are many other current commercial applications using AR throughout society. These include broadcasting sales and dining specials to pedestrians in busy metropolitan areas and other forms of targeted marketing. Readers may also be familiar with the short-lived Google Glass project, which was the first attempt to commercialize AR. Google Glass presented users with the ability to navigate the physical world while also gathering web-based information. Thus, the real world experience is enhanced in all the ways our access to data has changed in the past two decades, but with more immediate and transparent connections. These glasses were soon banned for drivers, business patrons, and others. While this project is no longer being supported, we will definitely see future iterations of this technology.

Educators, instructional designers, and students have the ability to create their own AR experiences. We can embed layers of digital information that enhance our understanding and perception of real world experience. This allows us to raise awareness of particular aspects of the landscape, increasing salience and redirecting attention toward educational goals. Such augmentation allows us to interact with the world around us in wholly new ways. We can design customized and individualized layers of information around any educational content in any language in a manner that allows users to select from myriad experiences. For example, in one physical space, we can design various contexts of information that defines a given space as an office, a restaurant, a shop or a museum. We can design AR experiences to highlight desired characteristics, such as historic events, literary connections, or geologic details related to the particular location. Consequently, users are able to engage in contextualized interactions that benefit from the richness of this additional information.

There are a handful of mobile app technologies that allow us to create customized AR, including Augmented Reality Interactive Storytelling Engine (ARIS) and Aurasma. Aurasma is a free mobile app that makes it very easy for teachers and learners to design their own AR experiences. By creating links between triggers and overlays, anyone can contribute to the digital enhancement of physical space. In fact, it has become quite popular in P-12 contexts and numerous examples are shared at Aurasma.com. We can anticipate that future iterations of AR will create varied opportunities for learners to interact with one another and instructional content in compelling social ways. ARIS is another example of AR that has found its way into educational settings. ARIS makes it easy for teachers and learners to create place-based games that can support learning. By focusing on the shared physical space, these games bring participants together to solve challenges together. They co-construct the experience in a manner very similar to the participatory culture of social media. In fact, they can create their own place-based games and share experiences about the games in the context of social media. The reliance upon place can also help raise the awareness of important features within a given environment. New environments can be navigated in depth and better understood as a result. Familiar environments are transformed and seen from a new perspective based upon the intentional focus of a game design. Of course, the effectiveness and flexibility of AR are dependent upon the data that drive it. Fortunately, we are living in a time with so much data that it is often difficult for humans to sort through it and make sense of it, but computers have become very competent at this. In fact, Big Data is bringing many new opportunities to education.

Big Data

Many of the most promising emerging technologies for education are built upon the foundation of big data. This term may not be clear to many readers so it worth explaining. Big data refers to the increasingly valuable, and enormous, collections of data typically made possible through digital networks. These enormous datasets are so large they can only be understood through the application of computer-based analytics. Together, big data and analytics have had the attention of leaders in education. In fact, there have been grandiose expectations for the myriad ways that big data would transform education. This is understandable since there is already evidence that big data has much to offer in predictive analysis. Some use these data to identify which activities will benefit different students, which group composition will best accommodate students and which students will succeed. However, all too often big data and analytics in education have been focused solely on assessment. Specifically, many have anticipated that large collections of testing data could be used to improve the test scores of future test takers and create models of successful students that can be used for predictive modeling.

My interest in the use of big data is somewhat different as it is more focused on using these large datasets of authentic human behavior, student learning, and real world communication to create improved learning experiences. I prefer to use the big data of social experience and language production, particularly the digital reflection of social and learning communities as a means of creating new authentic, compelling, and meaningful social experiences for learners to engage with others around the subjects they are studying. Big data, particularly when designed to be open, presents us with opportunities to adapt, archive and curate open educational resources for various applications. These resources are increasingly recognized as invaluable authentic content that can be modified for specific groups or individual learners at specific moments in their learning process (West 2012). Utilizing various extant datasets can help us to provide automated and differentiated information to students at moments in their educational experience when it is most useful and effective. Further, as we recognize the potential for such experiences, we can create customized datasets for particular groups of students that can even better address their unique needs. Such projects could ideally incorporate student-produced information, promoting student engagement through both involvements in a meaningful creation of materials as well as increased relevance of instructional materials. The more data we are able to collect and manage effectively, the more we will be able to create engaging and individualized instructional materials and experiences. The use of big data allows us to contextualize these social experiences, particularly when these large datasets are coupled with AI.

Artificial Intelligence

Perhaps the one technology that will transform education is another term that warrants explanation. AI involves computing that behaves in a manner that seems like human thinking. For our purposes, AI is the technology that allows robots, and other automated devices, to do tasks that we tend to associate with human performance, typically without our awareness. AI has become pervasive throughout our daily lives. In fact, when AI works effectively it is transparent and not obvious to the end user. We have become accustomed to getting general information from digital assistants like Apple's Siri and Amazon Alexa or seeking predictions about music we will like based on the music we listen to through Pandora or Spotify. We rely on AI embedded in email sorting at both the server and device level to quarantine spam, junk mail, and other suspicious messages. Watson, the AI created by IBM that beat the best human participants on Jeopardy, is now being used to help cure cancer. The AI is able to sort through all the medical trials and journals in ways no human or even group of humans can possibly do. With 8000 papers published a day, only an AI can manage this task. In an analysis of 1000 cases, Watson arrived at the same intervention as a human physician. In 30% of the cases, Watson identified issues that no team of humans had recognized. Watson also scanned through the raw data from the CT scans of the studies to successfully identify overseen cancerous growths (Rose 2017). If such technology can help medical professionals in this way, we can certainly apply similar technologies to assist educators. In education we have recently witnessed some significant developments in AI, including automated essay scoring that has performed at 92% reliability compared to humans (McNamara et al. 2015), and spaced interval learning that presents information to students repeatedly when it is most salient (Reddy et al. 2016). Many observers hope that these applications free instructors up to focus on more demanding abilities such as problem-solving and critical thinking. One of the most basic manifestations of AI is the bot.

Bots in Social Media

Bots have become so commonplace in social media that many are likely to have interacted with them without knowing. In April 2017, Facebook released chat extensions that included the ability to create group bots and discover existing bots. Readers can find collections of existing bots and bot creation tools across the internet. In fact, anyone can create a simple bot in a matter of seconds that will react to chat messages with basic stock responses. Some observers have expressed great concern about the role that bots may play in society. According to a report in the Atlantic, during the 2016 US presidential election, there was a significant presence of automated, or bot, accounts which appeared as if they represented actual individual people (Guilbeault and Wolley 2016). They suggest that one-third of tweets supporting Donald Trump and almost one-fifth of tweets supporting Hillary Clinton came from such automated accounts. There have been similar reports about the 2017 French presidential election as well. It is highly unlikely that individuals who observed and interacted with these contributions recognized that these were posted by non-human bots. Further, it is unlikely that most individuals understood the potential for such bots to engage in this manner. Researchers have found that people engaged in social media practices tend to treat bots as if they are actual people even when their automated nature may be fairly obvious. This observation is commonly referred to as the "Eliza effect" and attributed to research based upon an early chatbot. Further, bots have become so effective and commonplace that a number of recent studies have addressed the challenge of distinguishing them from actual human interlocutors (Varvello and Voelker 2010). There is great potential for using bots in education to identify, gather, and disseminate information and relevant digital artifacts in a manner that is salient and conducive to specific learning situations and needs. Bots could be used to identify authentic linguistic samples from the vast corpus of language available across the internet. This data can be used to model ideal interlocutors for a variety of interactive automated experiences that could be used by bots. They could also be used to identify characteristics of these linguistic samples that may serve as ideal feedback for students in specific moments in their learning process. The use of individualized bots or other digital assistants can take meaningful and engaging social experiences to new territory where learners interact in extensive exchanges around content and highly salient feedback in a manner that is socially compelling. Such experiences can also be customized to incorporate individual interests and needs of learners. In order to understand how learners will interact with technology when engaged in these experiences, it is important to observe them using it. The field of human-computer interaction (HCI) can help us gain perspective on this.

Human-Computer Interaction

The field of HCI has taught us much about how we use technology in various social and educational contexts (Berg 2000). This knowledge contributes to increased awareness as well as increased need to study more about the roles of individuals in specific language learning contexts. For example, we can observe learners as they use various functions to communicate with different interlocuters to better understand how they negotiate and navigate these spaces. This enhanced understanding will help us to design better software as well as better learning experiences. We can anticipate great improvements in this area in the future.

However, HCI currently only captures a fraction of the activity that is beneficial for those of us interested in understanding the future of educational technology. There are many aspects of human behavior that relate specifically to language learning, learning environments, learning tasks, and other characteristics that inform language pedagogy. These are beginning to be addressed by educational technology researchers across a wide spectrum. Our future applications of educational technology will be informed by a more sophisticated understanding of HCI focused upon specific teaching and learning contexts. Perhaps the environment that is most dependent on a thorough understanding of HCI is VR.

Virtual Reality

One of the most obvious future trends in social media is the integration of VR. Ever since the Occulus Rift first generation 3D goggle company was purchased by Facebook, observers have anticipated a dramatic shift in this direction. Of course, many other 3D goggles have been released since and these devices are becoming fairly commonplace. While many developments in VR are constructed around the use of goggles such as this, others are constructed within customized VR spaces that can be utilized simultaneously by multiple participants. Reshad et al. (2017) describe a simulation experience that engages students in virtual business experiences. Such projects allow participants to be immersed in any actual or imagined environment that may provide contextual support the subject of instruction. For example, students preparing to be medical professionals can be immersed in an operating theater, emergency room or other contextually specific and demanding context. This immersion creates a sense of locus that engages participants in authentic activities, including authentic social practices. Similarly, those studying a foreign language can immerse themselves in the target language context, resulting in demanding contextual social expectations that support authentic motivating opportunities. Yeh and Kessler (2015) outlined a number of pedagogical scenarios in which the use of social media can be greatly enhanced when used in conjunction with mapping software such as Google Earth, customized maps, geolocation, and big data aggregation. Designing lessons that rely heavily upon location using these tools adds depth and help contextualize the experience. While these current technologies offer much to educators, there is also much more to look forward to.

A Future of Possibilities

Throughout the history of educational technology, we have witnessed technological advances and identified ways to adapt or adopt these technologies for educational purposes. While the use of social media is already well established in educational contexts, largely due to the compelling social nature of the experiences associated with the participatory culture that it promotes, the integration of big data, AI, and other automated tools are likely to be much less familiar to educators and those who prepare them to teach. Readers may be surprised to learn how commonplace these technologies are in our daily experiences since they tend to function transparently for most users. As we have seen, the use of social media practices within academic contexts can promote greater engagement and motivation. Through the addition of big data, AI and VR-based simulation experiences we can customize materials to individualize and differentiate feedback while maintaining the sense of compelling engagement associated with participatory culture. Such participatory culture promotes more active engagement as well as a sense of belonging and increased motivation. Such practices have already become commonplace in the practices of social media-savvy organizations. Numerous examples across political and commercial domains may help us identify the potential for applications of such bots in education. There is a long history of automation seen as a threat to teachers, but this is consistently proven to be an exaggerated reaction. Nearly every day I come across another story of robots that will take over the jobs of teaching. At the time of writing this. a Google search with the words, “Fear robots teaching” resulted in 645,000 results. As you might assume, this indicates that we are on the verge of significant developments in automation, including robots and a variety of digital instructional assistants. Future teachers should not fear losing their jobs to robots, but they will need to understand these devices and how they can use them to target changing individual student needs.

Such engagement is likely to lead to conversations that are deep, meaningful, and rewarding and encourage participants to explore different perspectives. Students and instructors are likely to get more involved in the discussion and address aspects that would otherwise be overlooked, ignored or even avoided. Of course, such meaningful discussion will not always be easy, safe, or comfortable. This is reflected in these authentic online communities as well. Thus, it is important that participants be aware of the potential for disagreement, frustration, and even flaming behaviors. These are realities that all educated and involved citizens should be familiar with already so it is a valuable aspect of this kind of educational practice. Rather than avoiding conflict in the classroom, we can benefit from addressing it directly and discussing how to effectively deal with such circumstances in other domains of our lives. After all, some have suggested that meaningful and transformational learning is most likely to take place when we engage in such discussion (Sidorkin 1996). Such practice can take place in these familiar online contexts or institutional sites that mimic these contexts. The associated tasks, practices, activities, and forms of social interaction can also take place in non-technology face-to-face contexts. The design of these contexts will certainly improve as we learn to use automation more effectively with our educational contexts.

More Sophisticated Automation

We have seen a variety of impressive developments in educational automation in recent years. Automation in education is often the result of AI, big data, and other advances in computing. It is logical to begin with text-based tools since they are so common. The ability to aggregate and mine textual data is growing exponentially as this area becomes more commercially successful. Companies such as Google, Facebook, and Apple are both envied and reviled for their impressive developments in these areas. Many of the same capabilities upon which these technologies are supported can be repurposed or adapted for teaching and learning circumstances. Such repurposing is a critical aspect of understanding the true potential of emerging educational technology practices. We can anticipate many new opportunities to automate aspects of the design of educational experiences. Recognizing the opportunities and avoiding pitfalls as we navigate these new domains will be critical for teachers. Teachers will need to develop a basic literacy of instructional automation so they can make informed decisions about implementation. This awareness should help us to focus on the role of technology as a leveraging force within a system of learning. Within such a system, instructors, designers, and technology work in tandem. As our understanding and incorporation of these practices become more familiar and expected in educational contexts, we can anticipate that instructors and designers will begin to customize tools, materials, and experiences that harness a dramatically improved potential for learning. As these technologies become increasingly sophisticated and complex, the systems within which they exist will also become more complex. Thus, we will need to be able to develop a critical ability to navigate these new landscapes.

Future developments involving greater advances in big data gathering, more sophisticated methods of sorting through that data with AI, and the expansion of open educational resources will certainly challenge the profession. Those who are prepared for this future will find it much more navigable. They will also be likely to learn to take control over the design and function of the emerging technologies that best align with their context and approach to teaching. It will continue to be important to focus on social practices that support the exposure to and engagement with educational information, discussions, and engaging experiences. It will also be important to focus on the role of automation to increase access to information and refine results to better meet the interests or unique needs of specific individuals or groups. This teacher preparation will certainly be aided by the development of more accessible tools and resources to support these emerging technologies as they mature. This is a trend that we have witnessed repeatedly in educational technology. The teachers who embrace these new paradigms will likely be the educational leaders of tomorrow.

As we embrace these technologies and social practices that they support, we will certainly encounter ongoing developments that present new opportunities. These are likely to be even more dramatic than what has been presented in this chapter. Thus, teacher preparation needs to establish and maintain awareness of these developments and those who prepare teachers need to stay abreast of the potential of these changes. We should anticipate that there will be great demand for teachers who understand this landscape and the potential of these current and emerging technologies.

The current disparate and distinct educational technology preparation that teacher education majors are receiving is not adequate for the future we will face. This chapter outlines one path that we may follow. All other possible paths will also require that we do more to prepare future teachers for this emerging world. Such a focus does not need to be techno-centric. Rather, the focus should be on the social and experiential opportunities that these emerging technologies offer. Ideally, such preparation would strive to integrate technology use within extant teacher preparation contexts, allowing future teachers to develop their understanding and experience within a domain that is increasingly familiar and relevant to their ambitions. Integrating this preparation within these programs may help support teachers to experiment more with this rich and complex emerging world. One example on the horizon is the internet of things (IoT).

Internet of Things

Another emerging area of interest that is very connected to social technology practices is the IoT. Digital assistant devices such as the Amazon Echo, Google Home, and Apple Homepod represent the first generation of these devices, along with a variety of smart outlets, wall switches, lights, and thermostats with which these assistants are designed to interface. These devices allow us to expand our network beyond humans and bots to include the objects that surround us. We should expect to be deeply immersed in the use of these devices in the near future. Currently, manufacturers are embedding these devices in household refrigerators, thermostats, and automobiles. Of course, we already have the first generation of this on our smart phones in the form of Siri and OK Google. However, these offer only limited functionality. As we have already seen with the Amazon Echo and Google Home, we should anticipate that future iterations will be much more robust with many more options. Research into the use of IoT technologies is nascent, but some preliminary findings indicate that teachers are comfortable with these devices in the classroom and feel the IoT devices could allow them to access information more easily and have more time to focus on other important tasks (Incerti et al. 2017). We will definitely see improved functionality across the use of IoT tools that can access this data. We can also expect to have an increased ability to construct our own customized subsets of data that support specific activities, tasks, or needs of individualized students.

Conclusion

The Future Role of Educational Technology and Teacher Preparation

Perhaps the most important consideration when preparing for the future of education involves the evolution of teacher preparation. To make the most of these established and emerging technologies in educational domains, we need instructors and instructional designers who recognize the potential of these technologies and can apply them to specific teaching and learning contexts. There is a rich and diverse history in educational technology. Throughout this history, there has been an evolution of technologies, as well as pedagogical methods, materials, and practices. Recently, we have witnessed the emergence of social media and the participatory culture that has become so ubiquitous throughout society. Other trends such as crowdsourcing, data aggregation, and the use of geo-location technologies have created a variety of interesting and wholly unique opportunities for teaching and learning. There are also numerous automated tools that provide feedback and opportunities for interaction in varied and meaningful ways. In some cases, the interpretation of this feedback requires the intervention of instructors, but some can be utilized directly by learners. In some cases, these emerging technologies and the social practices they support are influencing how we communicate across society. The author believes these changes have been so dramatic (and we should anticipate this trend will continue) that they warrant significant alterations to the way that we design learning materials, activities, and spaces. We are only beginning to witness this evolution and it is not obvious how these tools and practices will change in the future. We should be conscious of these developments and reflect on how to prepare teachers to best integrate them into their instruction. We need to be rethinking how we prepare teachers to thrive within these emerging learning contexts.

We should also prepare for a future with much more active integration between teacher preparation programs and educational technology preparation. Currently, there is a very limited amount of exposure for those preparing to be teachers. With the extent and diversity of technological developments happening today and the pedagogical demands they present, it is critical that teachers are prepared more thoroughly and thoughtfully. We cannot simply expect them to recognize the role of these emerging technologies. We also cannot simply prepare them to be consumers of technology. To truly realize the potential, teachers must be prepared to take charge of the technologies mentioned in this chapter. They need to be able to apply practical applications based on big data and AI to create instruction that specifically targets their students' unique needs. They need to be able to design experiences that integrate the richness of this data in ways that the students find to be relevant. They need to be able to experience learning within these contexts themselves in order to develop and empathy for the experience of their students. Most of all, they need to be prepared to understand, evaluate, and integrate future iterations of technology that will emerge throughout their careers. After all, they will be teaching decades after they leave our teacher preparation programs, and the rate of technological advancement is only accelerating. In short, we need to prepare teachers for the future not for today. Such preparation will be invaluable. Hopefully, the field of education will recognize the need to embrace these various developments. Other disciplines are already embracing these trends. For example, political science professional organizations are hosting events such as the 2017 University of Sheffield event titled, "Automated social media bots and the non-human: opening a dialogue between political communication and science and technology studies." Hopefully, we will see similar events in the near future with a focus on the realm of education.

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CHAPTER 5

Signaling in Disciplinarily-Integrated Games: Challenges in Integrating Proven Cognitive Scaffolds Within Game Mechanics to Promote Representational Competence

Satyugjit S. Virk and Douglas B. Clark

Introduction

Interpreting, translating, and manipulating across formal representations is central to scientific practice and modeling (Pickering 1995; Lehrer and Schauble 2006a, b; Duschl et al. 2007). We have developed disciplinarily-integrated games (DIGs) such that players' actions involve the iterative development and manipulation of formal representations as the core game mechanics. These formal representations are computational and mathematized representations of focal science phenomena. Through playing a DIG, students investigate key conceptual relationships in the domain while also developing facility with the representations and inscriptions themselves.

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O. O. Adesope, A. G. Rud (eds.), *Contemporary Technologies in Education*, https://doi.org/10.1007/978-3-319-89680-9_5

Supporting students in engaging with these practices of manipulating and transforming across representations, however, is challenging. Madsen and colleagues have demonstrated the efficacy of signaling in helping students to concentrate on key relationships in diagrams (Madsen et al. 2012, 2013). Sweller (2006) and many others have demonstrated the efficacy of worked examples in both multimedia and educational games. Following those studies, the purpose of the current study is to (a) explore the potential efficacy of a DIG about Newtonian mechanics and (b) compare the relative contributions of a version of the game that incorporates into its design with a version of the game that does not.

Disciplinarily-Integrated Games

SURGE Symbolic (see Fig. 5.1) is the prototypical DIG template that we will consider in terms of generalizability to hypothetical DIGs for other disciplinary topics. More information and playable demos of *SURGE*

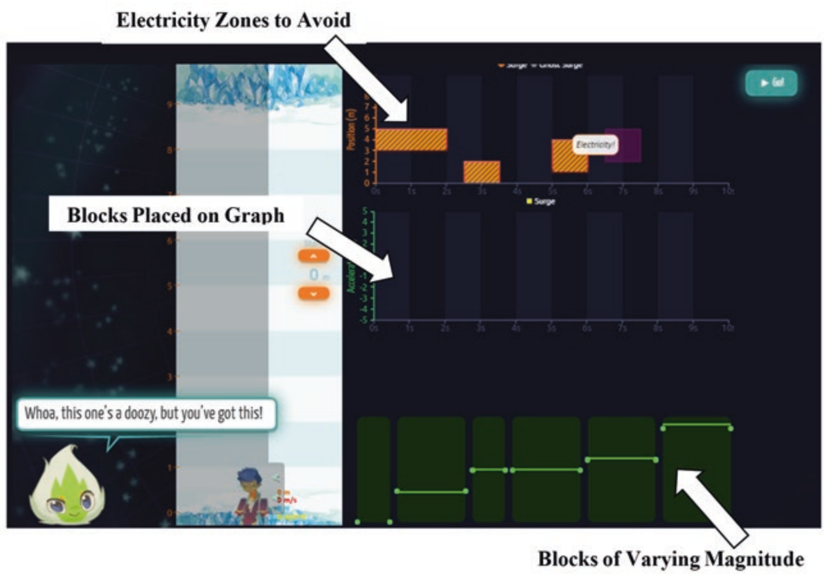

Fig. 5.1 Anatomy of an introductory block level. Blocks of varying magnitude of position, velocity, or acceleration must be placed in the correct order to create a path for SURGE to avoid the electricity zones and make it to the exit portal in the top graph

Symbolic and other *SURGE* games are available at www.surgeuniverse.com. *SURGE Symbolic* is a game that is the result of the evolution of design, research, and thinking chronicled in Clark et al. (2015, 2016d). Whereas earlier versions of *SURGE (*i.e.*, SURGE Classic, SURGE Next,* and *SURGE: Fuzzy Chronicles)* focused on layering formal representations over informal representations, *SURGE Symbolic* inverts this order, layering informal representations over formal representations while organizing gameplay explicitly around navigating, translating, and coordinating across representations.

Earlier versions of *SURGE* supported reflection on the results of game play through formal representations as a means to support strategy-refinement, but the formal representations were not the medium through which players planned, implemented, and manipulated their game strategies. Earlier versions of *SURGE* provided vector representations, for example, to help students understand what was happening and how they might adjust their control strategy, but these formal representations only communicated information that a player might or might not use. The challenges and opportunities in a given game level, however, were communicated through the layout of elements in the game world, not in the formal representations. Similarly, the player's controls for executing a strategy were also independent of the formal representations. Thus, while attending to the formal representations might help a player succeed in a level, earlier *SURGE* games did not use formal representations as the medium through which challenges and opportunities were communicated to the player, nor did earlier *SURGE* games use diagrammatic formal representations as the medium of control.

As discussed in Clark et al. (2015, 2016c), *SURGE Symbolic* builds on research on teaching physics using simulations and motion sensors (e.g., Brasell 1987; diSessa et al. 1991; Mokros and Tinker 1987), research on constructing graphs based on assembling relevant "pieces" of trajectories of motion, and research on SimCalc (e.g., Hegedus and Roschelle 2013; Kaput 1992; Roschelle et al. 2010). In the work of Tinker and colleagues, students have often been provided graphs of position or velocity that they were asked to replicate using the controls of the system, which might involve a motion sensor. Similarly, students have been provided with a dot trace representation overlaid on their phenomenological view that they worked to interpret in terms of a graph (diSessa et al. 1991), and SimCalc pioneered in scaffolding students' integration and differentiation between and across Cartesian graphs of position, velocity, and acceleration over time by dynamically linking across representations (Kaput 1992; Hegedus and Roschelle 2013).

DIGs build on these bodies of research by pushing more deeply on approaches for leveraging formal representations as the means of communicating challenges to players, as well as leveraging abstract formal representations as the players' means of control within the game. Furthermore, we propose that DIGs generalize beyond time-series analyses and multiple representation systems involving Cartesian graphs of change over time (Clark et al. 2016a).

DIGs, by definition, use formal representations as the medium through which challenges and opportunities are communicated to the player (Communication Representations), and DIGs use formal representations as the medium through which the player implements strategies and exerts control over the game (Control Representations). Some DIGs might use the same representation for both control and communication, while other DIGs might use one or more formal representations for communication and one or more other representations for control. All DIGs include a phenomenological representation (which in traditional digital games would be the primary focus). Furthermore, all DIGs include an intermediate representation to support players in translating from the phenomenological representation to the formal representations and to constrain their interpretation of the formal representation. The goal in all DIGs involves interpreting, creating, modifying, and translating across these formal and phenomenological representations.

The template for *SURGE Symbolic*, for example, presents the phenomenological representation (which we refer to as "the world") on the left side of Fig. 5.1. The phenomenological representation portrays the heroine, Surge, on her hoverboard moving forward and backward along a game map. The formal Cartesian graphs on the right side are the communication and control representations. The position and velocity graphs in Fig. 5.1, for example, can present information about the specific regions of the game world that will be affected by dangerous electrical storms at given times, as well as information about locations and times where rewards or allies will rendezvous with Surge. As a result of this design approach, the Cartesian space emerges as a set of scientific instruments for the player by communicating data about the game world that are not available through other means. While Fig. 5.1 shows an example where the challenges and opportunities are communicated through the position graph and velocity graphs, any subset (or all) of the Cartesian graphs could serve this role. Simultaneously, the Cartesian graphs also play the role of an instrument panel or mission planner, offering fine-grained control over the movement of the Surge spacecraft. In Fig. 5.1, for example, the player can exert control by placing forces of various magnitudes and durations at different time points in the force graph. Alternatively, the player can exert control through the other graphs using the toggles to the right of the graphs. The author of a game level designates which graphs are visible to the player, which graphs are used for which purposes (communication or control), and what challenges and goals constitute the level.

Thus, all DIGs have the following characteristics: (a) formal representations for controlling the game, (b) formal representations for communicating challenges and opportunities, (c) a phenomenological representation presenting the phenomenon being modeled, (d) an intermediate aggregating representation, and (e) game mechanics and goals focused on engaging the player in interpreting, creating, modifying, and translating across these formal and phenomenological representations.

Signaling Theory

Effective use of visual stimuli is highly related to efficient learning (Litchfield and Ball 2011). Likewise signaling, the process of using cues to direct a learner's attention toward key events in a multimedia presentation, has shown to be an effective tool in scaffolding students' multimedia experiences. Signals can help learners to understand content presented in multimedia presentations (Mautone and Mayer 2001), select relevant information using fewer cognitive resources (Britton et al. 1982), recall relevant information and ignore irrelevant information (Mautone and Mayer), integrate information effectively in transfer problems (Loman and Mayer 1983), and focus on perceptually striking features (Lowe 1999).

More specific to this study, signals have the potential to greatly enhance physics learning environments. Madsen and colleagues found that participants who answered physics problems correctly spent more time looking at relevant areas of physics problem set diagrams, while novices spent more time looking at irrelevant areas (Madsen et al. 2012). In light of these findings, they studied cuing in physics problem- solving and found that learners that viewed selection and integration cues overlaid onto physics transfer problems spent less time looking at irrelevant areas, and more time looking at relevant, "expert" areas (Madsen et al. 2013). Furthermore, Rouinfar and colleagues found that short visual cues overlaid onto physics problems facilitated immediate problem-solving and ability to transfer problem-solving skills to novel problems and such cues applied over multiple problems causes learners to automatically extract similar features in new problems (Rouinfar et al. 2014).

Signals can be implemented in multiple forms to help learners perceive relationships among representations, including altering the luminance of objects in a display (e.g., De Koning et al. 2007), altering font style (e.g., Mautone and Mayer 2001), flashing elements (Craig et al. 2002; Jeung et al. 1997), and orienting gestures guiding learners to related elements (Lusk and Atkinson 2007). However, not all forms of signaling work equally well in all instructional contexts (Hegarty et al. 2003). Signals should be carefully designed in light of the intended function, the expertise of the learners, and the nature of the relationships highlighted. For example, maintaining consistency in labeling and color choice is an effective way of representing that objects are similar across different representations because learners can more easily perceive the relationships among them (Dufour-Janvier et al. 1987; Zhang 1996). Ainsworth (2006, 2014) advocated for the importance of matching the scale of the representation of information to the scale of the display of this same information, later generalizing this idea as a design consideration.

Research Questions

The current study explores the overall efficacy of our current approach to designing DIGs as well as the potential contributions of integrating signaling into our design of DIGs. For this study, students in the baseline condition played a version of SURGE Symbolic without signaling added. Students in the comparison condition played the same version of SURGE Symbolic with the addition of signaling functionality in a subset of the game levels. The signaling functionality adds flashing signals that visually link conceptual physics imagery to the corresponding symbolic representation in the graphical view of the game. These conditions were designed to investigate the following predictions:

1. Students in both versions of the DIG will demonstrate significant pretest-posttest learning gains.
2. Compared to students in the non-signaling condition, students in the signaling condition will demonstrate (a) increased pretest-posttest gains, (b) progress significantly further in the game, and (c) display patterns in their gameplay behavior indicating deeper conceptual sophistication.

Prediction #2 is informed by the logic that students who experienced signaling would have an enhanced understanding of how actions of the game character and relate to the corresponding graphical representations of position and velocity, resulting in a better understanding of these concepts and their connections. Arguing against prediction #2 is the possibility that increased complexity and load resulting from the addition of the signaling functionality might actually result in diminished rather than increased outcomes for students in the signaling condition. We have observed this tension in our prior work when attempting to integrate approaches to scaffolding, such as self-explanation and worked examples, into game play (Adams and Clark 2014; Adams et al. 2018). More specifically, we have found that integrating scaffolding from educational and psychological research into the context of digital games requires iterative research and learning environment design to leverage the affordances of the scaffold in a manner that does not compromise gameplay in terms of flow or complexity.

Methods

Participants

Sixty-nine seventh and eighth grade students from a diverse public middle school in Nashville of fairly high socioeconomic status participated in this study. Fourteen students were dropped from analyses because of attendance issues and/or missing the pretest/posttest. Students were randomly assigned to either the signaling or non-signaling condition. Pretests, posttests, and engagement surveys were administered to all students. A short cognitive task assessing attentional ability was also administered, but not analyzed in this paper. Interviews/screen recordings were conducted for a subset of students who provided consent forms from their parents and themselves.

SURGE Symbolic Game Design

As described in the background section on DIGs, SURGE Symbolic is a DIG designed to support student learning of Newtonian dynamics. Students play from the perspective of the space navigator, SURGE. Game play is divided into levels, each focused on a specific navigational challenge or Newtonian concept. Students must move SURGE forward or backward on her space board to find the appropriate position, velocity, or acceleration to navigate SURGE to the exit portals, represented by a purple box, while avoiding electricity zones, represented as orange boxes (see Figs. 5.2, 5.3, 5.4). SURGE's path is traced onto a graph representing the magnitude of position and velocity over time.

Levels contain increasingly more challenging combinations of Newtonian concepts as the game progresses. Initially, students are required to manipulate SURGE's position in the worldview to guide her to the purple exit portal. The distance that students move SURGE is represented directly by the graph of SURGE's movement as seen in Fig. 5.2. When a student successfully passes all position levels, they advance to velocity based levels. On velocity levels, students must change SURGE's physical location to represent a position-over-time rate that successfully avoids the electricity zones. The change in SURGE's position over time is graphed in worldview velocity

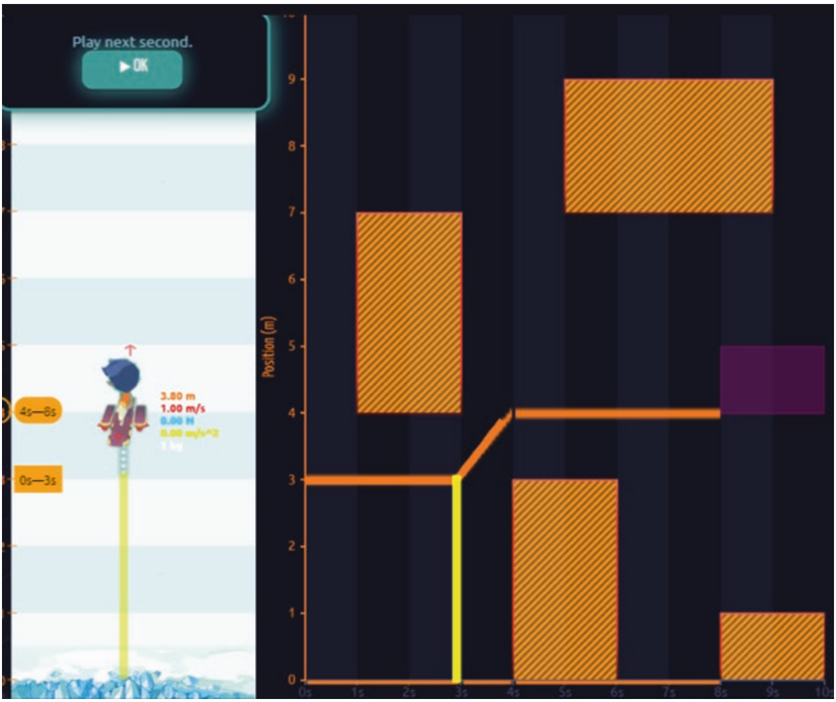

Fig. 5.2 Position WV level

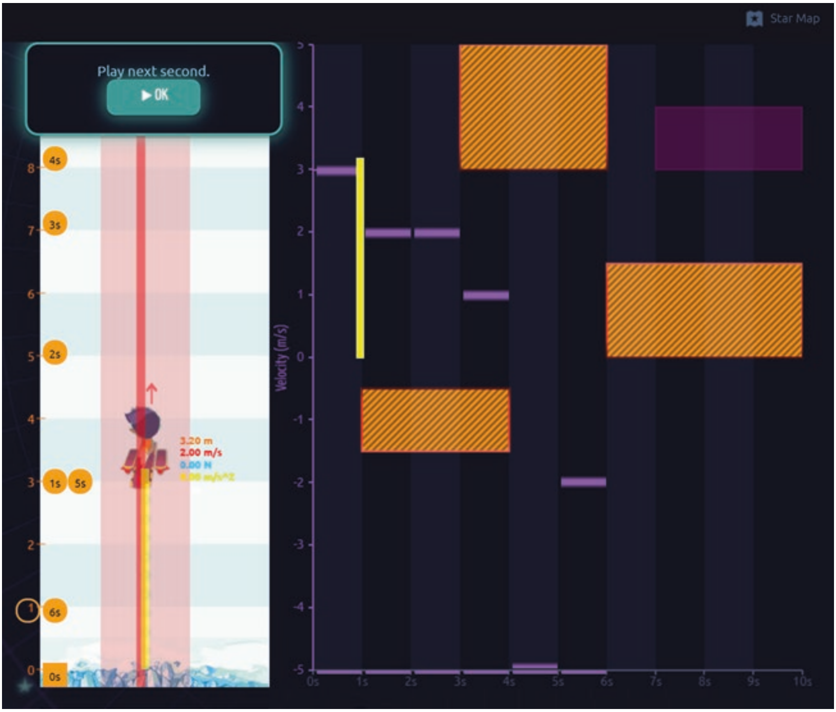

Fig. 5.3 Velocity WV level

levels (see Fig. 5.3). Students then progress to levels that require them to consider both position and velocity. On levels that combine position and velocity graphs, students are asked to manipulate SURGE's position to avoid electricity zones on the position graph as well as a worldview velocity graph (see Fig. 5.4). Finally, students apply concepts from position only, velocity only, and position/velocity combined levels to work through levels challenging their understanding of acceleration.

Depending on the level, students have two types of interfaces for setting up their strategies. In "world view" levels, the player drags the game character in the worldview to create the graph that will specify the position, velocity, or acceleration versus time for that level. In "block" levels, the player drags blocks that contain segments of a graph to create a graph to specify the position, velocity, or acceleration versus time. Block levels related to the preceding worldview topic are alternated with groups of

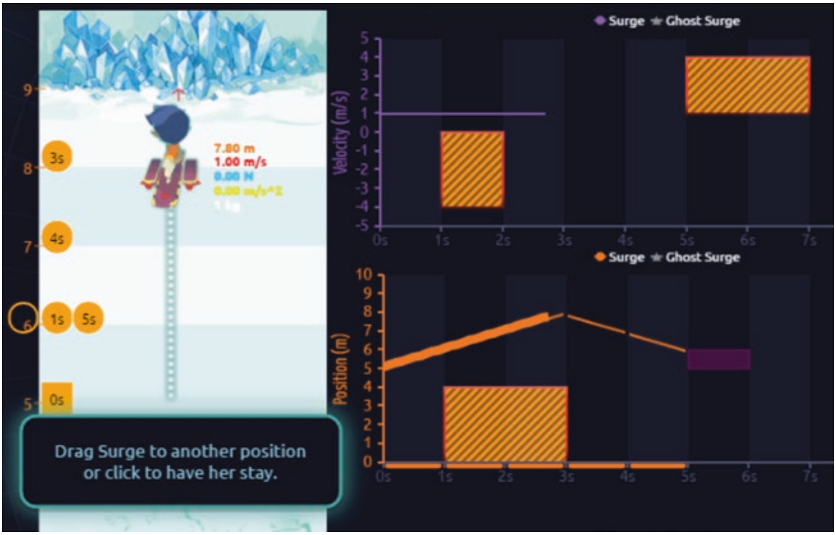

Fig. 5.4 Pos/Vel WV level

worldview levels to provide a different way to view the relationship between position, velocity, and time. Worldview levels serve as the introduction to each novel Newtonian concept. The rationale in terms of design was that the worldview interface would be more intuitive for students because students would drag the game character to the position on the map where they wanted the character to be at each time in the level. Then the block-level versions would require the player to think about what the graph should look like for the game character to be in the right place at each time in the level. We explain more about the worldview interface and the block-level interface as well as the nature of the signaling in the signaling condition in the following paragraphs.

Students have the flexibility and challenge to create any path that navigates SURGE safely through the electricity zones. Students use the toggle button to navigate SURGE and are able to test the success of their path by hitting the “Run” button. In worldview position levels, the signal in the signal condition represents the magnitude of distance SURGE is traveling during a set amount of time. The distance signaled in the game-worldview matches the distance graphed in worldview to facilitate student understanding of how the worldview graph is created. Unlike the worldview position level signal, the velocity-level signal highlights the rate at which SURGE is moving rather than the distance traveled. In worldview levels that display both position and velocity graphs, students are not given signals as the size of the graphs were smaller in these levels and no longer congruent to the height of the worldview. Hence, a signal between worldview and graphs would not make sense.

After three levels, students are able to deselect the second-by-second option of each run through so that each review is uninterrupted. It is important to note, however, that there was no tutorial showing students how to turn off this feature, so many students may have missed this option. This may have led to differences in game play results.

Students in the signaled condition are lead through worldview levels in an incremental method. They are first prompted to click and drag SURGE to a starting position and confirm that position by clicking the “OK” button in the dialogue box. This button has to be clicked before students can make the next move. Students have the option of moving SURGE to a new location to represent a change in position, or they can keep SURGE at the same value. After the students make their second move, they are again required to confirm the change or lack of change of location by clicking “OK.” Each movement is confirmed until a marked path is created for SURGE to follow to the exit portal. For each new movement, students have the option to choose the length of time SURGE needs in order to move the distance they set. This feature scaffolds student thinking toward understanding slope, or rate of movement.

When students have finished designing their path, they must click the “Run” button to evaluate the success of their plan. During the first execution of the plan, SURGE travels down the created path second-by-second and the students are signaled to progress to the next second after each move. Once students submit their first plan, the game plays the path from start to finish in real-time with no interruptions, with the signal present as well. If SURGE successfully reaches the exit portal, students have the choice to replay the same level or advance to the next. The signal itself is highly emphasized in the second-by-second run and the real-time presentation. The signaling button helps to breakdown each plotted movement to intentionally relate the worldview to the graph. In block levels (see Figs. 5.5, 5.6, 5.7), students are required to arrange blocks of various magnitudes in the correct order to navigate SURGE to the exit portal. Each block represents a rate that dictates how much SURGE moves on the position graph. When the blocks are placed next to each other on the

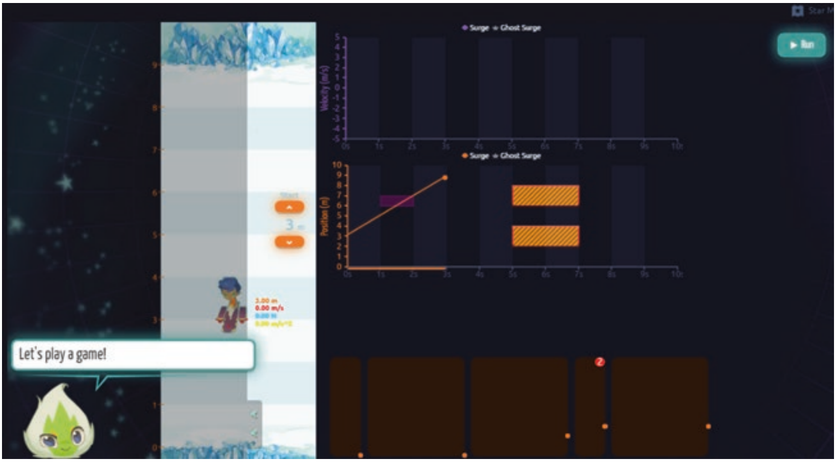

Fig. 5.5 Position block level

Fig. 5.6 Velocity block level

lower plane, they come together to create the graph of SURGE's movement. The student should now gain an understanding of the connection between real world movements and the production of a graph of movement throughout completion of worldview levels. The block levels reverse the representation, requiring students to analyze blocks of movement and

Fig. 5.7 Acceleration block level

connect them to individual movements of SURGE. Block levels also highlight the concept of slope more explicitly than worldview levels and they provide a different perspective for a student to approach Newtonian concepts. If a student can successfully navigate SURGE to the exit portal with the correct arrangement of blocks and without running into an electricity zone, the next level of the game is unlocked and the student can proceed. If the student is not successful, they can replay the level and change their initial actions. Therefore, players cannot skip ahead. Blocks can be dragged onto and off of the graph, as well as rearranged within the graph. The amount of total block movements and the individual types of block behavior were measured to evaluate how students interacted with block-level manipulatives.

Block levels are further categorized by the Newtonian concept they represented. Position block levels (see Fig. 5.5) represent a constant velocity between a start and an end point. Students organize position blocks onto a graph of SURGE's position to test whether or not their pattern of blocks navigate SURGE to the exit portal. Velocity block levels (see Fig. 5.6) requires students to place blocks signifying a constant velocity onto a graph of SURGE's velocity. Students have to avoid the electricity zones on both the velocity graph and the graph of SURGE's position over time. Acceleration block levels, represented in Fig. 5.7, require students to think about how the changing acceleration affects SURGE's position over time. This type of level was beyond the scope of expectations for students and was not tested directly.

Procedure

The study spanned six consecutive class periods over the course of a week. During the first session, all students took the pretest and completed a short cognitive task of attention that was not analyzed in this study. In all classes, students were instructed on how to navigate through initial steps in the game and received help as needed. Students were also encouraged to talk about the game, share strategies with their peers, and ask each other for help if they got stuck. Some students were interviewed about their thoughts and experiences in the game, and their screens were recorded under informed consent. Thirty minutes before the end of the last class on the final day, students were guided through the posttest and two short engagement surveys.

Assessment

A twenty-one question, multiple choice pre-posttest was created to assess physics understanding. The pretest and posttest were identical. Test questions assessed students' understanding of displacement and velocity graphically, mathematically, and verbally. Students often had to answer mathematical questions based on position and velocity graphs, or relate position and velocity concepts and/or graphs in order to answer questions correctly. Three questions assessed position-only concepts, two assessed velocity-only concepts, eleven questions assessed students' ability to link graphs or verbal descriptions of velocity and position together, five questions required students to link a graph of position to a verbal description of position or a graph of velocity to verbal description velocity, fourteen questions were modeled more after gameplay in the block levels, and seven questions were modeled more after gameplay in the worldview type levels. However, it should be noted that the block and worldview-based questions still utilized concepts that could be gleaned from either level type.

Students also completed two engagement surveys after they finished their posttest. The first was a standardized game experience survey (GEQ), which has demonstrated high reliability and validity. This survey had nineteen questions, with three possible responses ("yes," "no," "sort of") assessing students' positive affect, competence, immersion, flow, level of challenge, and other metrics of engagement. The second survey also used a three-item evaluation, assessing students' engagement in the SURGE Symbolic game both overall and for specific game features.

Results

Results are first presented within and across experimental conditions in terms of the pretest, posttest, engagement, overall gameplay metrics, and worldview level specific gameplay metrics.

Assessment Performance and Overall Gameplay Metrics

Pretest

A one-way ANOVA of pretest scores was conducted for the two conditions (see Table 5.1). As expected, there were no significant differences between the two conditions on the pretest $F(1,53) = .72$, $p = 0.40$).

Posttest

Next, a one-way ANOVA of posttest scores was conducted (Table 5.2). The one-way ANOVA showed that the difference in posttest scores between non-signaled and signaled conditions was significant, with the non-signaled condition outperforming the signaled participants with a fair effect size, $F(1,53) = 4.23$, $p = .05$, $d = 0.55$. Specifically, the section requiring students to link position and velocity representations showed significant differences across conditions, $F(1,53) = 4.53$, $p = .04$, $d = 0.58$, with the non-signaled group scoring higher than the signaled group. No other sections of the posttest were significant, however, the section that was modeled most after the worldview-based levels, had marginally significant differences, $F(1,53) = 3.67$, $p = .061$, where the non-signaled condition performed better than the signaled one.

To make sure that the significantly higher posttests in the non-signaled condition were not a factor of the non-significantly higher pretest in that condition, we also compared pre-post gains for both conditions. A paired

Table 5.1 Learning and engagement results

Performance metric	*Non-signaled condition*		*Signaled condition*		F	P	*Cohen's* d
	M	SD	M	SD			
Total pretest score	8.32	3.29	7.59	3.08	F(1,53) = .72	.40	
Total posttest score	9.64	4.23	7.52	3.38	F(1,53) = 4.23	.05	0.557
Position PTQ (posttest questions)	2.32	0.77	2.04	0.81	F(1,53) = 1.78	.19	
Velocity PTQ	0.68	0.77	0.74	0.0.66	F(1,53) = 0.10	.75	
Linking Pos/Vel PTQ	4.07	2.39	2.85	1.81	F(1,53) = 4.53	.04	0.58
Linking same concept PTQ	3.00	0.98	2.41	1.45	F(1,53) = 3.18	.08	
Block level PTQ	6.18	2.72	5.00	2.18	F(1,53) = 3.12	.08	
Worldview level PTQ	3.89	1.62	3.04	1.70	F(1,53) = 3.66	.06	
Total GEQ	10.5	8.04	11.78	7.84	F(1,53) = .36	.55	
Total game specific survey	9.39	5.53	9.44	5.49	F(1,53) = .00	.97	

Table 5.2 Pre/post gains across all students and by condition

Condition	*Pretest (SD)*	*Posttest (SD)*	*Gain score (SD)*	T	P	*Cohen's* d
All students	7.96(3.17)	8.60(3.95)	.64(0.77)	1.65	.11	N/A
Non-signaled	8.32(3.28)	9.64(4.22)	1.32(2.88)	2.43	.02	0.66
Signaled	7.59(3.08)	7.52(3.38)	−.074(2.73)	.14	.89	N/A

sample t-test was also performed to compare the average difference between pretest and posttest scores on various question types (see Table 5.2). The t-test was conducted to determine how gameplay affected students' understanding of conceptual questions. Means and standard deviations for the pretest, posttest, and gains scores can be found in Table 5.1. Overall and unexpectedly, there were no significant differences in learning across all students from pretest (M = 7.96, SD = 3.17) to posttest (M = 8.60, SD = 3.95); t(54) = 1.65, p = .11. There was a significant difference between pretest (M = 8.32, SD = 3.28) and posttest (M = 9.64, SD = 4.23) scores for participants in the non-signaled condition; t(27) = 2.43, p = .02, d = .66. Also unexpectedly, the posttest performance scores (M = 7.52, SD = .65) of students in the signaled condition did not show a significant difference to pretest scores (M = 7.59, SD = 3.08); t(26) = .14, p = .89. Therefore, game play for students in the non-signaled condition seemed to have a large impact on conceptual learning compared to students who experienced game play in the signaled condition.

Engagement

A one-way ANOVA of two engagement surveys across the two conditions found that there was no significant difference in engagement across the two conditions for either the GEQ survey, $F(1,53) = .36$, $p = .55$, or game-specific survey, $F(1,53) = .00$, $p = .97$.

Overall Game Behavior

Highest Level Completed

ANOVAs were conducted to compare the experimental conditions for progress in the game (see Table 5.3). Students could move onward to a subsequent game level only after successfully completing the game level preceding it. For this reason, the highest game level a student completed measured how far the student progressed in the game. A one-way ANOVA of the highest level completed among the two conditions found that there were no significant differences across the two conditions, $F(1,53) = 0.01$, $p = .91$.

Worldview Behaviors (Overall)

Three worldview behavior performance metrics were examined: (a) how many times students dragged SURGE within a worldview level trial, (b) the average time spent on each worldview trial, and (c) the average number of trials per worldview level. A one-way ANOVA of each of these metrics found significant differences across conditions for these behaviors with large effect sizes, (a) $F(1,53) = 15.87$, $p = .00$, $d = 1.07$ (b) $F(1,53) = 30.12$, $p = .00$, $d = 1.49$ (c) $F(1,53) = 103.31$, $p = .00$, $d = 2.72$. We explore the nature of the significant differences in a subsequent section below.

Block-Level Behaviors

Within block levels, we examined (a) the average number of times players moved blocks per trial, (b) the average number of times players dragged blocks out of play per trial, (c) the average number of times players rearranged already-placed blocks per trial, (d) the average number of times players moved blocks per trial, (e) the average number of times players moved SURGE per trial, (f) the average total number of block movements

Table 5.3 Overall gaming behavior by level type

	Non-signaled condition		*Signaled condition*		F	P	*Cohen's* d
	M	SD	M	SD			
Highest level completed	44.00	10.51	44.33	11.69	F(1,53) = 0.01	.91	
Average drags/ worldview level trial	6.97	1.35	8.62	1.72	F(1,53) = 15.87	.00	1.07
Average time/ worldview level trial	81.09	58.90	17.84	10.86	F(1,53) = 30.12	.00	1.49
Average trials/ worldview level	1.66	0.90	7.13	2.70	F(1,53) = 103.31	.00	−2.72
Average block moves to graph/trial	4.49	1.06	4.20	1.07	F(1,50) = .93	.34	
Average block drags out of play/trial	1.33	0.97	1.36	0.60	F(1,50) = .02	.90	
Average block rearrangements/ trial	7.53	4.80	6.45	3.08	F(1,50) = .94	.34	
Average total block moves/trial	13.34	5.27	12.00	4.15	F(1,50) = 1.04	.31	
Average SURGE moves/ trial	4.84	1.90	4.36	1.92	F(1,50) = 0.82	.37	
Averages total moves/trial	18.19	7.04	16.37	5.94	F(1,50) = 1.01	.32	
Average time/ trial	51.43	21.32	52.31	24.24	F(1,50) = 0.02	.89	
Average trials/block level	3.38	1.11	3.38	1.54	F(1,50) = .000	.99	

players made per trial, (g) the average time players spent per trial, and (h) the average number of trials they took to complete a block level. None of these metrics were significant, (a) $F(1,50) = .934$, $p = .339$, (b) $F(1,50) = .02$, $p = .90$, (c) $F(1,50) = .94$, $p = .34$, (d) $F(1,50) = 1.04$, $p = .31$, (e) $F(1,50) = 0.82$, $p = .37$, (f) $F(1,50) = 1.01$, $p = .32$, (g) $F(1,50) = 0.02$, $p = .89$, (h) $F(1,50) = .00$, $p = 98$.

Worldview Levels Dissected Game Behaviors

Worldview Position Level Behaviors

For worldview position levels, we examined (a) the average number of trials per unique position worldview level played, (b) the number of times players dragged SURGE per trial on these levels, (c) the average time players spent on worldview position levels per trial for these levels (see Table 5.4).

Table 5.4 Worldview sub-level gaming behavior

Performance metric (across all levels in category)	*Non-signaled condition*		*Signaled condition*		F	P	*Cohen's* d
	M	SD	M	SD			
Average trials/ position worldview level	2.16	1.60	20.37	14.67	$F(1,54) = 42.67$	.00	1.75
Average drags/ position worldview level	7.13	1.88	9.51	2.12	$F(1,53) = 18.84$	.00	1.19
Average time/ position worldview level	123.99	102.66	17.23	8.93	$F(1,53) = 28.95$	.00	1.47
Average trials/ velocity worldview level	1.01	1.17	12.76	40.86	$F(1,52) = 2.32$	.14	N/A
Average drags/ velocity worldview level	6.00	1.53	6.71	2.07	$F(1,47) = 1.827$	.18	N/A
Average time/ velocity worldview level	93.26	56.19	20.29	15.70	$F(1,47) = 37.55$	.00	1.77
Average trials/Pos/ Vel levels combined	10.00	4.84	16.85	19.76	$F(1,54) = 16.27$	.00	0.47
Average drags/Pos/ Vel levels combined	6.79	1.34	9.17	1.96	$F(1,53) = 23.51$	.00	1.42
Average time/Pos/ Vel levels combined	47.83	18.51	17.07	10.95	$F(1,53) = 31.20$	.00	2.02
Average trials/ Pos+Vel levels	1.75	1.59	25.04	17.24	$F(1,35) = 12.70$	.00	1.90
Average drags/ Pos+Vel levels	6.79	1.63	7.98	1.81	$F(1,35) = 5.07$	.03	0.69
Average time/ Pos+Vel levels	119.72	94.87	22.11	13.90	$F(1,35) = 22.23$	.00	1.44

A one-way ANOVA revealed significant differences across conditions for all of these metrics with large effect sizes. Here, the number average number of trials per level, $F(1,54) = 42.67$, $p = .00$, $d = 1.75$, and drags per trial, $F(1,53) = 18.84$, $p = .00$, $d = 1.19$, were significantly higher in the signaled group with high effect sizes. The average time spent per trial was significantly higher in the non-signaled group with a large effect size, $F(1,53) = 28.95$, $p = .00$, $d = 1.47$.

Worldview Velocity Level Behaviors

One-way ANOVAs were conducted to investigate the average number of drags and time spent per trial and the average number of trials per velocity worldview level. The average number of drags, $F(1,47) = 1.83$, $p = 0.18$, and trials per level, $F(1,52) = 2.32$, $p = 0.14$, were not significant between conditions, while the average time per trial was, $F(1,47) = 37.55$, $p = .00$, $d = 1.77$, where the non-signaled group spent significantly more time on average per trial than the signaled group.

Worldview Velocity and Position Levels Combined Behaviors

Combining all the signaled levels together, we see that all major metrics showed behaviors similar to the worldview position levels.

Specifically, a one-way ANOVA revealed significant differences across conditions for all of these metrics. Here, the number average number of trials per level, $F(1,54) = 16.27$, $p = .00$, $d = 0.47$, and drags per trial, $F(1,53) = 23.51$, $p = .00$, $d = 1.42$, were significantly higher in the signaled group with fair and high effect sizes. The average time spent per trial was significantly higher in the non-signaled group with a large effect size, $F(1,53) = 31.20$, $p = .00$, $d = 2.02$.

Position- and Velocity-Linked Worldview Levels Behaviors

We see an identical trend for levels where position and velocity levels were linked together (here no signal was used in either condition).

Specifically, a one-way ANOVA revealed significant differences across conditions for all of these metrics. Here, the number average number of trials per level, $F(1,35) = 12.70$, $p = .00$, $d = 1.90$, and drags per trial, $F(1,35) = 5.07$, $p = .031$, $d = 0.69$, were significantly higher in the signaled group with fair and high effect sizes. The average time spent per trial was significantly higher in the non-signaled group with a large effect size, $F(1,35) = 22.23$, $p = .00$, $d = 1.44$.

Discussion

The pretest and engagement were not different among conditions. Accordingly, prior knowledge and ability, overall engagement with the condition, and knowledge gleaned from completed game levels apparently were not factors for the significant posttest score differences and pre-post gain differences. The posttest and pre-post gains demonstrated significant differences in favor of the non-signaling group, where this group performed better on the overall test and also significantly better on the assessment questions which required the student to link position and velocity concepts together and marginally better on the subset of questions modeled after worldview gameplay. Overall significant pre/post differences were not found across all students, but this is because only the non-signaled group demonstrated significant gains in learning from pretest to posttest.

Signaling should have fostered stronger links between the graph and worldview, fostering students' understanding of position and velocity. While the signals used did not link between graphs in this experiment (i.e., the signals only linked the worldview with a single graph), an increase in gains for position or velocity concept-based questions that did not require linking across multiple graphs should have been present. Similarly, an increase in gains for questions that required students to link verbal and graphical representations of position concepts together or velocity concepts together should have been observed, but in fact were not. Nor were indirect effects of potentially enhanced understanding of position and velocity observed, such as higher scores on the questions where students had to link these concepts. Since signaling should have enhanced student attention to the worldview level, we might also have expected an increase in the signaling group's learning. Instead, we found the opposite.

Clearly, the signaling in between the worldview and the position and velocity graphs hinder student understanding in some way. It is odd that something which should make learning more accessible and reduce the cognitive load of merging representations would detract from students' learning, especially in light of research concerning physics problems in multimedia learning, which strongly suggests that signaling should improve learning. There is also a possibility that, in addition to disrupting game cognition, the signal may have overscaffolded students and thus prevented them from actively making key connections between the worldview and the graph themselves.

What about the design or implementation of the signaling might have resulted in these unintended and undesirable outcomes? Notably, the initial few position and velocity worldview levels had an automatic replay that worked as follows: After the student hit the "go" button, each second of their game play was enacted on the views one second at a time. Students had to click the "play next second" button to keep moving forward. Once they reached the end of the level, the game played their set course from start to finish at the normal speed so the students could see what that looked like in real time. After the first few levels, students could optionally click off the second-by-second button so that the signal would disappear, although it is doubtful that many students in the signaling group used this functionality as there was no explicit tutorial in the game highlighting it. The initial second-by-second functionality was added to ensure that students had time to truly understand the relationship between worldview and graph, and realize the importance of the signal, before toggling it off.

What does the gameplay data suggest? The highest level completed was not significantly different across conditions. This suggests that differences were not due to signaled students being held up by the presence of the signal. Similarly, the number of block levels completed, trials, or any behavior involving blocks were not different among groups, so it seems that there was no kickback effect of better learning from the non-signaled worldview levels transferring to non-signaled groups' understanding/cognition for the block levels. Looking at the worldview level data overall, we see that the signaled group had significantly more average trials per worldview level and also more average "mouse drags" of the game character per trial in setting up a plan for the level. The signaled group also spent significantly less time on average for each worldview trial. Hence, we see the group with the signaling required many more attempts to complete a level and utilized more actions to complete the level, but also spent far less time per trial. This set of behaviors could indicate students using more "brute force" to solve a level as rapidly as possible in the signaling condition, as opposed to thinking about each trial and utilizing only drag actions that seemed to make mathematical and scientific sense based on what they knew. This may indicate a lack of understanding of the physics concepts, resulting in frustration and subsequent inability to thoughtfully solve each level.

Accordingly, the signaling group scored lower on the overall assessment, including the subset of questions that require linking, and performed no better on questions that required them to match verbal and graphical representations of position or velocity together. This suggests a lack of understanding, potentially stemming from a deficiency in their responses to the signal and their gaming behavior. Additionally, repetitively and passively clicking each second by second at the end of each level may have encouraged more passive, autopilot cognition for solving levels.

Examining game behavior in the three types of worldview levels separately, we see that both the position and combined position and velocity worldview levels demonstrated a pattern of behavior similar to the overall worldview results. Specifically, the signaling students utilized significantly more drags and trials on average per level and significantly less time on average. This pattern holds true when we combine data for the position and velocity combined worldview levels, so all the levels with signals are aggregated. However, when we examine just the velocity worldview levels, we see no significant differences in drags or average trials per level. Yet, we still see significant differences in average time per trial, where the signaled group spent significantly less time on average per trial.

Accordingly, the game behaviors in the initial position worldview levels seem to be driving the overall results we see coupled with the position and velocity combined levels. It is interesting that the velocity worldview levels showed few differences in these metrics, perhaps because by the time students had gotten to these levels, they were more proficient in the game. Students in the signaled group still spent significantly less time on the levels on average, so some behaviors did persist, even in these levels. The reason for the differences in gaming behavior in the combined position and velocity levels observed later may be because these levels are much more advanced and more elicit and more aberrant behavior in gameplay due to deficiencies in learning. Interestingly, the combined position and velocity levels did not utilize signals in either condition. For this reason, the students were influenced to behave differently across conditions in these levels due to the presence or absence of signals in the prior position and velocity worldview levels.

Based on these findings, the signaling most likely disrupted understanding through the second-by-second playback at the start of the worldview levels, which might have never been turned off by students and could have easily disrupted and overloaded their cognition. Specifically, it may have disrupted them from holding the goal for the level in working memory, causing poorer understanding and gameplay. Even if slowing down the signal playback had some benefit for understanding what each point on the position graph meant, the overall learning benefit was compromised because of the disruption. Specifically, since students needed to go second-by-second to see the signal, it may have been too slow for their natural flow and could have disrupted their ability to examine incorrect answers at the end of a trial. This metacognitive examination would have helped students to think critically about the correct answer and what changes they would try out in a subsequent trial. This theory would help explain the inefficient game behaviors demonstrated across many worldview levels. The signaling may have also over scaffolded the students, preventing them from actively linking the worldview and graphs for themselves and instead promoting automatic, passive cognition and gameplay.

Possibly, then, it is the way the signal is specifically programmed and operated in the game levels. Our future research will compare groups in which the signal has no replay, optional replay, and mandatory replay with and without the second-by-second viewing mode. Monitoring differences between groups could help provide more evidence that mandatory playback design choices disrupt learning rather than signaling, itself. Likewise, comparing performances between a condition where the signal does not have the one second replay and a non-signaled condition may prove informative. Regardless, the findings of the current study are interesting and demonstrative of the power that early learning in games can have on understanding and success in later, more advanced concepts and levels.

However, that a change in the worldview foundational levels, especially position levels, would have such a striking effect on post test scores is, itself, interesting and demonstrative of the power that early learning in games can have on understanding and success in later, more advanced concepts and levels.

Conclusion

The Findings from the base condition of SURGE Symbolic without the signaling demonstrate significant pre-post gains on challenging physics and graphing concepts. In a prior study, we included a null condition with only a pretest and posttest but no intervention to determine whether a test/retest phenomenon could account for gains without an intervention (Martinez-Garza and Clark, submitted). That study demonstrated that gains on the test could not be attributed simply to a test/retest effect. We, therefore, interpret the significant pre-post gains in the base condition as demonstrating the efficacy of the overarching disciplinary integrated game approach enacted in SURGE Symbolic. Newtonian concepts as well as graphing concepts are very challenging for students, and often resistant to instruction (e.g. Hestenes et al. 1992; Hestenes and Halloun 1995). We are, therefore, pleased with the findings with regard to the base version of Surge Symbolic in terms of the overarching disciplinary integrated ideas that it represents.

The findings from the signaling condition, however, are disappointing and contrary to our predictions. Students in the signaling condition demonstrated no significant pre-post gains. While disappointing, we have encountered similar patterns in our prior research as we have attempted to integrate well-documented principles about scaffolding from psychology and cognitive science into digital games for learning. Our research has demonstrated that when worked examples come at the expense of time spent in gameplay, they can detract from game cognition and STEM learning (Adams et al. 2018). This research also found no benefit to worked examples embedded into game play for students with low prior knowledge. This is also consistent with Adams and Clark's (2014) findings, in which self-explanation prompts slowed students in the prompt condition such that they completed significantly fewer levels and scored significantly lower on a learning assessment. Looking across those studies and the current study, we see that the efficacy of implementing well-documented multimedia principles of learning in STEM games, here signaling, may not enhance learning if the design interferes with students' flow, cognitive load, or engagement with the game mechanics. In particular, results demonstrated that when signaling is overemphasized in a STEM game, it can disrupt or possibly overscaffold learners, resulting in detrimental learning gains and gaming behavior. More specifically, across all three of these studies investigating science learning games, we see that it is critical that scaffolds based on multimedia research (a) do not overscaffold the student or promote passive, automatic behaviors, (b) do not excessively detract from the student's gameplay time, and (c) do not disrupt game cognition and flow, especially the pace of flow. Tutorials are also imperative for all major features the student will encounter, such as the toggle off/on the button for the signal scaffold in this study.

This does not mean that these well-documented learning and scaffolding principles have no place in the design of digital games for learning. It simply means that refining designs that carefully integrate game mechanics and the design of the scaffolding can require careful iterative refinement. The meta-analysis of games for learning by Clark et al. (2016b) certainly highlights the key role of the specifics of design over simple binary comparisons of medium or approach. In the case of the self-explanation functionality, for example, building on the findings of the Adams and Clark (2014) study, we redesigned the self-explanation functionality to adaptively adjust to students' level of sophistication in terms of the abstraction of the prompts. We also adjust the timing and frequency of the prompts such that the prompts only appeared after the player had successfully completed a level. By timing the prompts in this fashion, the prompts were less intrusive and disruptive to players' gameplay and allowed more certainty that the explanation prompts would be appropriate to the player's current progress and solution. Our research on this refined approach to self-explanation demonstrated significant pre-post learning gains compared to a condition without the self-explanation functionality (Clark et al. 2016c). Similarly, we interpret these findings as implying the need to refine our approach to signaling within gameplay rather than implying that signaling is inappropriate for application in this setting. Essentially, we consider the findings a reminder of the complexity of integrating scaffolding that has been developed and other educational contexts into the context of digital games for learning.

Acknowledgments This material is based upon work supported by the National Science Foundation under Grant No. 1119290. 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.

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CHAPTER 6

Cognitive Tools for Scaffolding Argumentation

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Argumentation is a complex ability crucial to critical thinking in virtually all academic subjects. It underlies scientific and philosophical discourse (Bricker and Bell 2009), and its use is explicitly required in almost every discipline studied in higher education (Wolfe 2011). Developing the ability to argue is recognized as an important goal at elementary, middle, and secondary levels (e.g., Berland and McNeill 2010; De La Paz and Felton 2010). By the time they start school, most children are able to give reasons supporting claims; and the ability to refer to evidence and respond to counterarguments develops throughout elementary and secondary schooling (Felton and Kuhn 2001; Kuhn 1992). However, unless explicitly guided to do so, many children and university students never develop more advanced argumentation skills such as identifying and understanding arguments presented in prose and constructing warrants (Asterhan and Schwartz 2007; de Vries et al. 2002; Maralee 2011).

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O. O. Adesope, A. G. Rud (eds.), *Contemporary Technologies in Education*, https://doi.org/10.1007/978-3-319-89680-9_6

Technologies Scaffolding Development of Argumentation Ability

In this chapter we explore the potential of particular learning technologies—representational devices often referred to as cognitive tools—to advance students ability to argue and to develop subject area knowledge through argumentation. As technologies, cognitive tools are usually interfaces or media that allow users or designers to alter or enhance the way information is represented, and to do so in a way that potentially fosters learning. For example, in this chapter we describe how students can use simple tagging tools to mark and classify parts of an argument presented in text. In the research, we used a browser extension named nStudy (Winne et al. 2017) that allowed participants to tag text presented in html pages. They were able to tag content by selecting a text passage and choosing from nine labels (i.e., category names) preconfigured by the researchers.

Much of this chapter is concerned with the effects of using argument maps, diagrams, or interfaces that graphically represent the parts of arguments and how they are connected. Argument maps can be constructed by specialized authoring systems that offer considerable freedom in how an argument is visually shaped and spatially arranged (e.g., Argunet). However, in many instructional situations, interfaces that restrict the representation of arguments to a simpler, canonical form may be easier for students to learn and use. Two of us (Niu and Nesbit) designed an interactive web interface called the dialectical map (DM) that students can use to construct arguments. The DM, implemented in JavaScript, builds arguments in a consistent two-sided, pro versus con, pattern that has been shown to promote learning. We theorize cognitive tools such as argument tags and maps foster learning because they support the development of argument schemas.

Schemas

Schemas are hypothetical mental structures that cognitive psychologists recognize as encoding knowledge. Far from static, standardized modules, schemas are theorized to transform into new and unique structures as learners adapt to their environment and resolve discrepancies between assembled knowledge and new information (Dansereau 1995). Somewhat like a data structure that might be created by a computer programmer, a schema can potentially be constructed in whatever form is suitable for performing information-processing functions. Schemas are often depicted as combining semi-fixed, structural elements, and variable elements called slots. Learning may consist merely of changing the values in the slots and leaving the structure of the schema intact; or, when new information is inconsistent with the structure of the schema, the learner may search for and execute an adjustment to the structure of the schema in order to capture and more suitably represent the new information as knowledge. Construction and modification of schemas may be induced through interactions with the physical or social environment.

Schemas are the contents of long-term memory and are activated as needed for comprehension, problem-solving, and so on. One important function of schema construction is to aggregate and consolidate previously separate, simple schemas so the information they represent can be simultaneously activated in a single "chunk", thereby imposing less cognitive load on working memory.

Schemas are involved in learning both conceptual and procedural knowledge (Anderson et al. 1978). In the context of argumentation, a conceptual schema might be activated to identify and parse a claim-evidence relation that a reader encounters in text. A procedural schema, called a *script*, might guide a writer in generating a claim and then searching source documents for evidence supporting the claim.

Of the schema-related cognitive processes we have just described, it is schema construction—assembling and modifying schema structures so they are optimally adapted to the environment and to the goals adopted by the learner—that is the most difficult and has the most profound consequences for successful cognitive development. Consequently, scaffolding schema construction and consolidation is the type of instructional intervention that may offer the greatest benefit to learners.

Cognitive Tools: From Schemas to Software

Cognitive tools were conceived by Vygotsky as culturally evolved and socially transmitted ideas that mediate the relationship between learning, instruction, and cognitive development (Vygotsky 1978). In this view, cognitive tools are common in every school subject, examples being the number line in mathematics, foreshadowing in the study of literature, and the golden rule in ethics. Vygotsky argued that it is the specific characteristics of cognitive tools more than innate maturational tendencies that direct the path of cognitive development.

According to Arievitch and Stetsenko (2000), the research of the Russian psychologist Gal'perin can be credited with advancing the theory of cognitive tools initiated by Vygotsky. Vygotsky and Gal'perin understood that cognitive tools are not acquired by a copying process, but rather they are instructionally induced through interactions with others in relation to a task and an environmental setting. Observable actions, events, and conditions are internalized as mental symbols that are assembled to form a socially shared cognitive tool.

Gal'perin claimed that the major barrier to learning in typical instructional settings is that the scaffolding provided for knowledge construction is incomplete (Arievitch and Stetsenko 2000). Often, instructional support only represents the components of the learning goals that are overt and directly evident in the performance of those who have acquired the schema. They fail to represent implicit but necessary knowledge. Thus, learners are often left to discover the missing knowledge on their own by inefficient means such as trial and error. Gal'perin claimed that instruction can be significantly improved if students acquire cognitive tools that represent all implicit contextual cues, criteria, mental actions, and decision rules needed to perform a task. Gal'perin's research demonstrated that children guided toward complete and sufficient cognitive tools were able to master tasks more rapidly and efficiently. A key advantage of supporting acquisition of complete cognitive tools is that students can immediately begin solving whole problems without the need for extended prelearning of part-tasks. In this respect, Gal'perin's theory somewhat aligns with the instructional design model advocated by van Merriënboer and Kirschner (2007) which prioritizes whole-task instruction while allowing for part-task practice where necessary.

But cognitive tools that offer sufficient and complete guidance to perform a narrowly defined task do not necessarily support transfer of learning to related tasks. Gal'perin argued that cognitive development only occurs when learners acquire cognitive tools that represent the conceptual reasoning that generates the procedures to solve specific problems. Here, we see alignment with the mindful transfer of learning advocated by Solomon and Perkins (1989). Cognitive tools that support this type of general understanding emphasize analysis of conceptual distinctions. Where a complete cognitive tool of the first kind might allow a child to learn addition fluency in base ten, a cognitive tool of the second kind might enable the child to add in a number system of any base. Beyond guiding *when* and *how* to carry the result of addition in a single column, the more advanced kind of schema gives the *why*.

In the 1990s, English-speaking educational technology researchers adopted the term cognitive tools to describe tangible supports for learning provided in an instructional environment (Lajoie 1993; Jonassen and Reeves 1996). Consequently, at least in the English-speaking educational technology research community, the term cognitive tool no longer refers to culturally shared knowledge but instead to an objective, computer-mediated representation intended to foster development of schema. This new understanding of cognitive tools developed as part of a shift toward constructivist theory in educational technology research. Cognitive tools were presented as computer-based, learner-centered aids for knowledge construction. However, a search of recent educational technology research can readily demonstrate that the term cognitive tool is now applied to a wide range of educational software, often with no reference to its psychological roots.

In this chapter, we use the term cognitive tool to describe interactive computer programs designed such that usage by a learner induces construction, activation, or instantiation of a schema having particular properties. This definition implies that the process of designing a cognitive tool is guided by an analysis of the explicit and implicit decisions, actions, events and conditions comprising the goal task. Further, if we are to meet Gal'perin's criteria for transferable or generalizable knowledge, the analysis should examine the conceptual underpinnings of the task and, where possible, represent in the cognitive tool the means to performance in a wide range of circumstances.

Scaffolding Argumentation with Tagging Software

Cognitive tools are often regarded as visualizations that concretely represent interrelations among abstract concepts. That is ostensibly the case with argument maps, the category of cognitive tools with which we are chiefly concerned. However, argumentation can also be scaffolded by tools that do not present elaborate visual structures. For example, there may be cognitive benefits from using tools that label (i.e., tag) terms and phrases that learners judge as relevant to a task (Nesbit and Winne 2008).

Previous research in our laboratory (Mao et al. 2010) investigated whether learners' text tagging predicted reasoning they demonstrated in a subsequent essay about the ideas in the studied text. Undergraduate students were randomly assigned to a study group, a summarize group, or an argue group. All participants were asked to study hyperlinked web documents that explained competing theories about the origins of Hobbit-like

Table 6.1 Nine tags available to participants

Study tags	*Summary tags*	*Argument tags*
Difficult to remember	Main idea	Supporting claim
Detail	Key term	Counterclaim
Example	Explanation	Evidence

hominid fossils found on Flores Island (Homo floresiensis). The study group was instructed to use the text to prepare for a recall test. The summarize group was instructed to prepare for writing a summary of the text. The argue group was instructed to prepare to write an argument. Participants accessed the web documents via nStudy which has a feature learners can use to tag text (Winne et al. 2017). All participants were provided with nine tags they could use to color-code (i.e., highlight) terms and phrases in the web documents. Each of the nine tags appeared as text highlighting of a unique color. As shown in Table 6.1, there were three study tags, three summary tags, and three argument tags. Participants were free to use all nine tags regardless of their group membership. They were not instructed to use particular tags, and the tags were listed in alphabetical order (i.e., not organized as in Table 6.1). After studying, the participants completed recall tests, and then were given 15 minutes to write an essay evaluating the competing theories presented in the web documents.

The results showed that the different instructions given to participants affected their tagging behavior. Representing the frequency of each type of tagging as a proportion of their overall tagging, the study group did more study tagging than the other groups, the summary group did more summary tagging, and the argument group did more argument tagging. There were no significant differences among the groups on multiple choice or free recall tests, but in the essay the argue group provided significantly more reasons and other markers of the quality and quantity of argumentation than the other groups. A regression analysis found that even after controlling for group membership participants who made greater use of argument tags while studying subsequently provided more reasons in their essays.

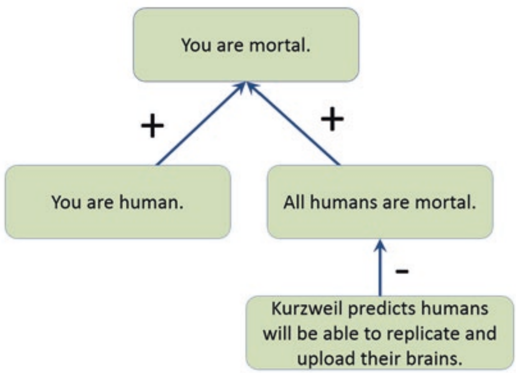
The significance of this research on scaffolding argumentation is that although the three groups retained and recalled similar amounts of information, the way they encoded the information as they studied—represented by how often they used argument tags—determined how well they were later able to use the information in forming arguments. The results are consistent with the theory that learners who study with an intent and expectation of arguing encode new information in argument schemas and later retrieve and apply those schemas when forming arguments.

Argument Maps

In their most common form, argument diagrams or argument maps consist of (a) text boxes containing sentences that present claims, reasons, or evidence; and (b) arrows connecting the boxes that denote the relationships among them (Andriessen and Baker 2013). Although they may be superficially similar to concept maps, argument maps differ greatly in form and function. A text box or node in a concept map typically contains a single noun phrase representing a concept, and usually a pair of nodes connected by a verb phrase is required to represent a single proposition. In contrast, a node in an argument map contains at least one proposition, and nodes are connected by a much more restricted set of relations perhaps consisting only of a supporting relation indicated by a plus sign and a contradicting relation indicated by a minus sign.

Figure 6.1 shows a simple argument map assembled from a few related propositions. It should be apparent that, unlike the syllogisms of deductive logic, the inferences and conclusions of argument maps are uncertain and demand subjective judgements about the truth of their propositions and the relevance of their connections. For example, the impact of Kurzweil's (2005)

Fig. 6.1 A simple argument map



prediction on your belief in human mortality depends on the degree of credibility you assign to Kurzweil as a futurologist, which in turn depends on how much you know about Kurzweil's credentials and previous predictions.

Since its earliest use in instructional systems such as Belvedere (Suthers et al. 1995), argument mapping has been seen as a way to support collaborative learning. In such systems argument maps are used to mediate debates or discussions that occur via specialized computer-based communication systems (Scheuer et al. 2010). Other argument mapping systems such as Reason!Able (van Gelder 2002) have been designed for individual learners to analyze arguments in texts or practice constructing arguments. Our research investigates individual use of argument maps with the goal of understanding how visually representing arguments affects learning and cognition.

Refutational Maps and Conceptual Change

One of the key findings in science education is that refutational text (instructional text which explicitly refutes a persistently held misconception) is more effective in promoting conceptual change than otherwise similar text which merely explains the intended scientific conception (Guzzetti 2000; Hynd and Alvermann 1986). Refutational text is inherently argumentative in the sense that it introduces claims and explicitly supports or opposes them by presenting reasons or evidence. Liu and Nesbit (2012) investigated the extent to which conceptual change can be promoted by studying a *refutational map*. We conceive a refutational map to be refutational text presented in the form of an argument map.

The study materials used in the research were adapted from texts on Newtonian laws of motion used in previous research on conceptual change (Alvermann and Hynd 1989). Participants were randomly assigned to an expository text group, a refutational text group, and a refutational map group. All three groups studied the concepts of Newtonian motion using a learner-paced presentation. The expository text group studied a text presentation that did not mention common misconceptions about the movement of objects. The refutational text group studied a text presentation that included all the text seen by the expository text group plus text that identified and refuted common misconceptions about the movement of objects. The refutational map group studied the same refutational text, but it was presented within the nodes of an argument map. Figure 6.2 shows a portion of the refutational map. The concepts of Newtonian

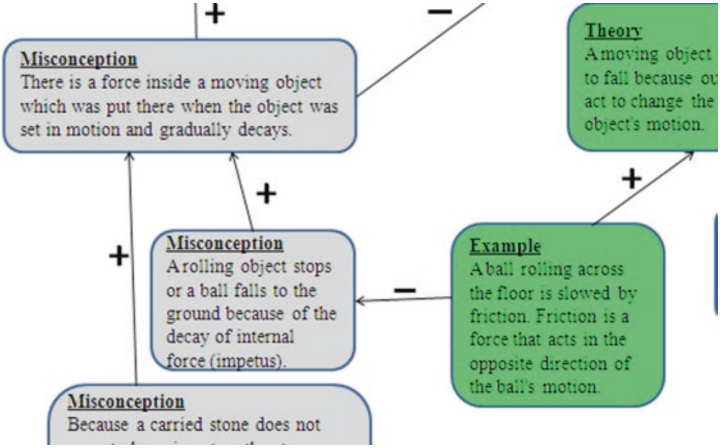


Fig. 6.2 A portion of the refutational map

motion appeared in green-colored nodes. Common misconceptions appeared in gray-colored nodes and were labeled as misconceptions. Supporting relations among Newtonian concepts were labeled with plus signs, as were supporting relations among misconceptions. Each Newtonian concept or example that contradicted a misconception was linked to the misconception by an arrow labeled with a minus sign.

After the study phase, all groups were given a free recall test and a knowledge transfer test that required application of Newtonian concepts of motion to qualitatively reason about physics problems. The refutational map group scored significantly higher on the free recall test than the other two groups. On the transfer test they scored significantly higher than the expository text group but not the refutational text group.

Prior to the study phase, the participants were given the Test of Logical Thinking (TOLT, Tobin and Capie 1981), a test of quantitative reasoning that previous research has found to correlate with conceptual change relating to force and motion (Park and Han 2002) and other topics in physics (Kang et al. 2004). Our research found that the TOLT predicted performance on the free recall test ($r = .47$) and transfer test ($r = .45$). Interaction analysis found that the TOLT moderated the treatment effect for the transfer test but not the free recall test. For the transfer test, participants who had scored below the sample median on the TOLT received more benefit from studying the refutational map than those who had scored higher on the TOLT. Further analysis of the transfer test scores found that among participants who scored lower on the TOLT, those who studied the refutational map significantly outperformed those who studied the refutational text (d = .73). Furthermore, the use of the refutational map by these participants raised their transfer performance to approximately the same level as the performance of participants who scored higher on the TOLT.

Why would the refutational map help learners with low prior ability to perform so well on the key measure of conceptual change? Both the refutational text and map interspersed and explicitly connected the claims of naïve theory with the specifically opposing claims and evidence of Newtonian theory. We speculate that the graphical features of the map—the boxes delineating separate ideas and the arrows specifying the relations among ideas—were more effective than the connectives and other verbal devices in the text in helping participants to construct or complete argument schema. We do not believe argument maps should be regarded as pictures of argument schema, but they may be information structures that can be more easily assimilated into argument schema than equivalent texts because they do not require the learner to make as many inferences in the assimilation process. The explicit labeling of misconceptions, support relations, and contradictions in argument maps decreases learners' reliance on context and the interpretation of somewhat ambiguous textual cues. Also, the features of the refutational map signal more clearly that the presented information is intended to be encoded in an argument schema rather some other schema.

The type of node-link format we used to construct the refutational map may not be ideal. As with node-link concept maps, a map containing a dozen or so links can appear dauntingly complex (Nesbit and Adesope 2013). Reading node-link maps, unlike the consistently linear structure of prose, requires frequent decisions about which links to follow and when to jump to a distantly connected node even though readers may have no heuristics on which to base their navigational decisions. One of the goals of the research we describe in the next section was to develop and investigate a type of argument map that is more readable and also represents more of the kind of the information used by expert arguers.

Resolving Thesis and Anti-thesis with the DM

We propose that the most effective cognitive tools are those whose repeated use shapes cognitive schemas which are optimal for solving a particular class of problems. As tools, they must be designed (or have evolved) so the learner can focus on the problem at hand and is not distracted by features of the tool not relevant to the problem. As scaffolds, they must be designed so that the more they are used the less they are needed. We have already described how the typical node-link format often produces a difficult-to-read representation of an argument, so how might an argument map be structured to serve as a more effective scaffold for advanced argumentation?

Designing the DM

Many argument maps focus on representing the evidential relations among components of an argument and offer no guidance on how to present both sides of the argument or how to resolve thesis and antithesis. Lack of scaffolding may work for sophisticated arguers, who tend to habitually synthesize and balance arguments and counterarguments, but for less skilled arguers the lack of scaffolding may lead to confirmation bias (i.e., attending only to information that supports their position) and arguments that fail to address opposing claims.

The Vee diagram (Novak and Gowin 1984; Nussbaum 2008) was designed to support argument-counterargument integration. In the Vee diagram, arguments are organized on the left side and counterarguments on the right. Related arguments and counterarguments (i.e., reasons that specifically contradict each other) can be placed in the same row. There is also space at the bottom of the diagram for writing a final integrated conclusion or rationale. A learner who focuses only on one side of an issue and fills out only one side of the Vee diagram is prompted by the remaining empty space to develop the opposing side of the issue. Although the Vee diagram prompts the learner to attend to counterarguments, it lacks scaffolding for other important aspects of skilled argumentation. It offers no representation of (a) warrants, (b) the hierarchical substructure of arguments whereby evidence can support reasons which in turn support claims, (c) the differing strengths of supporting reasons or evidence, and (d) the ordering of reasons for rhetorical purposes. What type of cognitive tool might scaffold argument-counterargument integration like a Vee diagram but also foster learning of other aspects of advanced argumentation?

To achieve this design goal, Niu and Nesbit developed a new type of argument map called the DM (Niu et al. 2015). The DM, which is implemented as an extension of a web browser, borrows several features from the Vee diagram. As shown in Fig. 6.3, a primary claim or question ("should corporal punishment be outlawed") can be entered at the top, by either an instructor or a student. The reasons supporting the primary

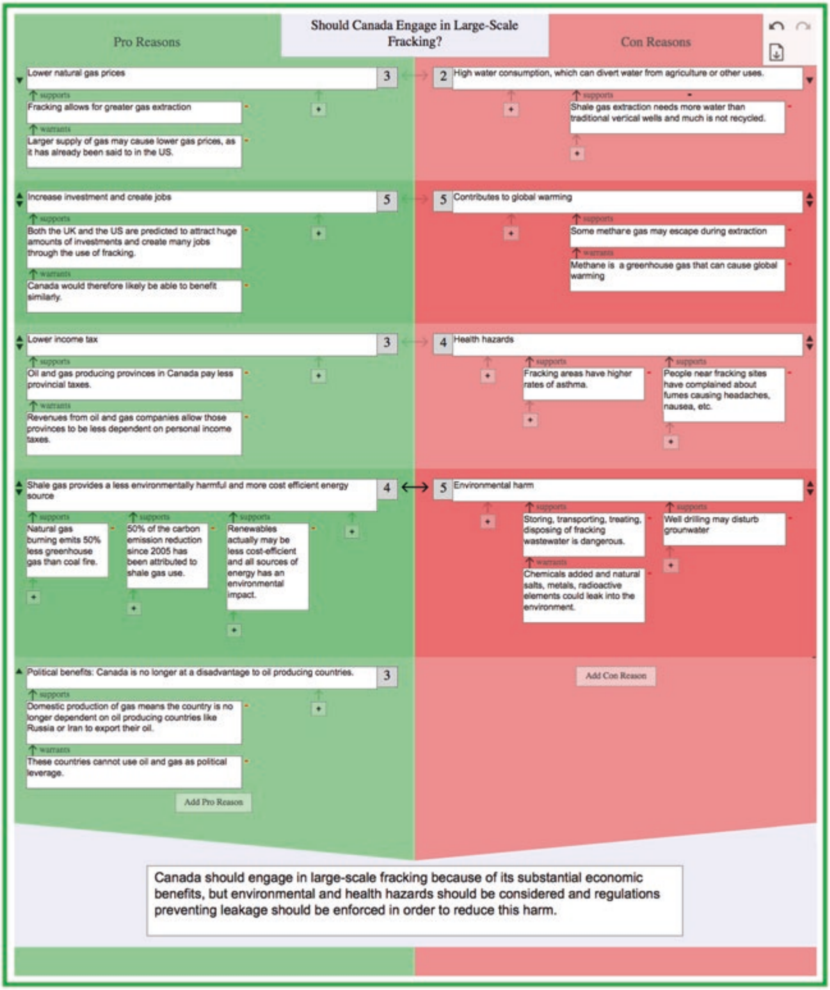


Fig. 6.3 An example of a dialectical map constructed by a research participant

claim are organized on the left side, and those contradicting it are entered on the right side. A conclusion that integrates the positions of the pro and con side can be entered at the bottom.

Interactive features of the DM were designed to exercise argumentative skills such as estimating the strength of support that a reason brings to a claim, generating counterarguments, distinguishing warrants from evidence, and integrating arguments and counterarguments. After a learner enters a reason they can select its strength of support on a scale from 1 to 5. The learner can put reasons in sequential order, perhaps to match how they will be presented in an argument essay to be written later. To aid integration and resolution of pro and con, pro reasons can be bound to related con reasons so that they travel together when one of them is pulled higher or lower on the page.

Assessing the Effects of the DM

An experiment reported by Niu et al. (2015) investigated how using the DM to study affected students' subsequent writing about the ideas in the studied text. University students who participated in the research were randomly assigned to a DM group, an argument group, and a no-training group. Both the DM group and the argument group were trained in the elements of argumentation (i.e., claims, reasons, counterarguments, rebuttals, and warrants). Only the DM group was trained how to use the DM. All three groups were instructed to study a text on shale gas extraction and hydraulic fracturing to prepare for a test. Only the DM group was instructed to use the DM to study. As expected, during the study phase the participants in the DM group were active extracting and paraphrasing information from the source text and entering it into the DM. The other two groups read and highlighted content.

There were four main outcomes of the research. First, immediately after studying, the participants were asked to judge how much they had learned while studying. DM group reported significantly higher judgments of learning than the other two groups. Second, the participants were asked to write a summary of the studied text. The DM group wrote summaries whose organization more closely resembled an introduction-body-conclusion format, perhaps reflecting the ordering of the primary claim, reasons, and conclusion in the DM structure. The DM group also made significantly greater use of argumentative lexical markers such as "because", "however", "furthermore" and "evidence" than the argument group. Third, the participants responded to several cued recall questions about the studied text. The DM group recalled significantly more main ideas than both the other groups. Finally, the participants were asked several questions that required reasoning about the studied material. There was no significant difference in the number of reasons provided by each group. However, when the number of reasons was normalized by number of words, it was found that the DM group's responses had significantly greater reason density than those of the other groups.

We interpret these results as showing that using the DM as a study tool affects how information is stored in and retrieved from long-term memory. It is likely that activity of selecting and paraphrasing information would have helped the DM group to encode the ideas in the source text more meaningfully, no matter what structure the paraphrased content had been entered into. However, the type of schema in which the studied information was stored was reflected in the ways students recalled, summarized, and reasoned about the information. More so than the other groups, the DM group responded to the post-test in ways one might expect if they were retrieving information from argument schemas.

The DM Goes to School

The DM was used in teaching two writing-intensive, undergraduate, biology courses at Simon Fraser University (Niu et al. 2015). In each of three separate assignments, each student drew from assigned readings to construct a DM. The three DMs were scored by the instructor for their use of relevant evidence to support arguments. Students were given detailed feedback on the quality of their arguments and evidence. The biology topics covered in the DMs were assessed later in the courses. In both courses, the instructor reported that students increased the quality of argumentation represented in the DMs across the three assignments. Student's comments about the instructional use of the DM tool were generally positive, and many claimed that it helped them to improve their argumentation skills.

Implications for Instructional Theory and Practice

In broad theoretical terms, the results we have presented can be interpreted as examples of transfer-appropriate processing. Transfer-appropriate processing is the idea that knowledge is better remembered and applied when the particular semantic codes formed during encoding are suitable for or transferable to the retrieval context or post-study task (Morris et al. 1977). It relates to the more fundamental phenomenon of encoding specificity whereby knowledge is better remembered and applied when the conditions at time of retrieval match those at the time of encoding (Tulving and Thomson 1973). Schema theory, then, can be seen as an explanation, but not the only explanation, for many research results in which transfer-appropriate processing is observed or plausibly inferred. Viewed from this perspective, an argument schema provides the conditions for encoding specificity and the semantic codes for transfer-appropriate processing. The three cognitive tools we have investigated—argument tagging, refutational map, DM—function as scaffolds for the activation of argument schemas and assimilation of new information.

In the first experiment (Mao et al. 2010), we theorize that learners who were instructed to tag materials in a way that would prepare them to write an argument essay activated a pre-existing argument schema. Their tagging activity entailed cognitive processing that filled in slots in their argument schema. The prepare-to-argue task instructions and the activation of an argument schema during study would have primed learners to re-activate the argument schema when asked to write a comparative essay in the post-study test. Because an argument schema emphasizes evidence and other reasons supporting a claim, the learners in the argue group tended to provide more reasons in writing their essays.

In the second experiment (Liu and Nesbit 2012), we theorize the features of the refutational map-led learners to activate an argument schema and made it easier for learners with low prior ability to fill in slots in the schema. To achieve conceptual change, it is crucial that learners not only accept the concepts of Newtonian motion but also cognitively process contradictions between those concepts and the commonly held naïve theory of motion. Because learners in the refutational map group with lower prior ability were more likely to have filled in slots in their argument schema representing those contradictions and to have cognitively processed those contradictions, they were more likely to show evidence of conceptual change on the post-test.

In the third experiment (Niu et al. 2015), we theorize that training in the use of the DM and using it during the study phase activated an argument schema and facilitated encoding of information in the schema. When the argument schema was re-activated during the post-test phase, it led learners to write more lexical markers for argumentation. It may have also led learners to recall more main ideas as they were more likely to be encoded as claims or reasons than other ideas.

The foregoing types of explanations assume that learners have already developed argument schemas that are available for activation and use in an instructional strategy (i.e., "argue to learn"), but there is more to the story. Although we might assume that almost all school-age learners have the cognitive ability to recognize and apply the claim-reason relationship, we have also seen that understanding of argumentation in many learners is limited. They may fail to acknowledge and rebut counterarguments (Nussbaum 2008). They may fail to recognize and weigh the relative strengths of supporting reasons. They may fail to consider that the validity of reasons is conditional upon warrants, and so on. We propose that learners who have developed more sophisticated argument schemas that incorporate these features have an advantage in leveraging argumentation as a learning strategy. Assimilating information into argument schemas that make such distinctions requires more elaborative processing of the information, and more elaborative processing makes new information more meaningful and memorable. Thus, the success of argumentation as an instructional strategy crucially depends on the progressive development of learners' argument schemas (i.e., "learn to argue").

We have described how cognitive tools can scaffold the activation and application of argument schemas as an aid to learning subject area knowledge. We propose that the same kind of cognitive tools can scaffold the development of more sophisticated argument schemas. In theory, schemas are not rigid fixtures but are instead potentially subject to adjustment, modification, and extension whenever they are activated. When a learner uses a "counterclaim" tag to classify text, the learner's argument schema may be extended to accommodate counterarguments. When a learner studying a refutational map sees a contradicting link from observed evidence to a claim labeled as a misconception, the learner's argument schema may be extended to accommodate rebuttals. When a learner adjusts the strength of a reason in a DM, the learner's argument schema may be extended to represent evidentiary strength. If arguing about subject knowledge has the dual effect of developing students' subject knowledge and developing their argumentation abilities, we propose that using appropriately designed cognitive tools in such learning activities can boost that effect.

A qualification is needed. Although argumentation ability develops naturally as children discuss and debate with others, and it seems that suitably adapted experiences with argumentation tools may accelerate that development, we do not mean to imply that subtle nudges from an interface and repeated practice of argumentation as a procedural skill are sufficient for optimal development. Recall Gal'perin's insistence that cognitive development requires acquisition of the conceptual reasoning that lies behind and explains procedural knowledge (Arievitch and Stetsenko 2000). In addition to scaffolded practice, learners must have opportunities to study and reflect on the concepts that generate and inform the cognitive skill. Learners can probably learn to introduce warrants in argumentative writing having never considered their properties or how they relate to other types of reasons. However, learners' use of warrants will be more adaptable to varying and novel conditions if they have studied how warrants differ from other types of reasons and why expert arguers will make them explicit on some occasions and not others. Cognitive tools can introduce learners to specialized terms and prompt their use, but we do not believe they can substitute for an exposition and discussion that deals with the underlying concepts of argumentation.

The Road Ahead

An instructional implication of the theory we have investigated is that the process of learning to argue should be embedded across the curriculum, and wherever possible the same cognitive tools should be used to foster argumentation in different subject areas. Tool-enhanced development of an argument schema that occurs in one subject domain (e.g., chemistry) can potentially transfer and enhance learning another subject domain (e.g., history). Suppose a student learns the idea of a warrant when using a cognitive tool to write a laboratory report about a chemistry experiment which concludes that a substance increased mass as a result of heating. The student might record the warrant as "measuring a substance before and after applying heat and finding an increase in weight is strong evidence that, by some means, the heat caused an increase in mass." Later, when writing an essay for a history class, the student might find an analogy to the chemistry warrant. Using the cognitive tool, the student might record a warrant as "credible population estimates of an ancient city showing the population was higher before than after a recorded war are strong evidence that, by some means, the war caused a decrease in population."

Kuhn and her colleagues have shown that students' argumentation skills develop gradually throughout their years of schooling (Crowell and Kuhn 2014; Kuhn et al. 2016). This suggests that a cognitive tool intended to scaffold the development of argumentation ability should model each learner's stage of development and adapt its features accordingly. Perhaps such tools could proactively suggest the use of a feature when the learner model indicates that the learner is ready to benefit from it. For example, a tool might at first only offer a tagging feature with the single tag "pro" which the student could use to tag statements supporting one side of an issue. When the model predicts the student is ready, the tool might notify the learner that a "con" tag is available and explain the conditions under which it should be used. The adaptation of the tool to the learner's increasing argumentation ability would proceed in this manner until the tool's interface offers multiple feature that equal or exceed those in the DM.

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CHAPTER 7

Learning Analytics: Using Data-Informed Decision-Making to Improve Teaching and Learning

Alyssa Friend Wise

Introduction

Learning Analytics is the development and application of data science methods to the distinct characteristics, needs, and concerns of educational contexts and the data streams they generate for the purpose of better understanding and supporting learning processes and outcomes (see also an earlier definition by Siemens et al. 2011). It is both a field of scholarly pursuit and a technology for making concrete improvements within educational systems by enabling data-informed decision-making by teachers, students, and other educational stakeholders. Learning Analytics has been identified as a critical emerging technology of the twenty-first century, with high expectations to make a positive impact on learning and teaching (Johnson et al. 2016), both through short-cycle improvements to educational practice and long-cycle improvements to our understanding of learning.

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O. O. Adesope, A. G. Rud (eds.), *Contemporary Technologies in Education*, https://doi.org/10.1007/978-3-319-89680-9_7

Although the collection and analysis of data to understand and support learning is not a new endeavor, there are three critical characteristics that distinguish learning analytics from prior educational research: the data the work is based on, the kinds of analyses employed, and the ways in which it is put to use. This chapter begins with an overview of the value proposition that learning analytics offers and is then organized around these three areas (data, analyses, and applications) to give readers a concise overview of what makes learning analytics a unique and especially promising technology to improve teaching and learning.

Why Develop Learning Analytics?

The basic value proposition for learning analytics is that generating more information about how learning processes unfold can help us better improve them. This is true not only over the long term (by better understanding how learning occurred in the current situation we can design in a more informed way for the future), but also in the short term (by better understanding how learning is occurring up to the current moment, we can act in a more informed way right now). It is the latter use, to improve teaching and learning in "real-time" that is most novel and exciting to educators. From an instructor's perspective, learning analytics can both provide a way to check if the planned activities are occurring as intended (e.g. the goal is for pairs of students to argue opposing positions about the culpability of Lady Macbeth—is this actually happening?) and to identify particular groups that may need additional support (e.g. in some groups the conversation is balanced but in others one student dominates over their partner or the partners simply agree). Similar information can also be provided directly to students (either individually or in collaborative groups) to prompt reflection and regulation of their own learning processes. Another attractive use of learning analytics is to tailor educational experiences to better meet the specific needs of one or more students. Higher education has been accused of a "one size fits all" approach, in part because identifying meaningful difference between students' needs and acting on them each appropriately is incredibly time consuming when done manually by instructors. However, if the right dimensions of difference are known and can be detected in naturally generated data, then the vision of education tailored to each students' needs becomes tractable.

What Kinds of Data Are Learning Analytics Based on and What Makes Them Distinct?

Learning analytics is not defined primarily by the source of data but by its size. Size here refers to two distinct characteristics. The first is the *overall quantity of data* involved. Simply put, the computational analyses used in learning analytics generally require a greater amount of data than that used in traditional educational research. The larger amount can, in part, come from a greater number of people; however, in large degree it is a result of collecting a much greater number of measurements on each person. So, for example, learning data from MOOCs (massive open online courses) is large not just because there are thousands of learners, but because we can collect a data point for every single action a person takes in the system (producing tens of thousands of data points per learner). The second element of size is the *granularity of the individual data points* themselves. Here, the measurements taken are generally more micro than traditional data, with learning analytics often looking at fine-grained elements of the learning process. Importantly, the smaller grain size is not created artificially to inflate the data available (e.g. taking the temperature of a room every 30 s instead of every 30 min creates more data but not necessarily more information). It is a reflection of new tools that allow for the capture of learning activity at the grain size which it actually occurs; that is, action by action. Together, smaller and more numerous data points are a hallmark of learning analytics research.

Source, Quantity, and Granularity of Learning Analytics Data

Where does the size of learning analytics data come from? The increase in availability of large quantity/small unit-size data can be attributed, at least initially, to the rise of digital technologies used for learning. From generic learning management systems (LMSs) to focused intelligent tutoring systems (ITSs), from virtual discussion boards (and other social media tools) to face-to-face classroom response systems (clickers) the dramatic rise of technologies used to support teaching and learning has facilitated the efficient collection of diverse (though not comprehensive) forms of data from large numbers of students at many points in time. This aligns with the essential attributes of big data, described as volume, velocity, and variety (Laney 2001).

For example, while previously an instructor might record the overall grades of class members on a quiz, online tools can easily track item-level responses for everyone in the class on every assessment across the term. Similarly, once built, technologies lend themselves to use at scale, allowing the collection of data from much larger numbers of students than was possible previously (this is true for both formal learning environments such as MOOCs as well as informal learning support tools such as Piazza or even Twitter). Furthermore, while prior data were limited to what could be captured in the classroom (or self-reported by students), internet-based tools allow (potential) insight into student learning regardless of where it takes place. In short, as more and more of our (academic) lives take place with the support of digital tools, the virtual "footprints" we leave behind also become more abundant and detailed.

Kinds of Learning Analytics Data

Learning analytics data relates to the *process* of learning (as opposed to just its outcomes). Current forms of data commonly used in learning analytics work include activity data (traces of what students did) and artifact data (things that students created). Often, a single action by a student can produce both kinds of data: for example, if a student attempts a quiz question in an online tool there is an activity trace (student *X* answered question *Y* at time *T*) and an artifact created (the actual answer they gave, which might later be evaluated in some way). A third form, association data, is often constructed based on the prior two to index relationships between students and students, students and artifacts, or students and instructors (see Hoppe's description of a trinity of learning analytics approaches aligned with these data types in Suthers et al. 2015). In addition to these core data sources about the learning process, learning analytics may also incorporate other kinds of data, such as learning outcomes (either prior or current performance) and demographic information (Sclater 2017); since these data are pre-existing rather than generated during the course of learning, they can be considered in the category of archival data. Traditional self-reports are less commonly used in learning analytics research due to problems of inaccurate and selective recall related to learning behaviors and the degree of intrusion required to collect the data (Baker and Siemens 2014; Winne 2010). However, if there is a need to document aspects of students' perceptions, experience sampling methods (ESM, Csikszentmihalyi and Larson 2014) via mobile apps can be used. Finally, learning environment data (such as a course's curriculum or pedagogical approach) can be important as an element of metadata (or secondary level data in a hierarchical analysis approach if multiple courses are studied) to contextualize the primary data and determine appropriate approaches to analysis.

Activity data most commonly take the form of log-file data, a record of actions a student took in an online system at specific points in times. Log-file data can be coarse or detailed depending on both the front-end user interface and back-end data structure. For example, an LMS record may indicate that a student "opened message #241783 in discussion #486" or simply that they "accessed the discussion forums." Similarly, some systems capture the exhaustive use of play/pause/rewind/ fast-forward controls used during video-playback, while others only indicate that a video was viewed. In addition to LMSs, activity data can also come from the use of digital library resources, e-books (if the publisher provides access), and other dedicated learning tools housed outside the LMS (e.g. adaptive testing, intelligent tutors, and simulations). While more instrumentation is required, activity data can also be collected from physical learning environments via multi-modal learning analytics tools. Multi-modal data can include the tracking of student gaze, gesture, posture, movement as well as physiological measures such as the heart rate, galvanic skin response, and electroencephalogram (EEG) readings (Ochoa and Worsley 2016).

Artifact data can be any object created by a student and stored by the system. Here, the level of granularity corresponds to the unit size submitted by the student. While audio, image, and video artifacts are certainly possible (e.g. Baltrušaitis et al. 2016; D'Angelo et al. 2015), by far the most common type of artifact is text-based, and includes objects such as answers to questions, discussion forum posts, student essays, and lines of code. Artifact data must undergo some assessment or decomposition during the analysis process to index a number of its qualities. In simple cases, an artifact such as a question answer (e.g. the number 7 entered by a student in response to the question "3×2=?") might be evaluated as correct or incorrect. In more complex cases, a series of metrics might be used to represent the artifact. For example, a student essay could be indexed by its word length, structural coherence (McNamara et al. 2010), and the extent to which vocabulary from the course readings was employed (Velazquez et al. 2016). Although traditional teacher assessment and educational research often involve the evaluation of student work manually by human raters using a rubric (e.g. in terms of the quality of writing, strength of evidence presented, or justification of positions taken), learning analytics requires such evaluation to occur at scale. Thus, one major stream of learning analytics research is devoted to the development of computer models that can "learn" to perform this task based on a training set of human-coded data (Mu et al. 2012). Artifacts can also be used to infer qualities of the student producing them; for example in the intelligent tutoring system (ITS) literature where students' answers to problem-solving steps are used to build a model of the students' underlying knowledge state (Corbett and Anderson 1994).

Association data are generally constructed post hoc from activity and/or artifact data. Associations can be made on the basis of similarity (e.g. two students took the same course) or interaction (e.g. one student sent another student (or the instructor) a message). Associations can also exist between people and artifacts (e.g. a student accessed a certain video resource) or between two artifacts (e.g. similar vocabulary used across two essays). When using association data, it is important to be clear about what kind(s) of elements are being associated and what the nature of the association (similarity, interaction etc.) indicates. The existence of association data points to an important question in learning analytics about the unit of the analysis. Most learning analytics to date have focused on the individual student (and their activity, their artifacts, their associations) as the object of interest. However, there is increasing interest in collaborative learning analytics in which the object of interest is a small group or community (e.g. Chen and Zhang 2016).

Data, Features, and Proxy Indicators

More data do not necessarily mean more information and an important challenge that learning analytics work must address is crafting meaningful indicators from what is available. Because learning analytics researchers do not always have control over the design (both front-end interface and back-end data structure) of the tools from which they collect data, they must be creative in devising proxies, measurements that serve as reasonable representations of the construct or phenomenon they wish to study. From an educational perspective, the justified linking of an observation to a conceptual entity is a critical piece of the logic chain for establishing the validity of learning analytics work. For example, should more time spent in an LMS be taken as an indicator of engagement or effort? The answer may depend on if the time relates to solving a problem (more time indicates the student exerted more effort) or reading discussion posts (more time indicates more engagement). Of course this also presumes a clear definition of what is meant by effort and engagement. When these are considered to be different things, aggregating the overall time will be problematic as it confounds the two.

From a data science perspective, the problem of selecting indicators focuses on how to transform the raw data into a set of features that best models the underlying phenomena. This process is referred to as feature engineering and includes feature construction (e.g. via various forms of data aggregation or decomposition), feature extraction (e.g. via dimensionality reduction techniques such as principal component analysis), and feature selection (choosing a subset of possible features to include based on some ranking of their anticipated importance in the model). See Sinha et al. (2014) for a particularly nice example of engineering interpretable learning features from low-level data using fuzzy pattern matching.

It is a debated question in the field as to what extent it is important for engineered features to be interpretable versus simply contribute strongly to a prediction (see Bergner 2017, pp. 41–42 for elaboration of the differences between explanatory and predictive models). While there are some cases where reliable prediction alone is useful, in the realm of education we generally want to understand why certain relationships exist and be able to take action to affect them. For example, it is difficult to help a student who is identified as being at risk for failing a course if there is no way to make sense of the factors that led them to be placed into this category. There are also concerns with the use of features that might (unintentionally) reinforce traditional educational inequalities (Slade and Prinsloo 2013). For these reasons, theory can be a powerful tool to constrain and shape the possible degrees of freedom for constructing, extracting, and selecting features (Wise and Shaffer 2015).

The Manufacture of Data

Finally, it is important to remember that learning data are neither natural nor neutral. Learning data are not "natural" because they are produced as students interact with designed environments. The data thus represent aspects of what students do in response to that *specific environment*. In order to properly generalize to other contexts, we need to index the important qualities of the environment which range from the technical (e.g. the tools available, how they are designed, interface and navigational features) to the pedagogical (e.g. is the course oriented toward acquisition of facts, problem-solving skills, or construction of conceptual schema). Learning data are also not "neutral" in that what is captured is often as much a product of what is feasible as what is valuable. The data that are easiest to acquire may not be the most useful or important; for example, indexing students' activity based solely on their use of an LMS when in-class lectures and tutorials are a greater part of the course's pedagogy may produce a skewed picture. Furthermore, once LMS data are reified as a measure of "student activity," they become a target to be optimized. Thus students who are active in class and tutorials, but less so online, may feel misplaced pressure to increase their use of the LMS. In general, it is easier to try to improve one's standing on metrics that do exist, than to remember the value of those things which we cannot (yet) quantify; thus, we run the danger of becoming what we measure (Duval and Verbert 2012). As the field of learning analytics matures, we expect to see learning tools for which the design of the data produced is an integral concern from the start rather than an afterthought. This will generate more useful data both through better back-end structures and through the creation of front-end interfaces that more readily support inference-making from data.

What Kinds of Analyses Does Learning Analytics Employ and What Can They Tell Us?

Learning analytics methods include human and computational processes and tools used to manipulate data in order to produce meaningful insight into learning. Much learning analytics works draws on educational data-mining approaches (see Romero et al. 2010), though given that learning analytics also seeks to attend to underlying conceptual relationships and the situational context, the metaphors of data geology and data archeology have been proposed as more appropriate than that of mining (Wise and Shaffer 2015). Avoiding the politics of language, learning analytics can be said to employ educational data science methods to detect underlying relationships and patterns among variables and cases. There are several classes of methods commonly used to achieve this. Each is discussed below with an emphasis on application, that is, the kinds of things that can be learned from each approach and the ways it can be used to support learning. In line with this focus on application, the references provided offer examples of the ways each approach has been employed to provide insight into educational data, rather than serving as authoritative sources on the technical details of the method.

Prediction (Supervised) Approaches

One of the most common and useful approaches in learning analytics is prediction (Baker and Yacef 2009; Papamitsiou and Economides 2014). Prediction is a form of supervised machine learning; the "supervision" refers to the fact that values for the thing being predicted (the target) are known a priori for a training/test data set and thus the accuracy of the model can be evaluated with respect to these known values. Prediction models use a combination of attributes for a case (the predictor variables) to predict the value of another attribute (the target).

Prediction models can produce several different kinds of results useful to learning analytics. First, they can be used to forecast an attribute for a case (e.g. an assessment score or at-risk status for a student) when it is not known, either because it was not collected or has not yet occurred. A common application of this is early-alert systems developed by universities to identify students at risk for poor performance or dropping out (Arnold 2010). For example, Jayaprakash et al. (2014) developed a classifier that predicted whether students were likely to earn a grade of C or higher in a course ("successful completion") or not ("unsuccessful"). Their model was built based on a combination of attributes including demographics and academic records (archival data), prior scores (evaluated artifact data) and LMS usage (activity data). With a predictive goal in mind, Jayaprakash et al. (2014) were interested in developing an accurate model so that they could apply it to students at the start of the course to forecast who was likely to be unsuccessful. When the predicted value is correctness on future learning assessments the result is often used to drive adaptation in systems such as intelligent tutors (see Corbett and Anderson 1994 for an expanded explanation of knowledge tracing). A special case of forecasting that is particularly useful in learning analytics is the combination of prediction models with natural language processing techniques (see description below) to perform automated or semi-automated content analysis of artifact data (Cui et al. 2017; Rosé et al. 2008). This can be used to provide feedback to students or instructors on the work performed.

A second kind of use of prediction models is explanatory. In this case the focus is not on forecasting values for new students but to better understand relationships between variables (though unless factors were manipulated experimentally, claims of causality should be avoided). For example, Svihla et al. (2015) used six different log-file metrics indexing the different ways students (the cases) revisited content in an online inquiry-learning tool (activity data predictors) to predict their score on a delayed cumulative project assessment (evaluated artifact data target). Their results showed that distributed visitation of a dynamic visualization was predictive of students' understanding of the content several weeks after the unit had been completed. Svihla et al.'s (2015) explanatory use of their model allowed them to make claims about the relationship between distributed revisiting and maintenance of understanding over time.

When prediction targets continuous variables (e.g. the delayed assessment score in Svihla et al. 2015), models such as linear regression, support vector machines, and regression trees are commonly used. For categorical (including binary) outcome variables, classification models (aka classifiers) are built. Common classification methods include decision trees, logistic regression, naïve Bayes and support vector machines. The quality of prediction models can be evaluated in various ways such as calculating accuracy, precision-recall values, AUC, or other metrics (see Zheng 2015); these metrics should be reported for cross-validation and external test-sets, not the same training set on which the model was developed. Generalizability can be assessed using similar metrics on external test-sets from different learning contexts (e.g. different populations, different years, different subject matter, different pedagogy). There is an inherent tradeoff in building models: sensitivity to specific features of a learning context comes at the cost of broad applicability to multiple situations while models built to be used across a wide range of contexts will be less sensitive to the data available in any particular one (Gašević et al. 2016).

Structure Discovery (Unsupervised) Approaches

Structure discovery is another common analytic approach that offers different ways to find patterns of similarity or relationship among cases (e.g. students, messages, essays, and curriculum) or variables (attributes of the cases). Unlike prediction, there is no predefined target to model or evaluate success against (for this reason, structure discovery methods are a form of unsupervised machine learning). Structure discovery methods such as correlation mining, association rule mining and factor analysis are useful to identify regularities in *variables* (e.g. students who re-watch online videos more tend to ask more questions in the discussion forum). Structure discovery methods such as clustering, social network analysis, and topic modeling are generally used to identify commonalities and differences between *cases* (e.g. this set of resources are used by students early, but not late, in a course; this set of students tend to access many resources but do poorly on quizzes).

Correlation and association rule mining are similar to prediction in that the underlying algorithms identify recurring relationships between variables; however, relationships may be found between *any* combinations of variables. Correlation mining focuses on linear relationships between continuous variables (e.g. the more time a student spends on online practice questions the higher their grade on the actual test) while association rule mining is typically used to generate if-then rules about the co-occurrence of categorical variables (e.g. if a student takes both biology and chemistry they are likely to also take biochemistry). Given the large number of possible variables and relationships that may be identified due to chance, it is important to carefully control for false discovery (see Hero and Rajaratnam 2016) and to critically evaluate results with respect to both empirical standards (e.g. see discussion of measures of support, confidence, and interestingness by Merceron and Yacef 2008) and theoretical soundness (Wise and Shaffer 2015).

Factor analysis is a technique that finds groups of continuous variables whose values (for a given population) consistently align with each other and thus can be combined as a representation of some latent factor. This can both provide insight into the underlying structure of constructs that the variables index and also be used for dimensionality reduction. Dimensionality reduction (which can also be achieved using principal component analysis) is important to avoid over-fit and uninterpretable models. For example, Ahn (2013) used factor analysis to reduce 12 variables of Facebook usage data collected from university students (e.g. wall posts made, links shared) into four latent factors representing different classes of Facebook activity: messaging, information sharing, friending, and affiliating. The factors were then input into a regression model to predict the students' new media literacy skills.

Clustering, social network analysis, and topic modeling differ from the above methods in that the focus is generally on regularities in *cases* rather than *variables.* Clustering is commonly used to identify cases (often students, but at other times resources, courses, etc.) who consistently have similar values to each other across multiple variables, and thus can be thought of as being of the same "type." For example, Wise et al. (2013) performed a cluster analysis on log-file data indexing how students "listened" and "spoke" in online discussions to identify three underlying groups: *Superficial Listeners, Intermittent Talkers*; *Concentrated Listeners, Integrated Talkers*; and *Broad Listeners, Reflective Talkers*. Importantly, as labeling clusters is a task of human interpretation, it can be useful to look closely at the data: Wise et al. performed targeted case studies on a representative member of each cluster that contributed important insight into cluster labels beyond that available from the aggregate variable values.

Topic modeling is a form of text-mining (other text-mining techniques are discussed below) that is used to represent the underlying structure across a corpus of documents (which could be student essays, social media messages, etc.) by identifying collections of topics (sets of co-occurring words) and the extent to which they are present in each document. A common application of topic modeling is to make sense of the large volume of messages that are contributed to online course discussions, MOOC forums, and social media. For example, Joksimović et al. (2015) examined what MOOC participants talked about in various social media venues and Vytasek et al. (2017) explored how topic models could provide classroom instructors with a useful big picture view of large and diverse online discussions.

Finally, social network analysis (SNA) is a technique that looks for regularities not in the attributes of the cases themselves but in the relationships between them. This can provide insights about individuals (e.g. measures of their centrality), the entire network (e.g. its density), or some subset of it (e.g. the presence of cliques). A key decision in SNA is how to define the nodes and the linkages between them. A common approach is to take nodes as students and to create linkages based on their interaction (e.g. Wise et al. 2017); however linkages based on similarities (e.g. Hecking et al. 2016) and bi-partite networks which include both individuals and objects they interact with (e.g. resources accessed) are also possible (Poquet and Dawson 2016). SNA has been useful for understanding general characteristics of social interactions and relationships (e.g. Dowell et al. 2015), exploring their relationship with learning outcomes (Dawson 2010; Rabbany et al. 2011), and identifying small groups within larger networks worthy of more detailed attention (Wise et al. 2017). While standard SNA approaches produce descriptions of connections in aggregate, more sophisticated techniques, such as ERGM (exponential random graph models) and dSNA (dynamic social network analysis), allow for inference testing and the study of network evolution over time respectively (e.g. Joksimović et al. 2016; Zhu et al. 2016).

Temporal Approaches

Similar to structure discovery, temporal approaches to data analysis look to discover previously undefined patterns in the data, but in this case, the patterns relate to the sequence and flow of events over time (Knight et al. 2015). Temporal approaches are a particularly important set of methods for learning analytics as they leverage traces of activity to address the field's fundamental concern with studying and understanding learning as a process (Suthers et al. 2015); however, they have been underutilized in the field thus far (Chen et al. 2016). Temporal approaches in learning analytics can be roughly divided as those which deal with time explicitly through examination of flow and fluctuation in features of the learning process over time (e.g. survival analysis, Yang et al. 2013) and those which deal with time implicitly through examination of sequences of events in the learning process (e.g. sequential pattern mining, Poon et al. 2017; lag-sequence analysis, Chen and Resendes 2014; (hidden) Markov modeling, Jeong et al. 2010). Temporal analyses can also be used to divide a learning process into different phases of activity (e.g. via sequential discourse analysis, Wise and Chiu 2011).

Natural Language Processing Approaches

Natural language processing (NLP) approaches in learning analytics use computational techniques to assess various linguistic features of texts (McNamara et al. 2017). It is an exciting area in active development that allows for direct inspection of a wide variety of textual data sources that includes: standalone student artifacts such as student essays or short answers; traces of dialogue among students and instructors; and collections of instructional resources. Roughly these differences align with the distinct concerns and applications of writing analytics (Shum et al. 2016), discourse analytics (Knight and Littleton 2015; Rosé 2017), and content analytics (Kovanović et al. 2017). NLP approaches are frequently used in combination with other analysis approaches already discussed including prediction (e.g. Mu et al. 2012), structure discovery methods (e.g. Dowell et al. 2015), and temporal analysis (e.g. Suthers and Desiato 2012). NLP approaches useful for learning analytics extract linguistic features about words and their assemblages. Analyses performed on words may assess basic presence (e.g. frequency of particular n-grams, parts of speech, or LIWC (linguistic inquiry word count) categories) or delve more deeply into their underlying meaning (e.g. via LSA (latent semantic analysis, different from the temporal technique of lag-sequence analysis, see Landauer et al. 2011 for a wide-ranging overview of theory, methods, and applications of the technique). Other techniques examine the use of particular parts of speech (such as verbs), syntactic structure, and the cohesion across a text (McNamara et al. 2017). When considering relations between texts, measures of semantic similarity (often calculated using LSA) are particularly useful.

Visual Approaches

Much of the work in learning analytics using visualization is not actual visual analysis per se, but the visualization of the outputs of other analyses for communication with various stakeholders. Learning analytics dashboards, for example, often employ graphical representations of analytic results designed to evoke particular responsive actions (Klerkx et al. 2017). In contrast, true visual analytics exploit visualization techniques and human perceptual abilities as part of the analytic process itself (Shneiderman 2014). This is done by visually representing data in ways that support human recognition of patterns and aberrations, often via an interactive interface that allows for manipulation and permutation of the visualizations (Ritsos and Roberts 2014). While some limited examples of static visual learning analytics exist, for example, human inspection of heat maps (Pecaric et al. 2017; Serrano-Laguna et al. 2014) and moment-by-moment learning curves (Baker et al. 2013), there is great room for further development of interactive visual analytics.

What Kinds of Pedagogical Uses Can Learning Analytics Serve and How Do They Support Learning?

Tailoring Educational Experiences

An initial class of pedagogical use of learning analytics is for tailoring educational experiences to better meet the specific needs of one or more students. In this model of use, the analytics are used to create some sort of a (static or dynamic) profile of learners with the educational experience provided for them differing in response to this. This has been referred to at times under the label of “personalized learning,” but such terminology is overly narrow because it assumes that the target for the tailoring is an individual, when it could also be a group of learners, and it implies that the activity is done for learners, when in many cases the learner must actively take up a recommendation that is provided. Tailoring of educational experiences for individuals or groups can occur through both adaptive (computer driven) and adaptable (human driven) changes to a system that makes it more appropriate for the learning of those involved. Common analytic techniques that drive tailoring include prediction models, clustering to identify groups of students with similar profiles, and association rule mining.

A high-profile class of tailoring applications are adaptive systems in which the resources, questions, or other learning materials provided to students are determined based on an underlying analytics model. One of the earliest set of adaptive learning tools were intelligent tutoring systems which construct a model of both the domain and learner in order to provide immediate customized feedback to students (Nwana 1990). Recently, a large number of companies, including textbook publishers, have also moved into the adaptive learning space. Adaptive learning tools may be designed around specific pre-determined content or exist as platforms for instructors or institutions to input their own content. They do not need to only involve static content and problems to be solved but can incorporate (or be embedded in) games and simulations as well. It is important to distinguish between tools which make adaptations directly based on learner activity versus those which use more sophisticated approximations of learner's cognitive skills.

Different from adaptive tools in which the tailoring is fully enacted by a system and may not be apparent to the learner, recommendation engines are systems that provide tailored suggestions (of courses or learning resources) to students. Two well-known course recommendation systems are Stanford's CourseRank system (Parameswaran et al. 2011) and Degree Compass (Denley 2013), originally developed at Austin Peay State University, and recently acquired by Desire to Learn. Systems for recommending useful learning resources (or useful sequences of resources) are generally developed in the context of particular learning tools (see Drachsler et al. 2015 for a review of 82 different recommender systems). Finally, early-alert systems use predictive models to identify students at risk of failing a course or dropping out of university. Studies have shown that simply making students aware that they are at risk can have an impact on their academic standing (Arnold 2010); though providing students with actionable strategies is much preferred. In a recent review of early alert systems, Sclater (2017) points out that more evidence about when and why such systems are effective is needed.

Informing Student Self-Direction

Different from tailoring the materials that are given to students, another pedagogical use of analytics is to support students in conscious attention to and improvement of their own learning processes. This model of use draws heavily on psychological theories of experiential learning Kolb (1984), self-reflection Schön (1983), and self-regulated learning (Winne 2017) in which learning analytics provide feedback that students can use to adjust or experiment with changes in their learning behaviors. A wide variety of tools exist to provide students with feedback on their academic status and study habits (e.g. E2Coach at the University of Michigan, Huberth et al. 2015; Check My Activity at the University of Maryland, Baltimore County, Fritz 2011), essays (e.g. OpenEssayist, Whitelock et al. 2015), and discussion forum participation (e.g. E-Listening Analytics Suite, see Wise et al. 2014). Such feedback can be provided in a variety of forms which may be embedded directly into the learning environment or extracted from it (Wise et al. 2014), for example via email messages or real-time dashboards that can be accessed at any time. The challenges for students in interpreting and using such information are great, however, and the most powerful systems provide not only the analytic feedback but also some sort of structure or support for making sense of and acting on the information provided (Wise and Vytasek 2017).

Supporting Instructor Planning and Orchestration

For instructors, pedagogical uses of learning analytics can be used to support refinement of both the overarching learning design and the decisions they make to orchestrate classroom activity within it. From the perspective of learning analytics and learning design, analytics offer a way to empirically verify (or refute) assumptions about the classroom (be it physical or virtual). The process for doing so requires instructors to document their pedagogical intentions (the design), describe activity patterns that indicate fulfillment of these intentions (targets), and then use the analytics to evaluate the degree to which the patterns occurred (Lockyer et al. 2013). Systems that provide feedback to instructors about their learning design are typically presented via teacher dashboards (see review in Verbert et al. 2013). Examples of this cycle in action are given in Brooks et al. (2014) who look at instructors' modification of their discussion forum practices based on SNA diagrams and Roll et al. (2016) who examined how course designers of a MOOC planned for revisions based on the analytic feedback provided to them.

In addition to supporting critical attention to the activity outcomes of course design, learning analytics can also assist instructors in orchestrating their class. Analytics can provide information that helps instructors identify struggling students (and ideally know how or why they are struggling), recognize groups that are collaborating more or less productively (van Leeuwen 2015) and pinpoint prevalent points of difficulty for a class (Ali et al. 2012). Ideally, the analytics are used not only to identify "problem" situations, but as part of a regular feedback mechanism of tuning and adjustment (Wise et al. 2016). In addition, another way in which analytics can help inform orchestration is by identifying types of students (or student behaviors) that occur repeatedly. Such information can be used by instructors to more easily identify and address common patterns or can be fed back to create accommodations or greater support structures in the learning design.

What Are Key Issues for the Future of Learning Analytics?

The optimistic vision of learning analytics in higher education described above is far from inevitable. Others have countered such images of a rosy future with the potential for (intentional or unintentional) misuse of analytics leading to a dystopian future of oversight and control (Rummel et al. 2016). There is also the concern that, like so many promising educational technologies, learning analytics will not live up to the hype and fail to make a substantial impact (Cuban 2001; Ertmer 1999). In a comprehensive review of the empirical research on learning analytics use to date, Ferguson et al. (2016) emphasize that expectations are yet to be realized and evidence of successful and impactful implementation is still scarce. Key systemic and societal issues that will determine the fate of learning analytics include deliberate consideration of the policy needs required to govern the ethical dimensions of analytics use and proactive planning for the required infrastructure.

In terms of infrastructure, universities need to consider now what kinds of data streams and stores they will want to be able to access in the next 5–10 years. Data infrastructure planning includes attention not only to what data will be collected, but how (and where) the data will be stored, what metadata will be used to index the data, and how (and by whom) the data will be queriable. Critically, system interoperability and the integration of multiple data streams (e.g. from learning management systems, student information systems, external tools, and human input) are core technical challenges to be addressed. Going further, universities will need to think about the analytic literacy of those who will want to ask questions of the data and what tools, people, and processes are needed to support these activities for both research and day-to-day teaching and learning purposes.

In terms of policy, institutions need to put in place clear guidelines for practices around data and analytics use (Prinsloo and Slade 2013). Specifically, policies are needed to: allocate responsibility for data assets and analytic processes; establish procedures for giving consent/opting-out of data use, providing students with access to their own data, and protecting student privacy; set-up systems to check that inferences made based on data and algorithms are valid and transparent; and maximize positive analytics implementations while minimizing any potential adverse impacts (Sclater 2014). Importantly, as students are critical stakeholders (and the primary intended beneficiaries) of learning analytics, they should be consulted as such policies are developed (Slade and Prinsloo 2014). Other overarching important ethical issues to keep in mind include broad attention to algorithmic accountability (ACM US Public Policy Council 2017), maintaining institutional value on those things that are not well-indexed by analytics, and remaining vigilant for unintended systemic consequences.

Conclusion

Learning Analytics is the development and application of data science methods to the distinct characteristics, needs, and concerns of educational contexts and the data streams they generate. The goal is to better understand and support learning processes and outcomes through both short-cycle improvements to educational practice and long-cycle improvements to the underlying knowledge base. This chapter has overviewed the distinct character of the data used in learning analytics, the kinds of analyses applied, and the pedagogical uses to which the analytics can be put; together these characteristics highlight why learning analytics is seen as an especially promising technology to improve teaching and learning. To make this vision a reality, universities will need to be proactive in building up the requisite technical and policy infrastructure.

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CHAPTER 8

Enhancing Self-Regulated Learning for Information Problem Solving with Ambient Big Data Gathered by nStudy

Philip H. Winne

Today's post-secondary students are more and more frequently engaged in learning projects. Learning projects are major assignments in which students research, appraise, organize and transform information. This work typically is oriented to producing a complex and multisection document, such as a report describing a science lab experiment, a course term paper, a plan for operating a business, a course of therapy or even an honors thesis. Some learning projects are coconstructed by a team of learners. This adds complexity to the work each individual does arising from needs to coordinate people, resources, subtasks, scheduling, and sometimes shared access to resources.

Learning projects almost always call for a complex activity called information problem solving (IPS). Synthesizing Brand-Gruwel, Wopereis and Walraven's IPS-1 model (2009) and the model of self-regulated learning (SRL) I codeveloped with A. F. Hadwin (Winne and Hadwin 1998; see

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O. O. Adesope, A. G. Rud (eds.), *Contemporary Technologies in Education*, https://doi.org/10.1007/978-3-319-89680-9_8

also Hadwin and Winne 2012; Winne 2013), round-trip IPS can be described in terms of six major components (cf. Eisenberg 2008; Winne et al. 2017a):

1. developing a clear understanding about resources available to support or that may impede work on the learning project;
2. designing a framework for the product of the learning project, and setting standards for judging how well information fits that framework;
3. searching for, then filtering sources of information (websites, documents) after scanning them for potential fit to the project's framework;
4. analyzing the set of filtered sources to extract information from them, and organizing these selections according to the framework previously set out;
5. planning and drafting a report, and
6. evaluating and revising the draft report to produce a final polished version satisfying requirements set for the learning project.

Learners who are productive in self-regulating learning to become better learners understand a seventh component should be added to the preceding six. That seventh component is reexamining the full scope of work to diagnose shortcomings, hypothesizing ways in which work might be improved, and planning how to launch this possibly better approach when they begin the next learning project.

Improving students' overall IPS along with component skills students engage when they work on learning projects are widely claimed to be keys to success as a student. These skills are often also described as significant contributors to personal well-being and the capacity to contribute productively to the national economy. The Social Science and Humanities Research Council of Canada implicitly takes this stance in identifying its Challenge Area #1, "new ways of learning, particularly in higher education [that] Canadians need to thrive in an evolving society and labour market" (SSHRC 2017). A survey undertaken for the Association of American Colleges and Universities was more direct in reporting "… employers indicate that they prioritize critical thinking, communication, and complex problem-solving skills over a job candidate's major field of study when making hiring decisions" (Hart Research Associates 2013, p. 4).

Post-secondary institutions recognize that they play a key role in helping students develop information literacy and other skills needed for successful information problem solving in learning projects. Commonly, institutions approach this charge by posting guides and tutorials online, distributing handouts and posters around campus, recommending self-help books on study skills, and offering face-to-face workshops. Across these various channels, the kinds of skills addressed mainly concern annotating, how to review content, and self-test mastery of it, writing, test taking, managing time and (variously labeled) thinking critically or argumentation (e.g., Hadwin et al. 2005). A trending theme augmenting this set of basic skills is searching for information. "Google it" might be almost everyone's first step when starting a learning project. Unfortunately, by and large, attempts to help students improve skills in all these areas are not as effective as might be expected (Hadwin and Winne 1996; Winne 2013).

One might predict learning science can remedy this situation with its wide array of research findings. In the next section, I critique a cornerstone for this belief. I argue experimental findings claimed to show "what works" are not as useful as has been claimed. This is because the preferred methodology for generating recommendations in learning science research, the randomized controlled trial (RCT), has significant limitations when one attempts to generalize experimental results as guidelines for any particular individual learner. Following my critique, I revisit and elaborate an approach to researching learning that I proposed some time ago (Winne 1992, 2006) and update in a recent article (Winne 2017a). The approach I commend rests on students' using software to engage in online learning projects. This affords opportunity to generate big, ambient data about learning at both individual and group levels. I suggest these data can be mined to bootstrap ever more useful and empirically grounded recommendations to guide individual learners toward better learning practices and SRL that leads to improving skills for IPS.

Challenges Using Findings from Randomized Controlled Trials to Improve IPS[1]

A widely held view is that recommending changes that will benefit learning requires carrying out a "true" experiment, that is, a randomized controlled trial (RCT). Two key requirements must be met to have confidence in the findings of an RCT serving this end (What Works Clearinghouse, n.d.):

[1] This section draws largely on Winne, P. H. (2017a). Leveraging big data to help each learner upgrade learning and accelerate learning science. *Teachers College Record*, *119*(3), 1–24.

(a) The sample of participants in the RCT must be representative of a well-defined population.
(b) Participants in the RCT must be assigned to each condition investigated in the experiment by random assignment or some method that is functionally random.

Assuming other features of an RCT's methods are well done, which is no mean feat (see Shadish et al. 2002), meeting both requirements sets a stage for a recommendation like this: "If a student is a member of the same population as participants in the RCT, changing how that student goes about learning by replicating the intervention operationalized in the RCT (or in a collection of RCTs examined in a meta-analysis) has a high probability of producing a result for that student like the result that was observed for the treatment group in the RCT." I argue RCTs can build only a "fragile foundation" for strong claims like this about what works (Winne 2017a). Main points are summarized as follows.

Findings of an RCT Are Unacceptably Elastic

RCTs produce findings about differences among mean scores of groups of participants who have different experiences in the experiment. Methodologists call this difference in mean scores the effect size. It is agreed that, unless the entire population of students can participate in an experiment, the real effect size is unknowable. Because only a sample of the population of students participates in almost any experiment, the effect size observed in an RCT is just one effect size sampled randomly from a huge (theoretically, infinite) number of possible samples. This description is tacit about methodologists' conservative approach in assuming the real effect size is zero—the null hypothesis—which is tested statistically for whether data sufficiently challenge that assumption. Colloquially, what you see in one RCT is a quite fuzzy image of what you might expect to see.

Fuzziness can be illustrated quantitatively if I make a few plausible (and arguable) assumptions. First, suppose the real effect size in the population, expressed as a correlation (ρ), ranges somewhere in the range $0.10 \leq \rho \leq 0.40$. Using another common metric, Cohen's d, this range is $0.20 \leq d \leq 0.87$. Yet another expression may be clearer to readers less steeped in statistical methods. If we say the comparison group's mean score lies at the 50th percentile of all scores in the population, a treatment in this RCT would be predicted to have a mean score ranging somewhere between the 58th percentile and the 81st percentile.

Second, no measurement is perfectly reliable. So, I assume the psychometric reliability of the outcome measure in this RCT is 0.70 in this RCT's sample.

These assumptions are backdrops for interpreting effects observed in this one RCT. Suppose it produces an effect size of $r = 0.30$, equivalent to $d = 0.63$. In this RCT, the treatment improved the mean score of students in the treatment group from the 50th percentile (the comparison group's mean score) to the 74th percentile. Now, imagine this *same* sample of students completely forgot everything about their experience in this RCT and participated in a perfect replication of the experiment. Results of this replication would have a 95% confidence interval that ranges from of $r = -0.33$ ($d = -0.70$, 24th percentile)—note: the treatment reduces achievement—to $r = 0.65$ ($d = 1.71$, 96th percentile)—the treatment is a potent benefit. It is worth pointing out the span of this interval grows *wider* to an unknown degree if *different* students experience the intervention. That, of course, must be the case when anyone applies findings of the RCT to a new sample.

As if elasticity in "the" finding of an RCT was not enough, it is actually even more elastic. A hallmark of RCTs is the C of this acronym. It identifies the trial (or experiment) as "controlled." This means the researcher did everything possible to insure that every other factor theoretically reasoned or empirically demonstrated to affect the outcome variable was controlled, that is, did not vary. This usually makes an RCT very unlike other contexts in which the experiment's intervention might be applied. Whenever one of these factors in the real world has a value or a range different than the value it had in the RCT, the confidence interval just described blurs. It may contract. It may elongate. The center point on which it pivots may slide up or down. In short, predictions about what to expect on "replicating" the intervention studied in the RCT become quite fuzzy.

This analysis of an effect size observed in a single RCT delivers an unhappy message. It is a *very* chancy proposition to predict what to expect about the mean performance of a different group of students who experience an intervention researched in one RCT. You might counter: "A meta-analysis, where a collection of RCTs are examined, will fix this problem." Unfortunately, no. The elasticity of the confidence interval for an effect size does not shrink if it is produced by a meta-analysis. The collection of statistically detectable moderator variables a meta-analysis identifies help to point out which factors moderate an intervention's effects but this list does not make generalizing "the" effect any more robust.

Means Cannot Predict an Individual Student's Results

It is easy to show the mean score of a group is useless as a prediction about the score of any individual in the group, such as a student who experiences a treatment in an RCT. Statisticians model an individual's score, which they represent symbolically as X_{ij}, in terms of three components. One component, symbolized by μ, represents the mean score of all students in the population to which an individual student belongs. The second component, τ_j, indicates how much the population mean μ changes as a result of everyone in the population experiencing the treatment. The subscript j is appended to signal a particular group in the experiment—say, the treatment group (1) or the comparison group (0)—to which a particular student belongs. Finally, the third component is an "error" term, symbolized ε_{ij}. This component reflects how much the score of a particular individual i who is in group j differs from the mean score of all the other students from the population who are in group j. Putting these all together, the ith individual student who is group j has a score equal to the sum of these three components. Eq. (8.1) shows how this is represented when a weighting factor, b, is applied to the term representing the effect of a treatment. If the student is in the treatment group, $b = 1$. If the student is in the comparison group, $b = 0$ and the effect of the treatment (τ_j) is nullified when it is multiplied by zero.

$$X_{ij} = \mu + b_j \tau_j + \varepsilon_{ij} \tag{8.1}$$

What is critical to know about how statisticians use this expression when they construct a statistical analysis is this: When an average score in a group, say the jth one, is calculated by aggregating all the individual students' scores, it is assumed the sum of all the individual ε_{ij} components will be zero. The average obliterates individuality; the ε_{ij} term is zero. If this is not the case, the analysis suffers bias. In short, knowing the mean score of a group of students offers no help in predicting what the score will be for any individual student.

Populations Are Ineffectually Described

At the outset, I noted the validity of inferring the presence of an effect in an RCT depends on the sample of participants in the experiment being a *random* sample from a *well-defined* population. The requirement that the sample be random arises because this is a critical assumption underlying statistical models used to investigate inferences about whether an intervention in an RCT produces a statistically detectable effect. If the sample is not randomly drawn from its population, inaccuracy is introduced into the inference of whether an effect appeared in the experiment. I believe it safe to say the vast majority of RCTs fail this requirement. Samples participating in RCTs are almost always samples of convenience. I (Winne 2017a) coined the term "pseudo-random controlled trial" or P-RCT to reflect this situation.

Another issue arises regarding the requirement that the population be well defined. In this context, "well defined" means the population is defined by factors that are empirically and reliably known to cause variation in the outcome variable measured in a P-RCT. Why is this a requirement? Consider an experiment in which high school students in the intervention group study new terms that will be important in an upcoming lesson. They study until every student can perfectly define each term from memory. Peers in the comparison group join these students after the intervention group's preparatory session, and all students are shown a movie about farming practices before they all take exactly the same achievement test. Now, suppose I define the population as 14-year olds and 60% female. (The *APA Publication Manual* requires noting these two demographic features of participants in studies.) My sample of 30 students in the intervention group, being a randomly lucky one, consists of only 14-year-olds and has 18 (60% of 30) girls.

Does age cause variation in, say, understanding why the early stages of root infection are greatly affected by soil pH? No, age is a poor proxy for opportunity to learn about content. Moreover, age is not at all a useful proxy for the quality of those opportunities as learning experiences. Is sex a cause of learning or lack thereof? No, it is a poor proxy for potential interest in or opportunity to engage in learning about this topic. Because these "defining" factors are poor proxies, and other factors that really cause variation in the outcome measure in this experiment are unspecified, this study suffers what statisticians call the specification error. If an effect is detected, there is neither theoretical nor empirical warrant to generalize the effect to people who happen to be 14 years old or have any basis for considering how much the effect might vary if the population of students is only 52% female or all female.

Summary

The randomized controlled trial (RCT), much acclaimed in research on learning science, is really a pseudo-randomized controlled trial (P-RCT). Even if shortcomings of P-RCTs could be redressed, a probabilistically inferred effect is limited to describing differences between the mean scores of groups. It cannot forecast what to expect for any particular student who later experiences the same treatment studied in the experiment. If we hold a view that each student is responsible for carrying out operations that generate learning, P-RCTs have significant limitations as sources of robust recommendations about "what works for you."

I hasten to emphasize the bulk of learning science should not, *ipso facto*, be ignored or discarded. Later, I suggest an important role for the current body of research in learning science. Moreover, I argue learning science can be accelerated and lend much value to helping students tackle learning projects and other IPS tasks.

To reach this point, I first set out goals to be achieved by a new approach to research. Then, I explore how modern software systems can support approaching those goals. The prize at the end of this journey is a systematic plan for helping individual students productively tackle information problem solving in the age of nearly unlimited online resources.

Goals for Research on IPS

There are two key goals for a new approach to research on promoting IPS. One is to describe, in terms that each student can understand and act on, what should replace the tactics and strategies they presently use in IPS that do not produce optimal results. It is important to emphasize: *Students* need to be clear about an intervention's operational definition because *they* enact the "treatment." Related to this goal are two assumptions.

Learning science commonly identifies the ways an author can structure information presentations (texts, videos, diagrams, etc.) to improve IPS. However, I assume very few authors posting information to the Internet know about or care to implement these recommendations. If my conjecture is valid, students must "fend for themselves" when they source and analyze information for IPS.

Principles of learning science are typically expressed in terms of unobserved constructs, e.g., rehearsal, decay, metacognitive monitoring, elaboration, etc. To most students, these are foggy notions. In contrast, students could readily understand operational definitions of these constructs, for example, considering the foregoing constructs: Retype text you highlighted. Of text you highlighted, you did not recall this (particular information.) List standards you use to decide whether you recall enough about this (particular information). Illustrate this principle by an example from your experience.

I recommend research in IPS be designed to generate learning analytics expressed in terms of operational definitions rather than theoretical constructs. I predict when learning analytics have this form, students can understand clearly what they did when they studied previously and what they can consider as supplements to or replacements for prior actions to improve learning.

A second goal for the new approach to research I recommend for improving students' IPS is to trace, as much as possible, everything students do *as* they work on IPS tasks. If this goal can be achieved, RCT's fetters to random sampling and random assignment can be cut. Here is why.

In the classical approach of experimenting to identify an intervention's effect(s) on outcomes, it is axiomatic numerous unknown factors causally affect the outcome. This is, in fact, how the normal distribution of scores acquires its shape. When the number of participants is large enough, and when other experimental controls are sufficiently well implemented, random selection and random assignment of participants to an experiment's conditions provide mathematical insurance that causes with positive influence and with negative influence "balance out." When this is the case, interpretations about the effect(s) of an intervention do not suffer confounds such that an effect is just as likely attributed to the intervention rather as to some unknown causal factor(s).

There are problems with this. Randomly selecting a sample of participants from a well-defined population is almost never achieved. Setting this aside, sample sizes would typically need to be prohibitively large. For example, a meta-analysis by Bakermans-Kranenburg et al. (2005) nominated six factors as moderator variables affecting the outcomes of early childhood interventions. If a new RCT was planned to investigate a new intervention, I calculated the size of a random sample of children from a well-defined population would need to be approximately 12,960 to avoid a confounded interpretation about whether the treatment was beneficial (or harmful) (Winne 2006). While samples of that size might occasionally be achieved, interventions requiring special training or unconventional environmental designs suffer erosion of control when samples are so large.

To recap, new research on IPS should strive to provide students with learning analytics describing operationally how to study rather than constructs that matter theoretically. To generate such learning analytics requires data fully describing what each student does while studying in every studying episode. Next, I describe software designed to accomplish meet this standard.

nStudy: Software for Everyday IPS That Generates Ambient Big Data

nStudy is an extension programmed for the popular Google Chrome web browser. nStudy's features are tools learners can use to operate on information presented in web pages, pdf documents and videos they find on the Internet. The software was designed, in part, to open the black box of learning, that is, to bring into observable form learners' cognitive operations on information and motivational states that shape what they learn (Winne 1982; Winne et al. 2017b).

Suppose Noah's project is to argue whether owning a hybrid car is a wise consumer choice. After opening his browser and logging into nStudy, Noah enters "hybrid cars pros and cons" in nStudy's search box. From Google's returns, he selects one source he judges should be rather positive (www.plugincars.com) and begins reading. Early in the text, he drags his cursor over "the cost per mile to fuel an EV is approximately one-third to one-quarter the cost of gasoline (on a cost per mile basis)" (Berman 2016). As soon as he lifts his finger from the trackpad, nStudy pops up a menu of options for operating on that selected information: *quote*, *note*, *term* (Fig. 8.1). Noah chooses *quote* and creates a tag for the information he selected, "pro." In response, nStudy (a) highlights the text Noah selected, (b) paints a small colored nub next to the scroll bar (a region we call the gutter) to mark the quote's relative location in the web page so Noah can see where he's made quotes, (c) adds beneath the Tags header in of the sidebar the new tag Noah created, and (d) copies the text Noah selected to a sector of nStudy's sidebar as a quote (Fig. 8.2).

Table 8.1 shows data nStudy records about Noah's work so far in a database on a server. Every event is time-stamped, accurate to at least 1/100th second. These data are ambient data; they are "collected as a matter of course"

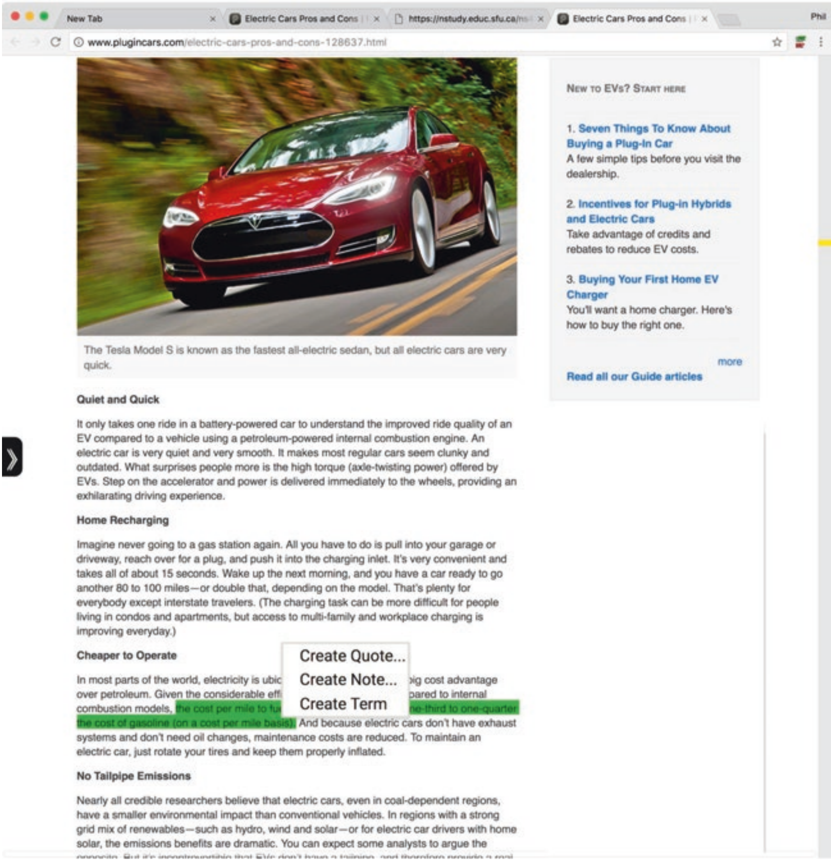

Fig. 8.1 Noah selects information to quote and tag “pro”

(Pistilli et al. 2014, p. 85) and trace, as much as possible, every event that could be observed as Noah worked on his learning project.

The principle guiding nStudy’s design was to record everything possibly observable about learners’ studying activities so that a full account of the studying episode was created. nStudy’s trace data help open the black box of learning (Winne 1982). For example, Noah’s choice of search terms reveals his judgment about key components in crafting an argument: pro, con. His search query also reveals a choice to focus on, or ignorance about, the difference between hybrids, all-electric plug-in cars,

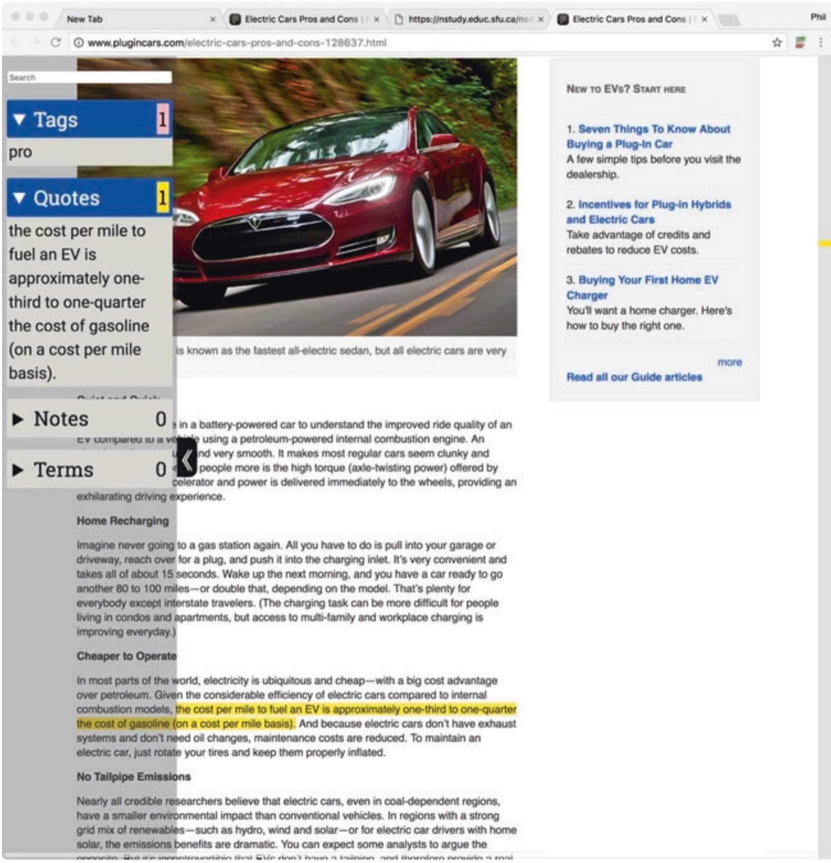

Fig. 8.2 nStudy's trace data mirror Noah's operations on information quoted and tagged

and hybrid plug-in cars. Noah's selection of text about cost per mile of ownership signals he was metacognitively monitoring information in the web page. The selection he quoted satisfied standards used in metacognitive monitoring. His specific standard is revealed by the tag he created.

nStudy offers an array of other features that students can use in IPS tasks. These features afford gathering data that can recreate the temporal, operational, and informational aspects of work on learning projects. Brief descriptions of artifacts and features in nStudy are provided in Table 8.2.

Table 8.1 Operations and information operated on in Noah's studying session

Operation	*Information*
Log in	Identity
Choose search	Place cursor in search box
Search	Search terms entered: hybrid cars pros cons
View	Search results
Choose URL	www.plugincars.com
View	Content of the page at www.plugincars.com
Choose text	The cost per mile to fuel an EV is approximately one-third to one-quarter the cost of gasoline (on a cost per mile basis)
Choose operation	Quote option on popup menu
Create tag	"Pro"
Quote	The cost per mile to fuel an EV is approximately one-third to one-quarter the cost of gasoline (on a cost per mile basis)

When learners create, edit, file, review, or destroy an artifact, nStudy logs the complete interaction. Similarly, when learners interact with a feature, for example, searching for an artifact, that interaction is also logged.

nStudy is now being extended to retrieve and organize data from one or multiple learners' databases for input to computations generating learning analytics. In addition to straightforward mirror reports (e.g., "You made 18 notes in today's 2 studying sessions, 8 of which you tagged *review later*.) comparisons can be ipsative (within one learner across time), criterion referenced or norm referenced (relative to a defined group of a learner's peers). Because inputs to learning analytics are operations a learner applies using nStudy's tools, for example, quoting or searching for a note about a particular topic, and because the information a learner operates on is recorded in nStudy's database, learning analytics can be presented in terms learners are accustomed to using when they use the software.

How Software Helps

Data that nStudy gathers approach big data. A common 500-page introductory textbook containing approximately 1000 terms, wherein the learner makes 2 quotes per page and 2 notes per page, plus searches for and reviews 25% of these artifacts, will generate approximately $500 \times 2 \times 2 + 1000 + .25 \times 3000 = 4000–5000$ records per student-semester. An estimate of data points generated in a typical IPS project, such as a term

Table 8.2 nStudy's feature set

Artifact/ feature	*Description*
Bookmark	Titled, clickable and searchable links to source content (pages, pdfs) in the Internet
Quote	Text selected in a source that is copied to and searchable in a learner's workspace. Clicking a quote returns the learner to its source and the quote in context
Note	Learners' elaborations and interpretations of quotes. Replacement text in a text field guides learners' entries, e.g., "title your note" or "describe your feeling"
Note form	Schemas guiding analysis of content. Forms can be configured with multiple kinds of fields: field labels, text, checkboxes, radio buttons, sliders, drop-down lists, dates, images, attached files and "see also" field which records hyperlinks between the active note and other nStudy artifacts
Term	Notes that name and describe key terms, characters, events, etc.; the term form includes a "see also" field
Termnet	A node-edge network in which nodes are terms and edges signify a relation. Clicking a node opens the term note for quick review. When a bookmark, essay or discussion (see Hub) is opened, nStudy identifies its subgraph of terms—a local glossary.
Tag	An index to be applied to a set of nStudy artifacts to classify them conceptually (e.g., "conjectures"), motivationally (e.g., "interesting"), qualitatively (e.g., "vague"), or in relation to tasks (e.g., "review for test). Tags can be restricted to a set provided by a researcher/instructor or freely created by a learner
Essay	A feature for drafting and formatting compositions, lab reports, business plans, diagnoses, etc. Quotes, notes, and terms can be incorporated into an essay by dragging or copy/pasting them into an essay
Hub	A feature for communicating with peers synchronously or asynchronously. Any nStudy artifact (bookmark, quote, note, term, essay, map) can be sent to collaborators
Library	A feature for browsing and searching for artifacts by title, content, kind, temporal attributes (e.g., edited this week) and other artifact metadata
Map	A feature for constructing and displaying relations (links) among nStudy artifacts (nodes); a concept map. Learners construct maps by adding items and linking them at will; or by filtering the library to a desired subset, then clicking a button, "map it." Artifacts in maps can be grouped to form submaps. An item's "conceptual neighborhood" can be shown at arbitrary "distance" measured by the number of links traversed
Queries	A special folder in the library of researcher-provided or learner-designed search expressions with optional fill-in text fields, e.g., "find notes made last week not reviewed about [topic]"

paper, might be 500. If a typical learner enrolls in four courses and data are available for a freshman class of 5000, the flow of data is approximately 100 million raw data points per semester, not counting time stamps and semantic features of information on which learners operate. Because nStudy's data share a common format independently of where students enroll, post-secondary institutions pooling data would expand this volume. There can be big data about how learners study.

Ambient data of this volume gathered in the natural ecology of studying and IPS projects offer significant affordances for mining to trace how students study and orchestrate their work in IPS projects. These data also can be mined to identify how naturally arising events as well as inserted learning analytics perturb patterns of IPS and nudge achievement (Winne and Baker 2013). It is practically inevitable within this volume of data that some naturally occurring patterns will validate findings already developed in learning science. It is also highly likely new patterns will be discovered that have not yet been explored in learning science. A particularly appealing opportunity is the ability to track the nature of IPS skills, study tactics, and their adaptations arising from injections of learning analytics over time. While time spans fall considerably short of "life long learning," there is an exceptional prospect of mapping the developmental trajectory of IPS skills over several years of an undergraduate career.

An additional advantage of software systems like nStudy is future capability to offer just-in-time responsive support for students. In conventional research programs, data for a single experiment may be gathered over 1–2 months. This is followed by a period where data are analyzed, a paper is drafted and submitted for publication, the publication is published with a lag of 1–2 years and, perhaps 2–5 years after that, someone synthesizes multiple studies in a meta-analysis. In contrast, when ambient data are collected using software systems like nStudy, data are immediately available for automated or hand-crafted analyses. The concept of a contained study disappears. It can be replaced by "overnight" updates to the state of the art. As and when findings cohere, so recommendations can be justified, these can be distributed directly and immediately to students. This sparks a continuous and rapidly responsive cycle of evidence-based investigation and adaptation. In addition, students are relieved of having to visit a tutor or study skills center. They can receive advice tailored to their idiosyncratic approach to IPS as they log in to the next study session.

Conclusion

Online information is a major resource students mine in learning projects, less extensive IPS tasks, and everyday academic work. With robust regard for privacy, as learners use online technologies for studying and other IPS tasks, unparalleled prospects arise to gather extensive ambient data about every learner's work over time and across learning projects. The data generated are significantly greater in volume and detail than has been possible to realize in a pen-and-paper world. But volume is actually a drawback unless it can be intelligently mined and analyzed. Powerful tools for mining and analyzing large sets of data knock down this potential barrier.

Data that software systems can gather will accelerate learning science and enhance learners' achievements (Winne 2006, 2017a, b; Winne et al. 2017b). The learning management systems in widespread use across post-secondary institutions miss this opportunity because data they gather cannot reveal what learners *do* in the IPS "activity stream" (DiCerbo and Behrens 2014).

As previously forecast, prior findings and models developed through diligent work in prior learning science should not be set aside in a frenzy to gather big ambient data about learning. Current findings are the best available hypotheses about how to support learning, increase motivation and enhance achievement. The very attractive opportunity afforded by software systems like nStudy is a hugely increased capacity to test such findings further and more penetratingly. Opportunity to identify moderator and mediator variables is hugely advantaged in this technologically supported ecology. And, because data are big, the pool of data can be stratified to finer grain and arrayed in more complex combinations than today's experimental samples or meta-analyses allow. Moreover, the scope of ambient trace data made available by online systems like nStudy opens doors to explore new research questions in far less costly and much greater variety than is possible today. A new era in research in IPS supported by software systems may help learning science evolve to its next level.

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CHAPTER 9

Project-Based Learning Progressions: Identifying the Nodes of Learning in a Project-Based Environment

Leonard A. Annetta, Richard Lamb, David Vallett, and Marina Shapiro

Introduction

Discussion and research into learning progressions and project-based learning have been at the forefront of the learning sciences for the better part of the last decade. The initial descriptions of learning progressions arose from developmental psychologists' understanding of how children's understandings in domains change with continued exposure to the content

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O. O. Adesope, A. G. Rud (eds.), *Contemporary Technologies in Education*, https://doi.org/10.1007/978-3-319-89680-9_9

of those domains. Learning progressions, by their very nature, are theoretical and require work toward validation and measurement. In addition, while there has been work outlining learning progressions in specific topics within the domains of science, there are currently no studies linking project-based learning, the design process, and learning progressions. Research indicates an ongoing need for the improvement of teaching and learning in science (Gonzales et al. 2008). This is particularly true as one examines the number of new STEM schools opening across the United States and other countries. One possible contribution toward the growth and improvement of teaching and learning in the sciences at the K-12 education level is the utilization of project-based learning.

The purpose of this theoretical chapter is to align project-based learning and learning progressions. A secondary purpose of this chapter is to align the resulting project-based learning progression (PBLP) with International Society for Technology in Education Standards and Next Generation Science Standards. Successful development of domain-specific PBLP would allow educators and researchers to understand and assess student development and learning in this unique context.

This chapter will review relevant literature on learning progressions, project-based learning, and measurement to present a project-based learning progression paradigm that has evolved over the past 15 years. More specifically, the synthesis will discuss the application of the synthesized project-based learning progressions in relation to game-based learning via game development related to STEM fields for students at the K-12 grade level.

Learning Progressions

Learning progressions, in general, are the meaningful sequencing of teaching and student learning expectations accounted for across disciplines, student developmental stages, and grades (Plummer and Maynard 2014). Often characterized by specific content area domains, learning progressions provide a scope and sequence for teachers to develop student knowledge and skills as students progress (Barnhart and van Es 2015). Learning progressions are typically characterized by two traits. The first is standards at each level of development intended to address student abilities, social, emotional, and physiological needs. Second, the standards are sequenced to meet necessary expectancy and actualization. Essentially this means that learning progressions ensure appropriate material that is neither too difficult nor too easy and that the material avoids unintentional repetition.

Building upon the general characteristics of learning progressions, learning progressions in science have been articulated by the National Research Council as providing for empirically grounded, testable hypotheses about learning. In this way, learning progressions provide a link to assessment and help to organize the data-rich environment many teachers experience in the classroom in a meaningful manner. These hypotheses describe the cognitive correlates that students use while understanding fundamental concepts in science, and include how students apply these scientific concepts to problems in science. Learning progressions describe how this practice of applying science concepts progresses over time, and how students are able to become proficient at these essential scientific concepts as they continue to receive adequate instruction (NRC 2007).

Learning progressions also provide a process framework that permits the configuration and alignment of scientific subject matter, methods of instruction, and strategies of assessment that make it possible for students to progress through scientific content domains. Stevens et al. (2010) defined scientific learning progressions as the knowledge that begins on a small basic scale and progresses to more advanced concepts, as well as the application of scientific ideas over a prolonged period. Jin and Anderson (2012) suggested that in order to successfully develop a learning progression in science or engineering, it is important to focus on a specific domain of a scientific concept, or the topic would be too broad to lend itself to the creation of a successful learning progression. We argue that in a project-based environment, the nodes within the project are more important than the content as it allows for the assessment of learning across the project continuum as opposed to the customary score at the project's conclusion.

According to Shavelson (2009), there are two different types of learning progressions; *curriculum and instruction* and *cognition and instruction*. One area of active research is the reconciliation of the types of learning progressions with each other. The *curriculum and instruction* type of learning progression consists of a series of concepts that are based on the empirical evaluation of the comprehensive scientific ideas that function as units in curricula. The *curriculum and instruction* type of learning progression greatly relies on context, which will affect student performance resulting from a specific type of learning progression. Conversely, the *cognition and in*struction type of learning progression plans out a progression that shows how a student arrives at accurate scientific understandings of concepts from their initial conceptions (Shavelson 2009).

Learning Progressions as Guides to Instruction

According to Furtak (2012), ideas that are described via learning progressions are able to assist teachers in identifying and drawing conclusions about evidence that related to student cognitive processing. This evidence can be used to help alter methods of instruction that would benefit students in ways that assist in progressions and advance their learning. Additionally, teachers are able to use learning progressions to understand how students' ideas are able to advance in a domain. Assessment in this manner is a constructive practice for providing a means for educators to examine the formation of ideas, and, more importantly, the sequence of students' thought processes. The author qualitatively examined teachers' views of how learning progressions supported their method of instruction and found that using learning progressions supported teacher instruction and greatly increased student learning. The learning progression examined in this study evaluated how students in a high-school biology class learn the concepts of natural selection. The study then analyzed the responses and interpretations of teachers in regard to these student ideas from the *Natural Selection* learning progression. From the videotapes and interviews conducted with the teachers, it was found that the learning progression served as a rapid approach for teachers to be able to identify student misconceptions about concepts related to natural selection. Teachers also used the learning progression as a logical arrangement to organize the unit that they taught.

Neumann et al. (2013) developed a learning progression to teach energy to students in grades 6, 8, and 10. In this study, the Energy Concept Assessment (ECA) was developed as a measurement tool for the collection of student data from the students understanding of energy concepts as they progressed through the primary learning progression to more advanced components of the learning progression. Results indicated that students developed an understanding of energy concepts, such as energy degradation, energy transfer, and energy transformation. This study detailed methods that offer beneficial support to the teaching and learning of energy concepts for middle-school and high-school students. An explanation was provided of what the primary focus of initial lessons should be and then when and which concepts should be followed, as well as the order in which it is best to teach those specific energy concepts (Neumann et al. 2013).

From each of these examples (Furtak 2012; Neumann et al. 2013) various methods of curriculum reform are proposed. These proposed reforms provide beneficial methods of instruction that would arise because of a learning progression. For example, a natural outgrowth of learning progressions is the inclusion of project-based learning, task-based instruction, and by extension inquiry-based instruction. Schwarz et al. (2009) developed a learning progression for scientific modeling in order to present scientific models as instruments that enable prediction and explanation. This learning progression was used to work with fifth- and sixth-grade students. As they evaluated the students' use of the scientific modeling, Schwarz et al. (2009) found that students were able to successfully progress through the content and develop more advanced views about the explanatory nature of the models using the learning progression. For instance, students were able to explain the essential processes and relationships between various phenomena that they had studied. The students were also able to move beyond explanation and assemble models of these phenomena such as the transition of water particles from the liquid-to-gas phase, and the motion of particles (Schwarz et al. 2009).

Duncan et al. (2009) developed a learning progression to teach genetics to students in fifth through tenth grade. The researchers provided evidence that the use of a learning progression is a more successful approach for teaching important concepts in modern genetics when compared to traditional curricula, in which the sequencing does not account for student development. The results of this study revealed that students do not develop an in-depth understanding of genetic concepts via traditional curricular methods alone. These results were consistent from elementary classrooms to high-school classrooms. Following the implementation of the learning progression, the authors of the study found that there were increases in student understanding related to genetic concepts. According to the study, these concepts should be taught in greater depth. The increased depth informs a suggested science curriculum reform (Duncan et al. 2009).

Gotwals and Songer (2013) conducted a validity study with sixth-grade students, in which student responses to a task were analyzed via think-aloud protocols and item difficulty analyses. These analyses evaluated how assessment tasks serve as evidence for knowledge levels within the progression. In this case, knowledge levels were a combination of information resulting from two learning progressions: one related to fundamental ideas in the field of ecology and a second that provides a mode of scientific practice for the creation of evidence-based explanations. Using the combination of item response and think-aloud protocols, the authors identified tasks that enabled students the opportunities to reveal learning and knowledge about various scientific concepts. The students also demonstrated the ability to develop evidence-based explanations as a result of exposure to the second learning progression (Gotwals and Songer 2013).

A final example of the power of learning progression is illustrated in a learning progression created by Plummer and Krajcik (2010). Developed due to elementary-school students' difficulties around understanding basic concepts related to the motion of the sun, moon, and stars, Plummer and Krajcik's (2010) learning progression assisted students with the learning and explanation of patterns of celestial motion. Difficulty in understanding the motion of the sun, moon, and stars prevents students from developing a more advanced understanding of the domain of astronomy. In this particular study, the authors observed that the learning progression related to celestial motion served as a tool to facilitate discussions between teachers, students, and planetarium directors, leading to the opportunities to better structure and sequence topics for student understanding (Plummer and Krajcik 2010).

Learning Progressions as Methods of Assessment

There are a variety of benefits to learning progressions and how they are used to support classroom learning and teaching practices for both students and teachers. Learning progressions have been used as the foundation for design practices of assessment and curriculum development (Corcoran et al. 2009) and the applications to classroom practice include improving science curricula via empirical feedback as the student progresses, the scaled assessment, and classroom instruction.

Learning progressions are commonly used as a method of formative assessment and growth modeling, which is a process that teachers utilize in order to institute learning goals, determine current knowledge of the students, and consequently offer feedback to students in order to assist students in the progression and advancement of their learning (NRC 2001). Under the growth modeling approach to learning progressions, the progressions represent discreet areas of growth anchoring the students' progress and ultimately their progress toward mastery of the particular progression (Cooper and Klymkowsky 2013). The intention of assessments that accompany learning progressions is to offer analytical information in regard to the intensity and type of student understanding (Steedle and Shavelson 2009). According to Songer et al. (2009), learning progression-guided assessments are able to offer an immense range and the amount of information that can then be used for the purpose of more in-depth analysis to be able to distinguish the various abilities of students, than can be determined via standardized assessments alone. Songer et al. (2009) developed a learning progression for this purpose in relation to teaching and assessing biodiversity content knowledge of sixth-grade students.

Johnson and Tymms (2011) developed and evaluated a learning progression for the instruction of chemistry and the concept of a substance for middle-school students. Using a computer-based assessment instrument in conjunction with video and animation, fixed-response items were developed and data were collected to learn about progressions of various ideas in middle-school chemistry. Data from the learning progressions was shown to fit the Rasch Model, allowing learning progression data to take advantage of the Rasch assumptions and be scaled for task difficulty (Johnson and Tymms 2011). Songer and Gotwals (2012) conducted a study that utilized a learning progression to examine the reasons why elementary-school students have a difficult time formulating scientific explanations. The use of this learning progression enabled researchers to combine traditional content analysis with students' developmental stages to go beyond the use of standardized assessments. Using learning progressions, educators acquire a more in-depth understanding of what areas of learning create the greatest difficulty for elementary students. Combining the learning progression with item response theory (IRT) models such as Rasch, educators can examine and scale the ability of elementary students to devise scientific explanations and track progress over time (Songer and Gotwals 2012).

The goal of learning progressions is to present educators with a framework that could be used to measure a student's level of understanding of a principal concept and then to direct the student to a more complex level of understanding (Neumann et al. 2013). From a study conducted by Mohan et al. (2009), it was concluded that while students may perform successfully on standardized tests, a deeper understanding of various global scientific concepts present in the everyday interactions of our society is obscured due to limited information garnered in standardized tests as a result of test sensitivity.

The identification of the principal concept in understanding biochemical processes was identified via a learning progression that was designed to study how upper elementary through upper high-school students acquire an understanding of essential biochemical processes that transform carbon in socio-ecological systems. For this reason, learning progressions that are empirically validated via Rasch or other methods and whose concepts are logically articulated can serve as a crucial instrument for the development of standards, formative, and summative assessments, and further development of curricular materials (Mohan et al. 2009).

Measurement of Learning Progressions

A key challenge in making full use of learning progressions in the classroom is the ability to successfully model resultant relationships that directly link student performance on tasks with the learning progressions themselves. While in theory learning progressions are leveled by individual ability and have tasks at each level clearly defined, this is not always the case in practice. Often, learning progressions and task linkage are inconsistent and subject to error with current statistical models. One recent approach that holds promise is the use of Bayesian networks (statistical models) for educational measurement. Bayesian network modeling is a means to simplify complex interactions in order to better understand and clarify complex causal relationships. An example of a Bayesian network is an artificial neural network used to examine the complex system of student learning (Lamb et al. 2014a, b).

When considering how learning progressions are modeled for assessment purposes, we can examine the probabilistic relationships among the completion of tasks in real-world settings to generate evidence about the students' ability to understand and recall information in a specific domain. Lamb, in a series of papers starting in 2013, outlined a similar process for use during video game design and science learning (Lamb et al. 2014a, b). During the process of designing the game, students completed virtual tasks. Data from each task, such as mouse clicks, interactions, and tool use as completed in the design processes, are analyzed and broken into task cognitive attribute relationships via cognitive diagnostics and item response theory. From these relationships, a rudimentary learning progression was developed based upon the difficulty of the tasks and the cognitive relationships. The progression of tasks was then entered into a Bayesian network and further developed using cognitive diagnostics and a *Q*-matrix. The students' capabilities and cognitive states were assessed using the output of the Bayesian network. Within this model, the different patterns of activations with the Bayesian network provide evidence of item difficulty, student level, and allow the concept to be placed into a progression and mapped over time.

Project-Based Learning

Project-based learning is a systematic instructional method which leads to captivating the interest of students through a desire to acquire knowledge and skills using carefully designed inquiry that employs challenging, in-depth, and authentic questions (Markham et al. 2009). Project-based instruction was originally designed with the intention to assist medical-school students with the problem-solving skills. This movement came about because young physicians would graduate from medical school with in-depth content knowledge but little diagnostic skill. In essence, the new physicians were not able to successfully apply the knowledge due to the lack of practice engaging in critical thinking and problem-solving (Gallagher et al. 1995). Critical thinking and problem-solving are key cognitive attributes when engaging in the application of science (Lamb et al. 2014b) According to Ravitz (2008), there has been growing interest in project-based learning because students are not adequately prepared for success in higher level STEM courses and subsequently the workforce by traditional instruction alone.

Project-based learning is a method of instruction that produces the skills and strengthens the cognitive attributes that are necessary for one to succeed in the twenty-first century (Ravitz, 2008). According to Markham et al. (2009), project-based learning guides students toward a greater level of cognitive development as a result of the student interaction with the thought-provoking and innovative problems. Examples of enhancing processes and skills that students gain as a result of engaging in project-based learning include problem-solving, critical thinking, planning, and communication (Markham, Larmer, & Ravitz).

Project-based learning differs from traditional learning in that it is an active learning method making use of student agency with the intent to transform students into active, rather than passive learners who learn via second-hand knowledge (Thomas 2000). The goal of project-based learning is for the students to understand science content through first-hand experiences, while solving authentic or real-world problems that occur in the context of the project (Thomas 2000). In the project-based learning pedagogy, the role of the teacher is to serve as a facilitator ensuring students' progress appropriately. This pedagogy emphasizes self-learning via a combination of practical activities, interactive discussions, independent operation, and team cooperation (Tseng et al. 2013). According to Lee and Lim (2012), team project-based learning is a suitable method to initiate interactions between students and to inspire knowledge building through collaborative learning processes. Peer evaluation within the Project-Based Learning is shown to be an effective method to lead to active participation of individual students in team projects (Lee and Lim 2012).

Often project-based learning and problem-based learning are confused. According to Markham et al. (2009), the functions of problem-based learning is: (a) recognize students' inherent drive to learn, (b) their capability to do important work, (c) their need to be taken seriously by putting them at the center of the learning process, and (d) engage students in the central concepts and principles of the content discipline. The project aspect of the work is central, rather than peripheral, to the curriculum. Highlighting provocative issues or questions that lead students to an in-depth exploration of authentic and important topics develops projects. The in-depth exploration requires the use of tools and skills for learning, self-management, and project management. Cognitively project-based learning leads to increased problem-solving, explains dilemmas, and presents information generated through investigation, research, or reasoning. Students produce multiple products during the development of the project permitting frequent feedback and consistent opportunities for students to learn from experience. Using performance-based formative assessments that communicate high expectations, presents rigorous challenges, and requires a range of skills and knowledge promotes prosocial environments and discourses through either small groups, student-led presentations, or whole-class evaluations of project results.

Project-Based Learning in STEM Fields

Studies have shown that there are numerous positive benefits toward student learning, attitudes, motivation, and cognition as a result of participation in project-based learning environments (Hawan and Chang 2011). In a survey-based research study conducted by Tseng et al. (2013), a significant change occurred in the attitudes of college freshman students toward engineering after participation in a project-based learning using a STEM discipline activity. Results of this study indicated that project-based learning environments integrating STEM discipline content have a positive increase in student attitudes toward STEM careers. This positive change in attitudes leads to meaningful learning due to a desire to achieve success in the career field of interest (Tseng et al. 2013).

Chu et al. (2012) conducted a study in which a novel project-based learning pedagogy was implemented during a laboratory on communications electronics. The idea behind this type of teaching approach is to motivate students in ways that the students can see that the material that they are learning as realistic and useful for applications outside of the classroom. As a result, students become engaged in applications from which they are able to relate. The findings of this study revealed that this project-based learning environment leads to high student motivation and effective learning outcomes (Chu et al. 2012).

Zeren Ozer and Ozkan (2012) evaluated the effects of project-based learning on science process skills of preservice science teachers. In this study, while the project was being created, the goal was to determine if preservice teachers demonstrated deeper learning of science process skills through participation in the project-based curriculum. The experimental group demonstrated more success in terms of science process skill tasks when compared to the control group. The experimental group showed higher scores on tasks such as making observations, designing experiments, and using deduction process skills (Zeren Ozer and Ozkan 2012).

According to Kim et al. (2011), a web-based learning environment was able to provide features that enhance project-based learning experiences and processes. These features included the ability to interact and collaborate with small or large groups not in direct contact with the student, access to large amounts of information and resources, as well as the ability to create, organize, and present digital media thereby reducing cognitive load (Kim et al. 2011). According to Lee and Lim (2012), a blended classroom, team-based e-learning environment made it easier to record both synchronous and asynchronous student interactions on the website. As a result of the ability to record large amounts of formative assessment data students were able to reflect on their performance and teachers were able to more easily track the learning processes and progress of the students.

Griva and Semoglou (2012) conducted a study with second grade students evaluating the effect of student participation in a game-based project and its impact on early foreign language skills. Within the game-based projects, the students participated in various gaming activities such as memory, word games, drawings, constructions, and role-play games. Results revealed that participation of young learners in the game-based project lead to a positive effect on the development of their language skills and motivation level in psychomotor activities (Griva and Semoglou 2012). While this study is not directly related to a STEM field, it illustrates the application of games and e-learning in project-based learning. The use of games in project-based learning has implications for fields in science and technology as well as education.

The final example of a successful project-based learning in a gaming environment is in a study conducted by Cappelleri and Vitoroulis (2013). Within this study, project-based learning labs were incorporated into an introductory robotics course that developed into a semester-long Robotic Decathlon in which students designed robots to complete a series of 10 events over a 14-week period. In this study, the experimental group took part in a hands-on project-based laboratory and an open-ended final project. By contrast, the comparison group consisted of a lecture-only type course. Results of the study indicated that students had greater preference and enjoyment toward the project-based labs and final project when compared to the lecture-only course. Results of the course assessment from this study also revealed that student learning is greatly increased as a result of the project-based labs and final project when compared to the standard lecture/test teaching style.

Creating a Project-Based Learning Progression and Measures

Through several funded projects from the United States National Science Foundation, a project-based learning approach has been developed and modified with students from grades 5 to 12. It is important to note that each of the NSF projects studied also investigated learning of various science concepts. For example, the first project explored invasive species and simple machines, the second project looked at renewable and reusable energy, and the third at biotechnology. Within this model of serious educational game (SEG) design and development, distinct nodes of learning were created to aid students in the design process (Annetta 2008). Figure 9.1 illustrates the Serious Educational Game design approach where students were challenged to become the teacher of science content through an SEG.

Each learning node in the progression depicts knowledge and/or skills a student must attain before moving along the learning spectrum. Within each node are subnodes that can actually be considered learning progressions on to themselves all the while the teacher facilitates understanding and conceptual change.

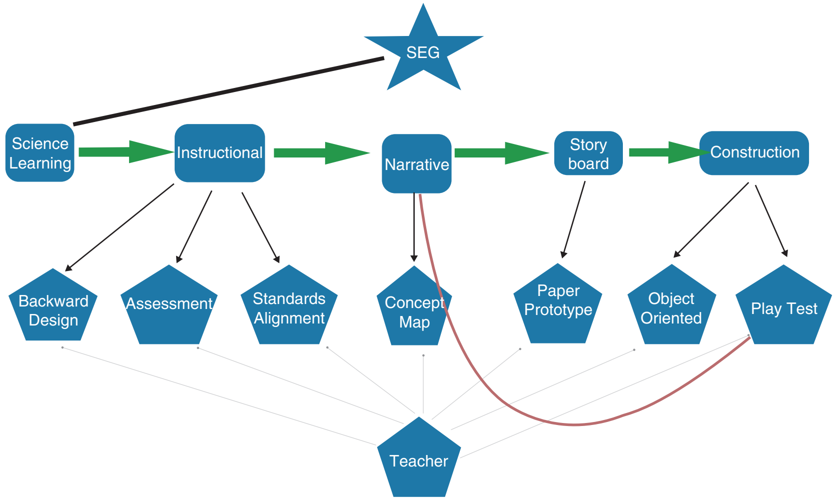

Fig. 9.1 Serious educational game design approach

If we critically look at each node within this example, we can further describe what a student needs to learn before progressing to the next node and how we can measure each node and subnode to accurately study the learning progression in a project-based environment.

NODE Measurement

Additionally, as learning progressions also consist of upper and lower anchors or boundary concepts, they allow for the scaling of tasks within the progression using item response theory measurement techniques and cognitive diagnostics. The upper anchor describes the knowledge that students are expected to acquire and apply toward the conclusion of the learning progression. Conversely, the lower anchor describes the assumptions of the developers about previous knowledge and skills of the students at the beginning and entry phase of the learning progression. In addition, the intermediate steps of learning progressions that occur between the upper and lower anchors, describe the fluctuating levels of achievement of the students as they evolve throughout the learning progression (Duncan and Hmelo-Silver 2009). Lower and upper anchors, when used in conjunction with scaled intermediate tasks, allow for accurate tracking of student understanding, and foster a link between the *cognition and instruction* view of learning progressions and the *curriculum and instruction* view of learning progressions by identifying intermediary concepts between concepts mandated by curriculum, and assisting with teacher creation of scaffolds between those concepts.

To summarize the value of learning progressions for measurement: learning progressions have learning targets, or nodes, that are defined by societal aspirations and analysis of the central concepts in science. According to the National Research Council (2007), there are five important elements of science learning progressions: (1) Themes in domains that are progress variables identifying the critical dimensions of understanding and skills that are being developed over time. (2) Levels of achievement or stages of progress that define significant intermediate steps in conceptual/skill development that most children might be expected to pass through on the path to attaining the desired proficiency. (3) Learning performances that are the operational definitions of children's understanding and skills. (4) Stages of progress that provide the specifications for the development of assessments and activities that locate where students are in their progress. (5) Assessments that measure student understandings of the key concepts or practices tracking student development over time.

NODE Description (Science Learning) Science learning can be accounted for through any of the currently published science learning progressions. There are clear progressions through this process although in the aforementioned funded projects, students learn science in different ways. Science was often taught in a traditional classroom but science was also learned in non-formal settings as well. We had students interact in science museums, zoos, and working with and shadowing scientist mentors working in their respective field.

NODE Description (Instructional) We subscribe to the notion that the best way to learn is by having to teach the content to someone else. To this end, we required students to become the teacher and overlaid instructional design in the game design criteria. With the aid of the science teacher, we taught students the basic pedagogy of backward design, to set and assess learning objectives and how those objectives should align with state and/or national standards. As previously mentioned, the subnodes of backward design, assessment, and aligning standards could be learning progressions unto themselves.

NODE Description (Narrative) Our game design projects are not only educational but fall under and action-adventure story-driven genre. Students must learn the parts of a story and create an interactive narrative where characters and nonplayer characters interact with the virtual world to teach about a given topic. One might remember the *Choose Your Own Adventure* books and how engaging they were for the learner. The same approach is taken in our projects where once a student learns the science and creates a learning scenario, he then must develop a story to articulate the lesson through a cause and effect manner and essentially become the author of his own *Choose Your Own Adventure*. By concept mapping or creating flowcharts of the player decision process, students must consider how to scaffold instruction to the game player if they do not master a content or skill, so that the player can progress in the game that the student is designing.

NODE Description (Storyboard) Like most narrative driven game designers and movie producers, we teach and expect our students to create storyboards that illustrate the critical junctures of their story. Once the story is complete, students then paper prototype the scenes and critical elements of the game. Paper prototyping allows the student game designer to test the interface and see potential pitfalls in his design. This allows the student to critically reflect on the previous nodes and fix any major errors before proceeding the final node of the project.

NODE Description (Construction) The final node allows the student to take all previous nodes and build a virtual space that is rich in content, pedagogy, and story. Our interface provides an object-oriented programming platform so students do not need to know code-based programming, 3D art or animation, or any other skill a commercial game design studio might require to build a game. The final and critical subnode is to play test the SEG. Play testing allows others to interact with the semifinished project and provides the student designers with feedback on whether or not the learning objectives were met.

Project-Based Learning Progressions and the NGSS

The Next Generation Science Standards, with their focus on science and engineering practices as well as a spiraling K-12 curriculum, lend themselves well to the use of project-based learning progressions (NGSS Lead States 2013).

The use of project-based learning, as discussed above, fosters the development of science and engineering practices including making observations, making determinations regarding data, and the construction of explanations and arguments. Likewise, well-identified learning progressions would prove useful not only in creating the deeper conceptual understandings that the NGSS purports to target but in vertical planning for the spiraling aspects of the content in the standards. For example, in the grant work described above, participants demonstrated deeper understandings of content than their peers in the comparison groups, coupled with improvements in associated cognitive skills such as visuospatial reasoning and computational thinking.

Conclusion

There are numerous teaching and learning benefits from both learning progressions and project-based learning in STEM fields for the K-12 grade levels. There is evidence to suggest that learning progressions occur through project-based learning paradigms. In particular, this appears when students are engaged in a project-based learning environment, such as gaming or more specifically when participating in the development of a game. Although this project-based model revolved around SEG design, we believe it can be used for any project-based approach with distinctive nodes along the learning spectrum that can be measured and analyzed before a learner progresses to the next node, and effectively employed to foster the science and engineering practices and deeper understandings targeted by the NGSS.

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CHAPTER 10

Massive Open Online Courses and the Future of Higher Education

Leonard J. Waks

Introduction

The global economic crisis of 2008 coincided with the emergence of new technologies for scaling up secondary and tertiary instruction. Initiated in Canada in 2008, and brought to global prominence by the big three massive open online courses (MOOC) platforms—edX, Coursera, and Udacity in 2012, which were rapidly copied by platforms in the UK, Europe, Australia, and elsewhere—early MOOCs promised to bring free university courses by global super-star professors at top-ranked universities to any student with Internet access, anywhere in the world. Anant Agarwal of edX said in his often viewed 2013 TED talk that "the last big innovation in education was the printing press" but MOOCs will be the next one—and it is starting now (Agarwal 2013). Just what are MOOCs and what are their likely contributions to the future of Higher Education?

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O. O. Adesope, A. G. Rud (eds.), *Contemporary Technologies in Education*, https://doi.org/10.1007/978-3-319-89680-9_10

What Are MOOCs?

The first course to be *called* a MOOC, "Connectivism and Connected Knowledge," was offered in 2008 by George Siemens of Athabasca University—Canada's Open University—and Stephen Downes of the Canadian National Research Council.[1] Siemens and Downes produced videos offering introductory definitions and ideas *about* connectivist learning theory, and student participants—both in-person and online—then critiqued and augmented them on blog posts, threaded discussions on Moodle (a free open source course management system), and social media. The course was an experimental "distributed" seminar. Dave Cormier of the University of Prince Edward Island called this experiment a MOOC—for Massive Open Online Course. Stephen Downes has labeled such experiments "c-MOOCs" (for connectivism).

In 2012, a different kind of massive online course emerged on the first three MOOC platforms—Udacity, edX, and Coursera—leading the New York Times to dub 2012 "The Year of the MOOC." Stephen Downes coined the term x-MOOC ("x" for extension, as TEDx is an extension of the TED Conference and edX began as an extension of Harvard and MIT), to differentiate the courses on these platforms from the connectivist MOOCs that he dubbed c-MOOCs (Downes 2012, 2013).

While each of the four terms contributing to the MOOC acronym—massive, open, online, and course—have been interpreted in different and sometimes conflicting ways, more or less standard meanings have emerged.

Massive The colossal size of the first MOOCs by Thrun and Agarwal in 2011 and 2012 gave the term *massive* the vague meaning of "very very big". But few successive MOOCs could boast student populations in the hundreds of thousands. A typical MOOC on a major platform might have 25,000 students (Jordan 2015). Smaller MOOCs on less prestigious organizations may have just a few hundred students or less. "Massive" has come to mean that the course can be scaled elastically and indefinitely—that there is no practical technological limit to the number of participants.

Open The term *open* in relation to MOOCs has come to mean "open to anyone at no or very low cost". For the MOOC founders, the key was *open access to world class education*—defined as education from the world's

[1] Other organizations such as ALISON had previously offered free online courses, but these were not labeled "MOOCs" until the term came into general use after 2012.

leading universities—with no-cost or low-cost *certificates of learning* for course completion. MOOCs have not in general been open in the sense of permitting their component parts to be "mashed up"—disassembled and re-used in new configurations.

Online MOOCs were initially conceived as online courses. But as MOOC developers came to understand the central importance of social interaction in learning, they built some face-to-face social elements into the MOOC experience. These have included student meetups and faculty roadshows.

Course A course is generally composed of a number of educational experiences—lectures, discussions, quizzes, projects—*sequenced for completion*. Initial MOOCs were sequenced like traditional college courses, starting on a specified date and closing down after the final exam. But MOOCs have gravitated away from the university course model, remaining open continuously on a self-paced basis, while Mini-MOOCs—brief lessons or lesson sequences—are now also common.[2]

Early Promises and Missteps

In the most developed nations, MOOCs promised to bring higher education to those poor and "middle class" students now excluded by rising tuition and stagnant or declining incomes. In the developing nations, MOOCs promised to contribute substantially—and at a manageable cost—to the underdeveloped secondary and post-secondary educational infrastructure, making advanced education and training broadly available. MOOCs, in short, promised to "level the playing field" globally (Kanani 2014).

These early claims were soon refuted. Few secondary or college-age students took an interest in MOOCs; they considered MOOCs irrelevant because their certificates could not be traded in for college credits. 96% of MOOC enrollees dropped out—often before completing a single lesson. The social environment for learning was discovered to be more motivating and engaging than isolated online learning—as though we needed a study to prove this—and the social element in MOOCs—the discussion boards—were so boring that students avoided or sabotaged them. MOOC platforms searched in vain for sustainable business models.

[2] See the MOOC platform Coursmos, https://coursmos.com/

To add to the growing disillusionment, a notorious case study at San Jose State College concluded that academically challenged students in a remedial math MOOC from the Udacity Platform performed significantly worse than a control group of matched students in a more "social" face-to-face class. This highly visible failure led Udacity CEO Sebastian Thrun to declare that his MOOCs were "a lousy product" and to withdraw from the college course market (Chafkin 2013). Udacity instead refocused on professional development, as the most engaged MOOC users turned out to be professionals with university degrees. Instead of "leveling the playing field" in higher education, MOOCs paradoxically added to educational inequality via the Matthew Principle: "those who had much got more, while those who had little got less—or nothing".

Three Contributions: Return, Revenue, and Revolution

Nonetheless, reflecting on the painful lessons of the early MOOCs, MOOC leaders have learned important lessons about how MOOCs can contribute to the crisis in higher education, and have made significant improvements—often under the media radar. In this chapter, rather than speaking in the abstract about MOOCs, I will be examining actual MOOCs that point to future developments. I locate three areas where MOOCs can make a positive difference. I organize these contributions under three headings: return, revenue, and revolution.

The first two—return and revenue—contribute to university students, faculty, and administrative leaders within the entrenched university. The "return" category indicates ways MOOCs can improve the "value proposition" or the rate of return for students and their families on their private investment of money, time, and energy in higher education. The "revenue" category includes the various ways that MOOCs can help universities earn additional revenues and hence improve their financial condition.

By "revolution" I mean the shift from the entrenched university paradigm to an "Education 2.0" paradigm—the revolution of access to online learning where outcomes can be documented through badges, certificates, and nanodiplomas, placed in searchable digital portfolios, and discovered by firms and organizations seeking workers with demonstrated capabilities. Higher Education 2.0 offers a revolutionary pathway to employment that completely by-passes conventional universities—and MOOCs can play a significant role in this revolution.

Contribution I: Return on Investment

Daphne Koller, the founder of Coursera, has stated that colleges are going to have to clarify their value proposition, and then deliver on it (High 2013). With the decline of full-time jobs with benefits for college graduates, the promise of college, in itself, is no longer that attractive; families are now carefully weighing costs and benefits, and withdrawing if the value proposition does not add up. Colleges can offer a better value proposition by reducing costs or increasing benefits. MOOCs can help in both ways. Here I consider (1) tuition reduction, (2) instructional improvement, and (3) new high-value curriculum content.

MOOCs Can Help to Reduce Tuition and Fees

MOOCs can help reduce costs by reducing tuition and fees—this is particularly important in the United States and those other advanced nations that impose high tuition fees for university study. They can also do so by enabling students to reduce food and lodging costs by living at home while studying, and by reducing the opportunity costs of education by making it easier to study while gainfully employed. These "helps" are useful everywhere, but perhaps particularly so for those students in lower income groups and in developing nations.

Let me offer some examples of how MOOCs can help to reduce tuitions and fees.

(i) Transfer Credits for Certificates First, MOOCs can enable students to obtain certificates that can be accepted as transfer credits in degree-granting universities. This was an early hope but has not played out as initially expected. Nonetheless, some recent steps are promising.

Agarwal, the founder of edX, predicted in 2012 that within a year many colleges would be accepting edX courses for credit. If they accept a physics course for credit from a local 2-year community college, he argued, they certainly would accept a physics course for credit from MIT or Harvard.

How wrong he was! EdX and Coursera both submitted MOOCs for approval as full-fledged college courses by the American Council on Education (ACE), and several were rapidly approved. Nonetheless, very few universities accepted these certificates for transfer credit. And the reason is not hard to find. Universities are now almost completely dependent upon tuition revenues—which are declining. If they accept MOOC certificates for credit, more ACE approved MOOCs will be offered and more students will present certificates for free or low-cost credits. Economically, accepting these certificates would be suicidal for most colleges and universities.

Nonetheless, some institutions have accepted them. University College, a school for adult learners at the University of Maryland, has long accepted "life experiences" for college credit. (Fain 2012). If such institutions accept work experiences for credit, how can they not accept MIT physics?

Or consider Ashford College in Iowa, a for-profit college known for luring underprepared learners into enrolling in its programs and paying tuition through government guaranteed student loans. Most Ashford students failed to complete courses and landed in debt, as did Ashford itself. Iowa Senator Tom Harkin labeled Ashford a "scam. " But the college has recently reorganized and now accepts up to 90 transfer credits (out of 120 needed for graduation). They grant credit for any ACE approved MOOC certificate (Biemiller 2014). Ashford may survive on tuition revenues from the remaining 30+ credits—which is 30+ credits of tuition revenue more than what they might otherwise get. For those students merely wishing to get a degree from an accredited college to pass through the college job filter, opportunities like those at Ashford are already available and more will open.

(ii) MOOC + CLEP The Advanced Placement program of the College Board is widely known, and MOOCs can help AP students gain college credits (more on this below). Perhaps less well known is the College Level Examination program (CLEP), also administered through the College Board. CLEP offers competency-based exams in 33 basic college subjects, and students who pass these exams can gain credit for some or all of them in almost 3000 colleges and universities. As the College Board exclaims in the CLEP website "Average College Course—$700. CLEP Exam—$80. You Do the Math!" Some thought leaders are now urging students to prepare for CLEP exams by taking MOOCs. A recent book lays out a plan for completing college in a single year using the MOOC + CLEP strategy (Warburg 2015).

(iii) Facilitating Success in High School Advanced Placement Courses Another method is helping students get college credit for advanced *high school* courses—a practice that is already well-entrenched. This method has several variants. First, some MOOCs are now being offered—by the University of Houston and others—to *augment* high school Advanced Placement courses and help students raise AP scores; those with high enough scores can transfer their AP courses for credit Second, MOOCs are now available to *train teachers* both to teach AP courses better and to raise their students' AP test scores (Schaffhauser 2014). Third, some universities including Rice University in Texas, are offering *entire* AP courses in the MOOC format (Anderson 2014). Students take the MOOC i*n place of* AP courses, and some high schools then grant high school credit to those who pass with a high enough score.

Offering more advanced placement credits in their degree programs to those with AP will reduce university tuition revenues, but it is difficult to see how they can stop the practice—as competitors who continue it will be correctly seen as offering talented recruits a better deal.

(iv) Cut-Rate Credits Some universities offer cut-rate credits for MOOC-based courses. The University of Alberta led with a MOOC in dinosaur studies—one of its strongest areas. Students who take the MOOC version instead of the face-to-face version pay only half of the tuition fee (Coughlan 2013).

(v) Course Waivers for Certificates Some universities now accept MOOC certificates as *course waivers*. Temple University's business school now offers the first three foundation courses in its business school as MOOCs (Lausch 2013). Students who complete the MOOCs and pass the final exams "pass out of" these courses and can thus take three additional courses for the regular total tuition cost. While this does not reduce tuition costs for students, it does provide three additional advanced courses—almost a complete additional semester—for the same tuition price tag as its regular program. Students get a more powerful education—and one more relevant to employer requirements—without paying more.

MOOCs Can Improve Instructional Effectiveness

Three of the important lessons learned in 2013, the *année miserable* for MOOCs, were that many less academically prepared students cannot learn college-level material successfully from MOOCs (the Udacity Pivot), that effective use of video (replacing talking heads with animations, on-location shoots, interviews, and demonstrations) introduces a "new" visual language of instruction that is both effective and welcomed by learners, and that learning is social—students who learn together in flipped classrooms or learning hubs do much better than isolated MOOC learners. How can these lessons help us make MOOC instruction effective and at the same time improve conventional classroom instruction at the same time?

(i) Better Precollege Preparation for University Studies Udacity's highly visible flop at San Jose State with less prepared students brought a lot of attention in the MOOC community to improving college readiness for these learners. Underprepared students pay dearly when they flounder in college in several ways: by failing to complete and thus foregoing the benefits of a diploma while undergoing unsustainable debt, or by extending their years of study—and their total tuition expenditures. Improving their readiness for university study would alleviate some of these burdens. Doing so is equally important for universities; they lose tuition dollars when they fail to retain such students through graduation. So how can MOOCs help?

College Prep Subject-Matter MOOCs First, some MOOCs offer supplemental materials for conventional secondary-level subject-matter courses needed for college success. A good example is the "College Readiness Math MOOC" offered by the University of Wisconsin at Lacrosse (University of Wisconsin LaCrosse 2012).

College Orientation MOOCs Shortly after Udacity's San Jose debacle, several MOOC platforms introduced MOOCs designed to orient incoming college students—especially those from less advantaged families lacking previous college experience. Some good examples of this genre include East Anglia University's course "Preparing for Uni" MOOC on the FutureLearn platform, and Charles Sturt University's "What's Uni Like?" MOOC. According to Professor Garry Marchant, Charles Sturt's Deputy Vice Provost, "The 'What's Uni Like?'" project aims to encourage students from low SES backgrounds to aspire to higher education and to improve their understanding of university culture and expectations in order to support their effective participation (Charles Sturt University 2014).

(ii) Backup MOOCs for Conventional College Courses Courses offered face to face in conventional college classrooms, of necessity, are aimed at the middle ability-level students in that class. The highest level students get held back—leading to boredom—while the lowest level students get by-passed, leading to frustration and failure. Back-up MOOCs have effectively addressed this problem by allowing students to view lectures and take practice tests as often as needed to master course material. Meanwhile, MOOCs offering advanced content for extra credit can keep the most academically talented moving ahead.

(iii) Blended Learning in Flipped and Wrapped Classrooms Face-to-Face courses using MOOCs in place of classroom lectures can devote more time to supervised discussion and problem-solving.

Khosrow Ghadiri, a professor of electrical engineering at San Jose State University, piloted a flipped classroom model for his course on circuit design. The goal was to enrich the content and increase the pass rate for this daunting course. The pass rates in the blended pilot rose to 91%, as compared to a 59% pass rate in the previous year's face-to-face lecture class. The evaluation study concluded that "high quality MOOC content using a blended approach in conjunction with a highly structured in-class team-based approach can produce significant benefits in transforming student learning and success" (Ghadiri et al. n.d.).

A variation on the flipped course is the *wrapped* course, where instructors offer a period (perhaps a week) of conventional F2F introductory classes, then use MOOCs for course content with weekly F2F sessions for discussion and problem-solving, and conclude with a period (perhaps another week or two) for summary discussions and exam preparation. The wrapped course has a good division of labor between live and MOOC instruction, with each component used for its highest value function.

(iv) Video as a "New Visual Language of Instruction" One of the largest complaints about conventional college education is its reliance on large lecture classes in which a "sage on the stage" delivers impersonal content to hundreds of students. Some early MOOCs did little more than scale up this kind of teaching, replacing "sages on the stage" with "talking heads" on the screen. But other early MOOCs, such as the Greek Heroes MOOC from Harvard X, made effective use of video to replace the professorial talking head. Students viewed performances of Greek tragedies, joined virtual guided tours of Greek cities and museums, and watched interviews with the leading experts (Haber 2014).

Another good example is the popular "Lean Launchpad MOOC" taught by Stanford professor Steve Blank on the Udacity platform. The first iteration of this MOOC was created by taking Blank's classroom lectures and slicing and dicing them into six-minute segments—the length that research showed to be optimal for student attention. This approach was unsatisfactory—students found it boring. The MOOC was recreated with visually engaging animations of the concepts and processes presented, with Blank providing a voice over. The second iteration has proven immensely popular (Udacity n.d.).

Jonathan Haber, a scholar who took forty MOOCs in one year as part of his study of MOOC learning, concluded that MOOCs have generated a "new visual language of learning". Subsequent research has shown that this language is both considerably more engaging than conventional lectures and better at prompting sustained learning (Haber 2014).

(v) Increasing Social Interaction Early MOOCs failed to engage isolated, online learners because learning is greatly enhanced when it is placed in a social context. As noted, the discussion boards could not provide a substitute for either classroom discussions (not that adequate time is set aside for discussions in large lecture courses) or student bull sessions.

MOOC leaders responded by adding additional social dimensions to MOOC learning. We have already mentioned the use of MOOCs in blended learning in flipped classrooms, to facilitate discussion and group problem-solving. Here are some other promising examples: Coursera has established face-to-face MOOC learning hubs in a number of cities. The city of Boston partnered with edX to create "Boston x" a program to establish MOOC learning centers throughout the city (Fox 2013), a practice that has been copied by a few other cities. EdX has also partnered with the New York Public Library system to create MOOC learning centers at two or more branch libraries in each of New York's boroughs—making MOOC learning groups readily accessible for learners throughout the city (Enis 2014).

Finally, through the use of social media sites such as Facebook, Twitter, and LinkedIn, MOOC learners and community volunteers are organizing informal MOOC learning hubs in coffee houses, pubs, and libraries. This trend is sometimes referred to as "Starbucks University".

MOOCs Can Help to Add High-Value (Twenty-first Century) Experiences

In preparing this chapter I examined several lists of so-called twenty-first-century skills, and discovered significant overlap. What are called twenty-first-century skills are just those skills and attitudes most desired by employers in the contingent workplace—skills for obtaining and performing "gigs": Technical Capability, Entrepreneurship, Marketing, Networking, Initiative, Self-Management, Listening, Amiability, Flexibility, and Collaboration—skills needed to market freelance services and perform in short-term jobs. These skills are not the focus of the received, conventional college curriculum. When employers complain that college graduates are unprepared for the contemporary workplace, they have a point—changes in the workplace have made the college curriculum less relevant, and the expectations for professional careers bred by college life less appropriate.

(i) High-Tech, Entrepreneurship, Team-Building and Collaboration Skills MOOCs exist in abundance to address every twenty-first-century skill. It goes without saying that many MOOCs address computer programming languages and high-tech basics. I've already mentioned Steve Blank's "Lean Launchpad MOOC" on Udacity, providing step-by-step guidance for entrepreneurs creating start-up firms (Empson 2013). Other "startup" MOOCs, moreover, can be found on most MOOC platforms.

At Harvard Business School, Professor Regina Herzlinger uses the software package Project Lever, which she developed with a colleague, to link students in her "Innovating in Health Care" MOOC on edX with those with complementary interests and capabilities, in virtual working groups with virtual advisors. The students meet up through video-conferencing to form innovative business projects. Project Lever has been described as the "e-harmony for business groups" (Choi 2014).

Some MOOCs transform their inchoate massive learner cohorts into large working teams. Cathy Davidson, a leader in interdisciplinary humanities formerly located at Duke University in North Carolina and now at the City University of New York, offered a noticeable and much-discussed MOOC on the "History and Future of (Mostly) Higher Education" in early 2014 on the Coursera platform. In this MOOC, as Davidson (2013) explained, each learner would be assigned to conduct research on a niche historical or contemporary topic in higher education. In the event, one group of learners studied early colleges in their regions. Another looked into new initiatives in today's universities. In the final project, the massive group, working as a whole through social media, assembled a comprehensive document and global map of higher education and published it on Davidson's project website. Meanwhile, the students in Davidson's simultaneous face-to-face section of the course at Duke networked with students in other course sections offered simultaneously at other elite universities and served as course leaders for the MOOC participants. In the process, these students learned how to manage complex large group projects engaging temporary virtual members. One can quarrel with this arrangement as reproducing the hierarchical structure of managers and workers; the point here is simply that it introduces real-world social processes into MOOC experiences.

Other MOOCs focus on collaboration. Stanford University, which spawned both Udacity and Coursera, has introduced a new MOOC platform, NovoEd, focusing exclusively on innovation and collaboration (Corcoran 2013). Designed by Stanford professor Amin Saberi and Ph.D. student Farnaz Ronaghi, the NovoEd platform claims that it facilitates the division of massive learner cohorts into small collaborative working teams (Empson 2013).

(ii) MOOCs for Experience in the Real Economy Some MOOCs package all of these skills together by placing students in real-world virtual "gigs". The Business Strategy MOOC from the Darden School of Business at the University of Virginia employs the Coursolve software package to crowdsource small- and medium-sized businesses seeking free help in its strategic planning efforts from business students. In this MOOC, hundreds of firms sought assistance and thousands of MOOC student volunteers provided it. Through video-conferencing and other modalities, 73% of the student volunteers participated directly in strategic planning of these firms as "consultants".

Another example is Buck Goldstein's "Big Idea" MOOC from the University of North Carolina, also on the Coursera platform (University of North Carolina n.d.). In this MOOC learners can either take the lecture course or add a practicum in entrepreneurship. The students opting for the practicum are guided in creating a start-up firm and then competing for real venture capital. Those winning the competition are then funded and trained in a virtual business incubator run by Goldstein at the university. Unlike Blank's Udacity "Lean Launchpad" MOOC, which offers "ideas" about entrepreneurship, the "Big Idea" MOOC practicum engages students directly as entrepreneurs in the real economy.

The point here is hardly to glorify either the gig economy or the twenty-first-century skills that support it. Until recently, university students prepared for lifetime careers in professions, by digging deeply into real knowledge. Those days are mostly over. Some twenty-first-century skills and attitudes are superficial—like the amiable smile on the face of the McDonald's associate asking whether you want fries with that Big Mac; or soul-destroying—like the skill of networking with people to use them or marketing worthless goods and services to vulnerable people. Some, however, can be beneficial. MOOCs may be better positioned than slow moving conventional university programs to develop them—and thus add to the value proposition of advanced education.

Contribution 2: Revenue

While MOOCs are often touted as tools for reducing student costs, their most important contribution may in the end be enhancing university revenues by attracting tuition-paying students, government and corporate grants, and private donations. In this section, I consider three ways that MOOCs can contribute to the revenue side of the higher education equation. First, MOOCs offer a relatively inexpensive tool for positioning and niche marketing of universities and their specialized educational programs. Second, MOOCs can be instruments for profitable special projects. Finally, MOOCs can be used as tools for retraining and reorienting faculty members to make them more economically productive in current circumstances.

MOOCs Can Help with Positioning and Niche Marketing

(i) Positioning Universities are caught up in the reputation game. They are subject to ranking by *U.S. News and World Report*, among others, to which tuition-paying students and their counselors attend. Universities thus need to *position* themselves to preserve and extend their reputations to tap into both tuition revenues from lucrative domestic and overseas markets and to acquire the best and the brightest students, (2) to obtain government and corporate grants, and (3) to get generous donations from alumni.

By "positioning" I mean situating an organization in its competitive landscape in a way that makes it visible and thus "well positioned" both to attract unpredictable opportunities and to market goods and services. Positioning is about broad market visibility and differentiation in a shifting competitive landscape. It prepares the organization to make specific marketing offers.

The term was first used in the business literature by Jack Trout (1969). Trout argued that in such landscapes consumers and other revenue sources are overwhelmed and develop a defensive posture toward any information not already possessing a comfortable place in their minds. Positioning establishes such a place, and thus renders prospective revenue sources deaf to competitors' communications. As co-author Al Ries and Trout (1981) put it, positioning is "an organized system for finding a window in the mind" (p.19). Positioning differentiates the organization as the best, or the first or the fastest, or the least expensive.

We can view MOOCs as positioning efforts intended to create revenue streams through reputation management. With edX, MIT and Harvard positioned themselves as MOOC *pioneers*—further cementing their reputation for innovation and excellence. Stanford did likewise with Udacity and Coursera, both based on in-house Stanford software. Other prestigious universities jumped on board to prevent being eclipsed by these leaders. EdX and Coursera rapidly acquired the most visible and highest ranked universities globally as partners and positioned themselves as *dominant*. With their MOOCs, Wharton and Johns Hopkins positioned themselves globally as top business and health sciences schools, respectively. UK, Europe, Australia and Asia, sensing that they were losing out to the United States, established competitor platforms, the most successful of which were soon dubbed the "Coursera" or the "EdX" of their respective regions. The UK entry, FutureLearn, was created explicitly to sell the concept that UK is the world leader in higher education; FutureLearn's failure to recruit Oxford and Cambridge as partners, however, undercut that effort. Other regional platforms are competing on specialized knowledge and unique relevance to regional needs.

Karl Ulrich, Vice Dean of Innovation, Wharton, and Christian Terwiesch, Wharton Research Professor, conducted a cost/benefit analysis of MOOCs. They concluded that relative to any other form of global positioning, MOOCs are very cheap. In a recent interview (University of Pennsylvania, 2014), Terwiesch stated:

> We, elite universities are in the business of creating a reputation. Reputation will drive our demand; it will drive how our graduates are viewed in the market.
>
> How do you create reputation? The traditional vehicle of reputation building was research. It takes us somewhere around \$300,000 to \$400,000 of research investments to just get one scholarly article out.
>
> For that money, for one single paper, we can basically create somewhere around three, four, or five MOOCs…

Ulrich added:

> MOOCs are actually not very expensive. MOOCs cost about \$70,000, but we reach with a MOOC several hundred thousand students. If you look at it on a per viewer basis — it runs to about 50 cents per person. That's cheaper than almost any other form of outreach. Fifty cents for that kind of engagement is very, very inexpensive.

(ii) Niche Marketing Few universities in the world can compete with MIT, Harvard, Stanford, Wharton, Hopkins, Oxford, Cambridge, etc. for general reputation. But the higher education landscape is littered with niche programs that can claim comparable visibility and authority in their narrow fields. And these organizations have also rapidly moved into MOOC production as they seek to solidify their reputations globally.

Some examples include the Berklee College of Music in Boston, a school specializing in jazz and pop music; the Writers Workshop at the University of Iowa, the top US writing workshop; HEC Paris's program in French Language Business Management; and many others. All of these have been early leaders with MOOCs in their specialties.

Many less visible organizations have also produced MOOCs to call attention to their special curricula: for example, Southern Mississippi State University's Faulkner Studies program.

A “me too” attitude, however, cannot position a university and must be avoided. Southern Birmingham University, for example, offered a “History of Terrorism” MOOC in Spring 2014 on CourseSites by Blackboard—a platform any university with a Blackboard contract can use. The “school is hoping to show the rest of the world that its faculty members are true ‘All Stars’ in their fields,” according to its press release (Canning 2014). Professor Randall Law, the course leader, is no doubt a fine scholar—the press release notes his recent book published by an academic press—but that does not differentiate the university sufficiently to draw even regional students to its programs. In the United States, given the glut of doctoral graduates from leading universities, talented and well-trained professors visible in their specialized fields can be found just about everywhere.

Another caveat: MOOCs are proliferating exponentially and like new blogs, new MOOC platforms and courses have to compete for a MOOC audience whose rate of growth is slowing. Each new entry will have to be calibrated carefully to its potential markets. Even Harvard—yes HARVARD—can no longer count on “massive” audiences for its MOOCs. Lisa New, who teaches poetry MOOCs on HarvardX, chose to record videos of the Harvard men’s basketball team reading poems, and post them on popular sports websites, to beef up her numbers (Bernhard and Rothberg 2014).

Many opportunities lie in wait, however, for programs that *can* differentiate themselves by virtue of high-need specialized knowledge or training programs.

MOOCs Can Help with Special Projects

There are several kinds of MOOC-related revenue-enhancing special projects. I will consider four: Special MOOC-based degree programs, Media-Tie-Ins with Super-Star Professors, Government-Sponsored Economic Development Projects and Corporate Partnerships. I will provide an example of each.

(i) Special Degree Programs MOOCs have been used as course components of new university degree programs sponsored by external organizations and aimed at providing high quality job-specific training at greatly reduced cost.

The best known MOOC-based degree program is Georgia Tech's Master's Degree Program in Computer Science on the Udacity platform. Georgia Tech provided the expert faculty, Udacity the expertise in educational technology and course management, and AT&T—which needed a ready source of engineers with industry-specific knowledge—$2 million in funding and two/thirds of the first cohort—230 students. It also plans to employ many of the program's graduates (Georgia Tech 2014). Some prominent leaders in India's education sector see the Georgia Tech program as a model for the global south, because of the large gap between growth opportunities and workers with job-ready skills in these nations (Jain and Balasubramaniam 2014).

Many similar opportunities present themselves. Employers unceasingly claim that they cannot find employees with job-ready skills. In the gig economy firms are not going to provide preparatory training, but they may sponsor MOOC-based programs they can shape to their own needs.

(ii) Super-Star Professors with Media Tie-Ins Many universities have distinguished and media savvy faculty who can draw grant funding from government agencies or private foundations to produce engaging courses for mass audiences.

Larry Sabato, a professor at the University of Virginia Center for Politics, is a leading expert on the Kennedys. As the US Royal family, the Kennedys get unending media attention. Sabato made a Kennedy MOOC entitled "The Kennedy Half Century"—with tie-ins including a PBS Documentary, a book deal, and a major foundation funding. In addition to enhanced visibility, the MOOC project was profitable for the university. A previous Sabato documentary had won an Emmy—television's top award (University of Virginia Center for Politics 2013). At Columbia University in New York, super-star professor Eric Foner has produced a MOOC on the Civil War and the Reconstruction Era in the United States. Foner, a Pulitzer prize winner who makes frequent television appearances, is aware that many of Columbia University's most famous lecturers from Lionel Trilling and Meyer Shapiro to Jacques Barzun were never filmed, wants to preserve his legacy by getting his lecture courses on video for future generations (Colman 2014).

(iii) Government-Sponsored National Development Projects Governments and government-funded agencies around the world draw on their universities to achieve National goals.

The British Council has partnered with UK's Open University and the FutureLearn MOOC platform to produce "the world's largest English class" (British Council n.d.). The Council, an independent agency funded by the UK government's Foreign and Commonwealth Office, was founded prior to World War II to engage in "cultural propaganda" to promote British interests globally by offering instruction in the English language and British culture. The Council's English language MOOC has enrolled more than 20,000 students (FutureLearn 2015).

GCHQ, the British Spy Service, has produced a MOOC on Cybersecurity. The service is eager to build a strong base of cybersecurity skills throughout the population and to encourage young people to consider careers as spies (Pinsent Masons 2014).

Singapore's Infocomm Development Authority is depending on MOOCs to achieve the national goal of making Singapore a "Smart Nation and a global leader in "'big data" (Yu 2014). The "Smart Nation initiative" aims to improve government, business and the lives of ordinary citizens. Singapore has developed a suite of Big Data MOOCs for university students and knowledge workers, to spread Big Data Analytics skills throughout the nation (Prime Minister's Office Singapore (n.d.).

Many opportunities exist on national, regional, and global levels for similar uses of MOOCs. If nations want to "position" themselves by educating large fragments of their populations in specialized areas of national or global need, MOOCs—with their unlimited cohort sizes—are ideal vehicles.

(iv) Corporate MOOC Partnerships A notable MOOC trend after 2013 is a shift away from college student audiences. MOOC production has also spread from universities to business firms, government agencies, and non-governmental organizations. Some corporate MOOCs have been produced without university partners, while others have relied directly on university resources.

SAP, a multinational software firm in Germany that has been an early a leader in corporate MOOCs, relies on its suite of software MOOCs to train employees and outside contractors, to educate clients and supply chains in order to fuel demand, and to position themselves in the global marketplace. SAP has turned to MOOCs because of their broad reach and relatively low cost (Open SAP n.d.).

M&S, a large British retailer, offers a Futurelearn MOOC through a partnership with the University of Leeds on innovation is business (Education News 2014). Like all corporations, M&S has a large inventory of documents and training materials that can be repurposed for broad educational use. Corporations lack internal resources for designing engaging courses for general audiences. Like M&S, they can partner with universities to produce MOOCs that will provide visibility and goodwill for both.

Universities and corporations can find many other opportunities for partnerships where corporations shape content while universities provide underlying research and course production.

MOOCs Can Help Universities in Faculty Reorientation and Retraining Efforts

Earlier, I spoke of the changing occupational order, the shift from the job economy to the "gig" economy—to what Daniel Pink calls "Free Agent Nation" (Pink 2001). I suggested that we can gain some leverage on the otherwise empty phrase "21st Century Skills" by conceiving them as the skills and attitudes needed for adjustment to the gig economy—of contingent workers on temporary teams—often as "consultants" without benefits—marketing their services as entrepreneurs, collaborating with people they hardly know on unpredicted tasks requiring flexibility and adaptability.

The gig economy has already impacted the university. Adjuncts and temps bear an ever-increasing share of the teaching load. Departments and programs close as tuition and research revenues contract. Professors are corralled in composite units—holding areas for several disciplines and fields. They are increasingly pressured to cut costs and generate revenues by functioning as "project shops" like consulting firms—hustling for money by doing whatever the client will pay for. These short-term extra-academic projects often require interdisciplinary teams, and professors are discovering that their disciplinary knowledge and skill are either inadequate or thoroughly irrelevant. Faculty members are, like all other workers, adjusting to the gig economy and need some twenty-first-century-skills of their own.

Making and using MOOCs can help, by placing faculty in situations calling forth these new capabilities. To make a MOOC—or to use a MOOC in a blended classroom—requires imagination and a willingness to experiment with new modes of behavior. MOOCs shaped by new research on learning (e.g. the six-minute rule) or using the new visual language of instruction, or forging close connections with real-world learning opportunities, are gradually establishing new standards and expectation for organizing and presenting instruction in face-to-face settings.

While most faculty members retain negative attitudes about online learning experiences and especially about MOOCs, those who have produced them are largely positive. According to *Inside Higher Ed's* survey of 2251 professors' attitudes about technology, conducted by Gallup, only one in five think online courses can achieve learning outcomes equivalent to those of in-person courses. But appreciation for the quality and effectiveness of online learning grows with instructors' experiences with it. Of those with MOOC experience, 50% agree or strongly agree that online courses in their own department or discipline produce equivalent learning outcomes to in-person courses, compared to just 13% of professors who have not taught online (Lederman and Jaschik 2013).

Making a MOOC is like producing a movie and this can be challenging and invigorating. Faculty "stars' have to relate to many other professionals: writers and editors, designers, videographers, journalists, and other media professionals, as well as faculty from other "silos." They also have to adjust to new teaching environments—media studios on campus or off.

Some universities are explicitly using MOOCs to generate twenty-first-century faculty skills. Johns Hopkins University, which has positioned itself as the leader in health and medicine, is using its MOOCs to bring faculty together from every college in the university. The University of Pittsburgh is using MOOCs and blended classrooms explicitly to move its faculty toward learning how to use technology to enhance learning. The University of Georgia System has produced a MOOC for faculty and other members of the university community to brainstorm together about the future of the university. The university's officers present content about current trends and uncertainties in higher education and university stakeholders think collaboratively about future possibilities. The goal of the MOOC is to call attention away from the urgent crisis of today and toward collective positive visions the community may realize by 2030 (Raths 2014). At the University of Pennsylvania, faculty members have been recruited to offer a blended course for high school students based on Penn Prof. Peter Struck's MOOC on Greek and Roman mythology. One goal of the program is to make faculty members aware of the creative possibilities of online education.

New opportunities in the lucrative online education and training industry open up once these tech skills are broadly distributed throughout the faculty. MOOCs and blended classrooms are the training grounds for revenue generating research and consulting projects for elementary and high schools, 2- and 4-year colleges, government agencies, and corporations—where online learning is trimming millions of dollars from training budgets. I expect universities to compete more aggressively in the online education and training industry; if they do not, firms like Udacity will "eat their lunch."

Contribution 3: The Higher Education 2.0 Revolution

From Jobs to "Gigs"

I now want to carry the discussion beyond the entrenched paradigm—to Higher Education 2.0. Today's higher education paradigm came into existence in both the United States and Great Britain only in the late 1870s—rather late in the industrial period—when the scale of production, distribution, and administration reached continental and global scale and organizations needed a large and steady flow of technical and commercial workers with a standard level of knowledge and skill to perform standard professional tasks. A new paradigm of university education as professional training emerged. Even scholarship was reconceived as a scientific profession requiring a Ph. D.

Once a sufficient number of college graduates were available, organizations could adopt the college diploma as a filter for professional employment. Universities produced more and more graduates, and more occupations were redefined as "professions" requiring a diploma. Aspiring young people *had* to go to college. In the developed world today, as a result, a large fragment of the youth cohort has diplomas.

The employment of professionals is, however, costly to organizations. Those identifying themselves as professionals demand high wages, professional discretion, job security, and benefits. Firms have to keep their full-time employees occupied even when they have no tasks demanding their highest value professional skills—even when outsiders can perform these tasks more efficiently at lower cost. Firms bear these costs because the alternative is continually to acquire capabilities in labor markets. The transaction costs of hiring on that basis out-strip the costs of steady employment.

The World Wide Web, however, has changed this equation. Firms can now find highly skilled workers through social networks, with or without diplomas—and hire them to join their firms' work teams on limited contracts for particular projects, and then get them out the door as soon as those projects are completed. Because of the greatly reduced transaction costs of bringing workers on board, firms no longer have to pay a premium of higher wages or steady work or benefits (Shirky 2008). And because of the increased costs of keeping workers occupied—paying high wages and benefits even when the workload is light—firms will avoid long-term employment contracts whenever they can.

Lou Gellos of Microsoft explains why his firm makes such extensive use of contract workers: they do only the part of the project where their capabilities are needed. "They're experts at it. Boom boom, they're finished." Maynard Wells, a former COO at e-bay who now runs the labor services firm Live Ops, stated the primary advantage of contract workers to firms: "You have access to the talent you need. And when the need is gone, the talent disappears" (Coy 2010). That is why "gigs" are replacing "jobs. "

A New Vision

Middle-class incomes are stagnant or falling. The concept of investing in college to gain steady professional employment with decent wages, job security, and benefits is no longer valid. The situation is thus ripe for a new vision of higher education in tune with contemporary realities. Here I want to outline such a vision.

Many free or inexpensive learning opportunities have always been available. These opportunities become devalued, however, when diplomas are used as job filters—a prime cause of inequality in modern societies. The rich have more opportunities for formal education and get richer; the poor get trapped in a catch-up game, and by the time their cohorts get their diplomas, at great cost, the payoffs are meager. This is what Thomas F. Green (1980) called "the law of last entry"—those groups that arrive later at any level of the system get fewer benefits, and those who arrive last get little or nothing because their diplomas differentiate them from nobody.

Today it is possible to acquire personally meaningful, knowledge and many high demand capabilities online for free. Online learners can also make themselves and their capabilities known online for free, and firms can find them. Employers hiring workers do not need to concern themselves with the standard knowledge represented by university diplomas because they are not making long-term commitments. All they need are ready capabilities for the tasks immediately at hand.

MOOCs contribute to the knowledge and skill mix by providing courses with certificates or badges upon completion. These can all be bundled with other forms of documentation in searchable digital portfolios. The portfolios can also contain goal statements, papers, and reports produced during academic coursework or self-directed study or work projects; statements of specific capabilities claimed, multimedia presentations demonstrating possession of those capabilities, reference letters from teachers, and prior employers and coworkers—especially coworkers who have worked at targeted firms. These forms of documentation are already engendering new forms of low cost higher education. Here are three interesting examples:

First, the NGO Enfants du Mekong in Cambodia finds impoverished students with high academic potential and brings them to its Centre Docteur Christophe Mérieux in Tuol Kork, where they receive housing, educational, and financial support while they attend the local university. Starting in 2014 their studies are augmented with MOOCs. The center's director says that the MOOC format is "exactly what we need" (Murray 2014). Some students are using MOOCs to prepare for exams to obtain competency-based degrees. Others are relying on MOOC certificates for courses not available in their universities. Grant Knuckey, Chief Executive of ANZ Royal Bank in Cambodia, says his company may consider MOOC certificates in hiring decisions if they grow more common in the Kingdom. Like college diplomas at the end of the ninteenth century, MOOC certificates have to reach a critical mass before they can be institutionalized as qualifications. Knuckley notes that MOOCs are becoming "increasingly sophisticated and relevant and cannot be ignored," and adds that firms in the United States and Australia are beginning to take them seriously (Murray 2014).

Second, many nations in Africa and Latin America suffer from underdeveloped educational infrastructure at both secondary and post-secondary levels. Thus, as these nations are brought into the global economy through increased foreign investment, firms cannot find enough capable young people to meet their labor needs. In response, ALISON—the very first MOOC platform—is filling this need with basic short courses with "badges" for completion. ALISON focuses on high-need subjects—basic math, bookkeeping and accounting, marketing, foreign languages, and many others. But academic courses are also offered on the platform.

ALISON MOOCs are shorter than typical MOOCs from Coursera or edX, but ALISON offers them in sequences that culminate in a "diploma" involving more hours of study than a typical MOOC. In Africa, where there are not enough secondary school and university graduates, employers are already recognizing ALISON's MOOCs as qualifications. ALISON shows that young people can obtain a useful education without passing through a compulsory curriculum.

Finally, Udacity has developed MOOC-based "nanodiplomas" to break higher education up into short, low-cost stages. Upon leaving high school, young people may start with a one year "nanodiploma" course to obtain an entry-level qualification. In their early working years, they may then focus on suitable areas for further study based on experiences and goals, and take additional "nanodiploma" courses to qualify for more advanced positions. This pathway with its nanostepping stones by-passes the use of college diplomas as job filters. It also provides a sensible alternative to the time-consuming, frustrating and expensive search for self in college through repeated failures and changing majors. Coursera and edX have offered their own versions of nanodegrees. Coursera Specializations are sequences of MOOCs in high-demand fields. The website states: "You'll complete a series of rigorous courses, tackle hands-on projects based on real business challenges, and earn a Specialization Certificate to share with your professional network and potential employers."[3] EdX offers "XSeries" programs in similar fields. The pitch on the XSeries website: "Created by world-renowned experts and top universities, XSeries programs provide a deep understanding of exciting and in-demand fields. Earn a certificate of achievement to demonstrate your knowledge."[4]

Mainstream universities are tracking this development closely. A recent article in *Inside Higher Education* states that colleges are now using badges to help students display skills and accomplishments not captured by transcripts. The badges are public credentials designed to assist students to position themselves in the job market. A 2016 survey showed that 20% of college-level institutions have started issuing digital badges, which their students and graduates can place on badge platforms where potential employers can readily find them (Fain 2016). In 2015 Georgetown University made headlines as the first highly prestigious private university to jump on the badging bandwagon; Georgetown joined George Mason

[3] https://blog.coursera.org/about/
[4] https://www.edx.org/xseries

University, University of Maryland Baltimore County, The University of Baltimore and other regional institutions in a badging cohort (Anderson 2015). University-based badge programs appeal to both undergraduates positioning themselves for entry-level opportunities and seasoned professionals with advanced degrees seeking to demonstrate cutting-edge knowledge. The purpose of university badging efforts, says David Schejbal, dean of continuing education at the University of Wisconsin-Extension, is "to create a structure of alternative credentials that students could acquire relatively quickly and inexpensively that will also be immediately useful from an employment perspective" (Zalaznick 2015).

The university-based badging effort may be seen as a defensive maneuver, an attempt to catch up with non-university micro-credentials providers such as the MOOC platforms and Udacity. It is a reflection of the changing occupational structure—the gig economy. As firms shift from full-time "professional workers" to short-term, low obligation contract workers, they search for those who can perform specific tasks at high competence levels without further training. In the process, university degrees and transcripts become less important, searchable credentials of capabilities essential. This has created pressure to break apart or rearrange the elements of a college education. The established pattern includes a two-year program of general education in the liberal arts and sciences followed by a pre-professional or technical major.

Learners now have many opportunities to acquire and demonstrate technical and professional-level *skills*. Nonetheless, the defining features of professional leaders have not changed in the information era. Leaders still have to think conceptually, critically, and strategically, see the big picture, solve unstructured problems creatively, read widely across disciplines and professional fields, and communicate with peers from many professional and cultural backgrounds. No badge or agglomeration of badges is likely to rival a residential university degree program with a serious liberal arts component any time soon.

The expectation that a worker would possess a college degree is of recent origin. As recently as 1950, only one out of three in the United States possessed a high school diploma, the mark of an educated elite. By 2000, that number reached 80%, which, given differences in circumstances and abilities, may approach the upper limit. While just 5% of the adult population had earned a bachelor's degree in 1940, 25% had earned one by 2000 (US Census 2000), a number that kept increasing until 2011. The huge jump from 10% to 25% in the two decades from 1980 to 2000 can be accounted for by de-industrialization and the disappearance of jobs with middle-class wages, job security, and benefits for high school graduates. Young people from working-class families flocked to colleges not because of a sudden yearning for higher learning, but because they came to believe that if you wanted a decent job you had to go to college. Today's cohorts of 18–21-year olds, however, understand that college is no longer a ticket to a decent job, and are seeking alternatives.

These trends pressure for a new pattern for post-secondary education, with MOOC-like experiences before, during, and after university matriculation.

A significant fraction of high school graduates may seek badges (or similar credentials) connecting them rapidly and inexpensively to entry-level employment before college—or after dropping out due to academic, financial, or family difficulties. Once connected to the workforce, these learners can further their education through on-the-job training, self-directed learning, structured MOOC-like badge programs facilitating "badge stacking," or university degree programs.

Universities, having lost their near monopoly in post-secondary education, now compete with MOOC providers at the entry level, but retain their advantage in education for leadership roles. This suggests that we may see a new kind of technical and pre-professional emphasis earlier in the college curriculum, followed by a new kind of liberal arts and science education—geared for older students with greater maturity and workplace experience—later in the college curriculum sequence. Advanced training combining liberal and technical arts may then take shape in graduate programs leading to advanced degrees.

The period after college and graduate school is now characterized by employment turbulence due to mergers, outsourcing, digitization, and obsolescence. Even the best-educated professionals may need to retool from time to time with cutting-edge skills. Those with advanced degrees are likely to find cost-effective MOOC-like badge programs more appealing than additional campus-based advanced degrees.

Conclusion

MOOCs burst upon the higher education scene eight years ago, in response to rising college tuition and declining employment prospects for college graduates. MOOC founders promised to solve these problems by offering free or low-cost college-level courses from leading universities with certificates of completion. The initial MOOCs suffered from a number of technical problems, which have to some extent been resolved. They also failed to attract much attention from college-age students, because contrary to the expectations of the founders, the certificates of completion have not been widely accepted for college transfer credit.

Nevertheless, MOOCs have helped to improve the "value-proposition" of college in several unexpected ways. They have: reduced total tuition costs for some by providing educational backup for advanced placement and competency-based examinations for college credit; improved instructional effectiveness through new video-enhanced instructional methods and flipped or blended courses; and added to the dollar value of college by introducing new twenty-first-century skills into the curriculum. MOOCs have also helped to support the revenues of colleges and universities through low cost, externally subsidized MOOC-based degree programs and corporate partnerships.

The biggest contribution of MOOCs, however, will be derived from MOOC-like training programs leading to public credentials—badges—in high-demand technical and professional fields. Such programs offer a low-cost alternative to college for young learners—especially from working-class families—seeking entry-level positions. These programs focus narrowly on the skills needed for high-demand fields and are often produced in association with firms seeking such workers. MOOCs also offer seasoned professionals with advanced degrees a way of retooling without taking on the burdens associated with additional advanced degrees.

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CHAPTER 11

Just Posting in the Same Place: Confronting the Paucity of Collaborative Behavior in US K-12 Wikis

Justin Reich

Introduction

Wiki adoption has grown incredibly quickly over the last decade in primary, secondary, and tertiary institutions throughout the world. In a recent National Center for Education Statistics survey, 38% of public school teachers reported using blogs or wikis for class preparation and administration, and 21% of teachers reported requiring students to contribute to these online environments (Gray et al. 2010). As these platforms have grown in popularity, educational researchers have contested the utility and promise of wikis as collaborative learning environments, where students are immersed in communities of practice (Wenger 1998) engaged in knowledge-building practices (Scardamalia and Bereiter 2006). Much of this literature—design research, case studies, and theoretical

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O. O. Adesope, A. G. Rud (eds.), *Contemporary Technologies in Education*, https://doi.org/10.1007/978-3-319-89680-9_11

development—has been derived from the investigation of individual classroom environments, even though one of the signature characteristics of wikis is that they can be published openly to the world.

To contribute to the debate over the viability of wikis in typical educational settings, I examined a large, representative, and diverse sample of wikis created in US K-12 classrooms. From analyzing these wikis, I developed a taxonomy of collaborative behaviors found on classroom wikis, and then measured the distribution of these collaborative behaviors in a sample of 406 wikis drawn from a population of nearly 200,000 wikis. I situate these findings in the context of the lack of collaboration in other peer-production environments used within and beyond education. One of the signature challenges for advocates of technology-mediated collaborative learning must be to confront the paucity of collaborative behaviors found in peer-production platforms used in typical educational settings.

Contested Views of the Possibilities of Wikis

Glassman and Kang (2011) argue for an optimistic view of wikis in the classroom, where wikis provide affordances that allow for the fulfillment of a progressive educational vision devised by John Dewey nearly a century ago. They argue that Dewey, Charles Peirce, and other pragmatists developed a system of logics known as abduction, as an alternative to the well-known logics of deduction and induction. Rather than following first principles or inferring directly from data, abduction calls for developing a series of hypotheses to be tested through scientific experiment. Glassman and Kang argue that Dewey's pedagogical efforts were an attempt to infuse this "logic of discovery" into educational settings, and Dewey failed in his time, at least in part, because he lacked the technology to implement a "democratic classroom" where students have a meaningful voice in hypothesis generation. For Glassman and Kang, wikis provide a technological foundation that allows education to shift from the practice of transmitting known facts to the practice of generating and testing hypotheses. They argue that wikis allow Dewey's vision to finally be realized: "Wiki technology may fit the promise of Web 2.0 in education more than any other technology. It fosters integrated problem solving, and advanced understanding of the fungible nature of information and cooperation" (lines 703–5). They describe this moment in history as a "cusp of a revolution in education" where new technologies allow a fundamental shift in learning practices.

In contrast, Dohn (2009) argues that the attractive affordances of wikis are systematically undermined by the educational imperative to grade and rank students individually. Dohn further argues that Web 2.0 activities—which involve sharing, co-constructing, and publishing for a wider audience—operate under a participationist metaphor that appears to be fundamentally at odds with the accumulationist metaphor of schooling, where individual students are responsible for their own preparation and teachers assess and sort students as individuals. Dohn shares the view with Glassman and Kang that a pedagogy capitalizing on the affordances of wikis would be novel, powerful, and well-suited to an increasingly networked and interconnected world; however, Dohn argues that such a pedagogy is nearly impossible to implement in schools. Institutional imperatives for measuring individual achievement are one major hurdle, and even where these can be institutionally modified or neutralized, students still come to school acculturated to the norms of an environment that only measures individual competencies.

Glassman and Kang; Dohn can be positioned as two poles of thought on the pedagogical possibilities of wiki-integration. One emphasizes the transformative potential of wikis and the other emphasizes how institutional constraints of formal schooling restrict (perhaps necessarily) the capacity to use wikis in transformative, or even meaningfully collaborative, ways. Other case studies can then be located on this spectrum.

For instance, in the article "I DON'T CARE DO UR OWN PAGE," Grant (2009) examined the use of wikis in a grade 9 classroom in the UK. The class used a wiki platform to create collaborative presentations about the history of modern technologies. Grant found that classroom norms around the individual ownership of text powerfully constrained the collaborative potential of wikis. Since students were used to controlling their individual contributions and to being evaluated on these contributions, very few students approached the wiki project collaboratively and those that did were rebuffed, sometimes harshly. Even efforts at commenting on other students work tended to be no more than perfunctory. Ultimately, students used a divide and conquer approach, where each student individually produced discrete content which was then assembled into a "shared" product.

Forte and Bruckman (2009) offered a somewhat more promising case study from an AP science classroom. They also found that "institutional assessment regimes for both students and teachers inhibited collaboration" (p. 23) and that students used wikis primarily as sites of individual production. In the course of struggling to produce *ScienceOnline,* a wiki-based website for publishing science reports and articles, students developed a richer understanding of the "genre" of wiki writing. Participants became more aware of the norms of standard, individually produced school writing, and the norms of collaborative writing within peer-production systems. In other words, even if students could not overcome hurdles to collaboration or successfully produce work within the genre of collaboratively produced writing, they learned from the process of becoming aware of these norms and barriers.

In a third case, Pifaare and Staarman (2011) described a highly structured wiki project in an elementary classroom, where students wrote an opinion piece about the feasibility of developing a colony on Mars. Students first worked in pairs to develop initial positions. They then formed groups of six students and they used a wiki platform to negotiate the synthesis of all three positions and develop a final product. Pifaare and Staarman argued that students in the project actively discussed each other's positions and then jointly created a final product, and in doing so the students developed digital competencies needed for collaborative knowledge creation. As presented, the case appears to warrant some of Glassman and Kang's pedagogical optimism.

In all five wiki case studies cited above, broad agreement exists over the theoretical potential of wikis to support collaborative learning. All five articles argue that wikis provide a technologically robust platform for co-constructing knowledge, for developing collaboration skills, and for nurturing dialogue about the contested nature of knowledge. All five articles discuss the theory of knowledge-building from various papers by Scardamalia and Bereiter (2006), as a useful framework for examining the social constructivist practices enabled by wikis and attempted in their own case studies. Four of the five articles cite theories of situated learning (Lave and Wenger 1991) or communities of practice (Wenger 1998) as additional lenses through which wikis can be seen as technological enablers of established pedagogical frameworks of social learning. Broadly speaking, these articles share a vision of how wikis might help prepare students for a globally networked world, and the locus of debate—as highlighted by Dohn versus Glassman and Kang—is whether this vision can be realized in the structures of actual classrooms around the world. The three subsequent case studies represent various points along a spectrum of success in nurturing collaborative learning with wikis, and thus they provide evidence that might support both the optimist's and the pessimist's position on wikis. (I have chosen three case studies drawn from primary and secondary educational settings, and similar examples from higher education supporting the optimists' (Wichman and Rummel 2013) or pessimists' (Cole 2009) view on the potential of wikis can be found as well.)

One approach to testing the merits of the optimists' and pessimists' perspective toward wikis would be to continue to accumulate these kinds of case studies and attempt a meta-analysis or synthesis of these cases. Such an approach, however, has several important limitations. In the five cases cited above, the classrooms being studied were taught or assisted by a wiki researcher, and/or used a special researcher-designed curriculum, and/or used a special build of wiki software, such as a MediaWiki installation with a series of modifications. It is not clear how well findings from these "hothouses" generalize to the experiences of wiki-using classroom teachers without such supports. In addition, the cases are from classrooms in different countries, in different subject areas, serving different grades of students, from different cultural backgrounds. Such diversity provides a richness of examples to spark provocative thinking, but it presents challenges for systematic comparison. Thus, this debate can benefit from research employing methods that allow for evaluating patterns of activity across large, diverse, and representative samples of typical learning environments. Close examination of particular learning environments should be complemented by studies that can provide a wider view of the educational landscape.

Examining Wiki Practices at Scale

Part of the Glassman and Kang, and Dohn debate hinges upon the impact of the hundreds of thousands, probably millions, of wikis that have been created for use in classroom settings. Is the wiki-inspired "revolution in education" underway or do these thousands of new learning environments show little sign of nurturing Dewey-inspired forms of collaborative learning? One way to contribute to this debate is to address research questions about how wikis are used in typical settings. What kinds of collaborative behaviors do students perform when using wiki learning environments? To what extent do students perform these different collaborative behaviors when using wiki learning environments?

In a sense, the Glassman and Kang, and Dohn debate is about what we should expect to happen when wikis are used in typical classroom settings. Their theories postulate competing "expected distributions" of collaborative activity in classroom wikis. The data warehouses of public online learning environments create tremendous new opportunities to give researchers insight into those settings. They allow researchers to estimate actual distributions of collaborative behavior in the population of classroom wikis, which can be used to test competing theories.

In this study, I examined wikis produced on the PBworks platform, one of the three largest hosts for free wikis. Hundreds of thousands of PBworks education-related wikis are publicly accessible on the Web. For each of these wikis, researchers are able to access the complete edit history, maintained continuously to the second, of every word and tag added, changed or deleted by teachers and students in these environments. These data provide both tremendous scale, with the many thousands of cases, and rich historical depth, with their real-time edit histories.

I drew a random sample of wikis from a population of nearly 180,000 publicly viewable, education-related, and then research assistants under my direction used the Wiki Quality Instrument (Reich 2012a, b) to measure opportunities that each wiki provided to develop twenty-first-century skills such as collaboration, expert thinking, or new media literacy. While coding wikis, research assistants used a special browser interface—called the Wiki Coding Tool—that computationally generates basic information about each wiki, facilitates the rapid viewing of a sequence of edits to a single page, and allows researchers to restrict their viewing to only certain time periods (such as the first seven days of a wiki's lifecycle). Using these strategies, I identified a taxonomy of defined collaborative behaviors, measured the presence of those behaviors on a sample of wikis, and estimated the distribution of those behaviors in the population of US K-12 wikis. In this paper, I then use those empirical findings to contribute to the Glassman and Kang, and Dohn debate about the potential of wikis in educational settings.

This approach complements case studies and design research in several important ways. First, by randomly sampling from a large population of wikis, I examine typical settings rather than "hothouses" with special instructors, curriculum, or resources. While special settings can be very helpful in mapping out the possibility space for a learning theory or a technology, exclusively studying special environments can result in the literature providing a biased impression of the implications or implementation of tools, practices, or theories. Relatedly, random sampling allows for the study of wikis that are rich, complex, sustained, and successful, as well as those that are incomplete, useless, or a failure. In previous studies, I showed that nearly one-third of wikis do not persist past 24 h (Reich et al. 2012).

Because of their short lifetime, these wikis are very hard to investigate through qualitative methods (since they exist too briefly to be observed). Nonetheless, studying these short-lived experiments is very important to developing a complete understanding of wiki usage in schools. Finally, random sampling from a large population of wikis allows me to make claims about the degree of collaboration in wikis across the US K-12 system.

Research Questions

To summarize my argument to this point: Glassman and Kang, and Dohn provide two competing perspectives about the potential of wikis to support rich learning experiences. Glassman and Kang argue that wikis allow the instantiation of Dewey's pedagogical vision, and Dohn argues that the individual logics of assessment in school prevents the theoretical affordances of wikis from actually being realized in classroom settings. The scholarly literature on classroom application of wikis provides a variety of case studies that can contribute to this debate and to theory-building around peer-production tools in education, but researchers need to be careful about drawing conclusions exclusively from research conducted in special "hot-house" environments.

This study attempts to advance our understanding of classroom wikis specifically, and peer-production environments in education more broadly, by conducting a large-scale content analysis of wikis used in typical settings. In this study, I posed two research questions: (1) What kinds of collaborative behaviors do students perform when using wiki learning environments? (2) To what extent do students, in US K-12 schools, perform these collaborative behaviors when participating in wiki learning environment?

Research Design

In this section, I describe the dataset, sample, instrument, and data-analytic strategies used to evaluate the distribution of collaborative behaviors in US K-12 wikis. This study was part of a larger research program, the Distributed Collaborative Learning Communities project, to comprehensively examine the use of wikis in US K-12 settings, and more detailed descriptions of these methods have been published (Reich 2012a, b). Below, I describe the relevant research design information for this study of student collaborative behavior.

Dataset

PBworks.com is a wiki-hosting service that allows educators and students to set up free wiki workspaces and it ranks among the top four most-visited sites providing free wikis (Alexa 2010). From this company, I obtained longitudinal usage data on all 179,581 publicly viewable, education-related wikis that had been created between the founding of the company in June 2005 through August 2008. These were wikis whose creators designated them as for "Education" during the creation process, as opposed to "Business" or "Personal."

Each of these 179,581 wikis represented a discrete subdomain on PBworks. The unit of analysis in my study was the wiki subdomain. Hereafter, when I refer to a "wiki" in my dataset, I refer to a publicly viewable, education-related wiki subdomain hosted by PBworks. I had both a set of usage statistics on each of these 179,581 wikis and the capacity to examine closely the content of each wiki. I could examine the present state of any wiki, and I could also access every version of every page ever saved during the lifetime of the wiki. In this study, I worked with the entire population of publicly viewable, education-related PBworks wikis, without restricting my population based on the number of edits, the number of days of activity, or other similar criteria. This preserved my capacity to compare the full range of wiki learning communities.

Sample

For the analyses presented here, I drew a 1% random sample of 1799 wikis from the population of 179,581 education-related wikis made available to me by PBworks. From the 1% sample of 1799 wikis, I identified 406 wikis created in US K-12 schools for further study. I disqualified 18 wikis that were set to be privately viewable (removed from public view) during the observational period, 502 wikis that were either deleted or never changed (which unfortunately are collapsed in one category—I believe that the vast majority of wikis in this category were never changed), 448 wikis that were used exclusively outside the United States, and 425 US wikis that were not identifiable from K-12 settings (most of which were from higher education).

These 406 US K-12 wikis were used in different institutional contexts. Within the sample, 322 wikis were created within the US public school system. Of the rest, 43 were created in independent schools or home-schooling organizations serving K-12 students, two were created in public libraries, three in university settings serving K-12 students (e.g. a summer school) and

36 were from sources serving K-12 students but with unclear institutional affiliations. Wikis were used throughout the grades levels, with 27% serving elementary school students, 29% serving middle school students, and 44% serving high school students. We found wikis used throughout subject areas including language arts, science, mathematics, computer science, social studies, and other subjects. These wikis were used for a very diverse range of pedagogical purposes: teachers posted syllabi, assignments, class newsletters, and course content; students posted papers, introduced themselves, described hobbies, planned presentations, curated portfolios, engaged in academic discussions, and wrote stories. As noted in previous research, teacher activity dominates most wikis. Only 26% of wikis have any student involvement at all; 38% of US, K-12 wikis are "trial balloons" and cease development almost immediately and 34% are platforms for teacher-centered content delivery (Reich et al. 2012).

Sample Limitations

There are two important limitations of this sample. First, we have access only to PBworks wikis, raising questions as to whether PBworks wikis are representative of freely available wikis hosted by other providers. The only major comparable alternative host of free online wikis for education is Wikispaces.com. PBworks and Wikispaces trade places from week to week as ranked 3 and 4 on the Alexa rankings site for wiki-hosting services (Wikia and WetPaint, which do not have a significant share of educational wikis, ranks 1 and 2 typically).

There is one structural feature of PBworks that substantially differs from Wikispaces, MediaWiki, and most other wiki-hosting solutions. At the bottom of each PBworks content page, there is a space for comments and discussion. This is instead of the "Discussion" pages that are paired with content pages in Wikispaces or MediaWiki. This may influence the distribution of commenting and discussion behaviors on PBworks wikis, though a systematic comparison with Wikispaces or MediaWiki wikis would be necessary to determine whether or not this is the case.

The second limitation of my sample is that it does not include privately viewable wikis. Publicly viewable wikis represent 70% of the wikis created on PBworks from 2005 to 2008, so even if my findings are only generalizable to the population of public wikis, they are generalizable to the majority of wikis. It is not clear whether one should expect privately viewable wikis to be used differently. While many might assume that most wikis with student activity would be kept private, there was extensive evidence of publicly viewable student activity in my analytic sample.

Instrument

To measure the collaborative behaviors of students in wiki learning environments, I used the Complex Communication subscale of the Wiki Quality Instrument (WQI). The WQI is an instrument designed to assess the opportunities that wikis provide for the development of twenty-first-century skills such as expert thinking, complex communication, and new media literacy (Reich 2012b). The complex communication subscale operationalizes a taxonomy of collaborative discursive moves made by students participating in wiki learning environments.

With a team of colleagues, I developed and piloted the WQI over an 18-month period using a rigorous design process. A full description of the development of the WQI and associated protocols is available online (Reich 2012a, b), and below I describe key features of the development of the instrument.

Instrument Development

I used three research strategies to develop the taxonomy of collaborative behaviors in the Wiki Quality Instrument scale. First, I conducted a thorough literature review to assess whether existing measures of online collaborative behavior might be available. Second, I conducted multiple rounds of preliminary content analysis on our wiki samples to identify patterns of collaborative practice on wikis, then to test a series of preliminary measures of collaboration, and then to iteratively refine these measures. Third, I triangulated this content analysis with descriptions of student collaborative behaviors from wiki-using students and teachers in interviews, focus groups, and classroom observations.

In developing the taxonomy of collaborative behaviors on wikis, I conducted an extensive literature review to investigate how other researchers and scholars had approached the evaluation of Web 2.0 learning environments. Research into Web 2.0 learning environments—wikis, blogs, discussion forums, proprietary environments, and other platforms—has primarily been conducted through design research experiments and qualitative case studies. Most studies examine one or a few classes of students, often in courses taught by the researchers. Often these studies were conducted within a single subject domain, such as algebra (Chiu 2008), business ethics (Jeong 2003), or American history (Lawrence 2009). One result of this pattern is that existing measures of collaboration developed in the literature tend to be particular to a certain subject, classroom, or even a specific assignment. For instance, Trentin (2009) developed measures of individual contributions to a wiki project by looking at four sites of participation in particular wiki: (1) in the forum used for the planning stage, (2) in the peer review, (3) in the development of the wiki's reticularity; (4) and in the development of its contents. These kinds of specific indicators provide examples of venues for collaboration in a particular wiki learning environment, but they would not be adequate for mapping the full range of collaborative activity that we found in my diverse sample of K-12 wikis. Since the measurement strategies that I found in the literature had similar levels of specificity, I developed a taxonomy of collaborative behaviors that could be applied to a much wider array of wiki learning environments.

I developed this taxonomy of collaboration through a series of content analysis exercises guided by a grounded theory (Charmaz 2006) approach. Research assistants under my direction coded wikis in multiple iterations guided by a series of increasingly refined questions. In the first round of coding (used to separate the US K-12 wikis out of the full sample of 1799 publicly viewable, education-related wikis), researchers evaluated each wiki and identified its purpose and the kinds of activities found on the wikis. Coders were given no instructions or definitions for "purpose" or "activity", although they were asked to attempt to use consistent language in describing similar wikis. From these codes, I developed a sense of how wikis were used, by whom, and to what ends. In a second round of coding on the set of 406 US K-12 wikis, I directed research assistants to evaluate "patterns of practice," routine moves made by teachers and students, that seemed likely to promote twenty-first-century skill development, including collaboration and complex communication. I then attempted to winnow down these descriptions of patterns of practice into a formal taxonomy of collaborative behaviors.

In parallel with these wiki coding activities, I also conducted an extensive program of qualitative research. My team conducted 68 teacher interviews, observed 19 classrooms in 6 states, and held 40 focus group sessions with students from these 19 classrooms. In these qualitative research activities, I sought to evaluate how teachers and students used wikis, how they defined high-quality work with wikis, and how they assessed quality in wiki learning environments. The interview transcripts and field notes were coded multiple times, first through a round of open coding, and then through a more focused examination looking for teacher and student descriptions of students' collaboration and communication practices. I triangulated these data sources with data from our content analysis to develop a taxonomy of collaborative behaviors in US K-12 wikis.

Taxonomy of Collaborative Behaviors: The Complex Communication Subscale of the Wiki Quality Instrument

At the completion of this design process, I developed a taxonomy of seven common collaborative student behaviors in wiki learning environments, which I summarize in Table 11.1, and I describe in greater detail in section "Findings". The Complex Communication subscale of the Wiki Quality instrument, measures the presence or absence of these seven moves on a wiki at a particular occasion of measurement, as described below in section "Procedures".

Procedure

The wikis in my sample are extremely diverse. They are used with elementary schools through high schools, in nearly every subject area imaginable, and for a wide variety of educational purposes. They range in size and complexity from a single page with no revisions to wikis with hundreds of

Table 11.1 Taxonomy of collaborative student behaviors that comprises the coding categories in the complex communication subscale of the Wiki quality instrument

Complex communication	
Concatenation	Do multiple students add discrete sections of text to the same page?
Copyediting	Does at least one student copyedit text created by another student?
Co-construction	Does at least one student substantively edit text created by another student?
Commenting	Does at least one student comment upon another student's work on the wiki?
Discussion	Do students respond to each other's comments for at least four conversational turns?
Scheduling	Do students schedule meetings or tasks?
Planning	Do students plan for future work?

pages revised thousands of times. Accurately characterizing the activity on wikis is very challenging work. In this section, I present strategies to meet these challenges.

To measure collaborative activities on my representative sample of US K-12 wikis, research assistants used the Wiki Coding Tool (Reich 2012b). This tool is a Web interface that draws on the PBworks' data warehouse and permits a coder to examine the appearance of a PBworks wiki at any particular day in the wiki's development. Because the entire historical record of every edit to every page of every wiki is stored by PBworks, our Wiki Coding Tool is a "time machine" for assessing wiki usage. The wiki coding tool also allows raters to rapidly scroll between page revisions and examine differences between two revisions, allowing much more efficient evaluation of collaboration moves than allowed by the native PBworks interface. The wiki coding tool provides the "distillation for human judgment" in Baker's (2011) taxonomy of educational data mining methods.

Each wiki was coded by two raters at six occasions of measurement, on 7, 14, 30, 60, 100, and 400 days after the wiki's creation. (These occasions were determined by quantitative analysis of wiki edit histories see (Reich 2012a).) Each wiki was coded as long as the wiki continued to change. Thus if a wiki's final change was on day 25, it was coded on days 7, 14, and 30, but not further. On each occasion of measurement, the two raters evaluated every revision to every page, all page comments, and all documents uploaded to the wiki up to that time period. On small wikis with only one page, this might take only a few minutes. On the largest, most complex wikis on their 400th day, this process can take several hours. For every item on which the two raters disagreed, a third rater reconciled the disagreement. As I explain later, in this paper I do not present my findings in a longitudinal framework, but understanding these multiple measures is important for evaluating our inter-rater reliability.

One limitation of our procedure is worth highlighting. In evaluating students' collaborative behaviors, research assistants were dependent upon students logging in with their own user ID or leaving bylines associated with their contributions (e.g. "Irish History, by Jane McDonnell"). In many cases, students adhered to these norms, and researchers were able to measure collaborative activity with precision. I know from classroom observations, however, that sometimes students do not log in under a unique ID and sometimes multiple students work on a page while logged in under one ID, while sitting next to each other and sharing a computer in a school lab. Research assistants could not credit collaborative activity that they could not identify affirmatively. Therefore, it is possible that I have underestimated collaborative activity within my sample of wikis. This was a topic of discussion on several occasions in our weekly team meetings, and the consensus of my team was that over the hundreds of wiki we evaluated, raters felt that there were few occasions where they believed they might be under-representing collaboration because of ambiguities in user identity (usually because wikis appeared to be unambiguously created by one person). In one sense, this issue is resolved by clearly defining the collaborative behaviors in my taxonomy as those that observably occur *within the wiki environment*. The instrument and my procedures did not measure dimensions of collaboration happening within classrooms and computer labs, dimensions which are certainly important and worthy of anthropological study.

In terms of quality-code agreement, our research team coded 406 US K-12 wikis at 1219 time points, an average of 3 occasions of measurement for each wiki. Average inter-rater agreement across all five subscales of the Wiki Quality Instrument at all occasions of measurement was 0.92 and inter-rater agreement on the Complex Communication subscale was 0.96 (Reich 2012a).

Measures

Though my data gathering procedures were sophisticated, the presentation of my measures in this paper is simple. Although my team measured wiki quality at multiple time points across each wiki's lifecycle, two features of our data rendered it unnecessary to present my findings with such precision. First, collaborative activities occurred very infrequently in our sample of US K-12 wikis. Second, in most wikis, if collaborative behaviors occurred they were evident within the first few weeks of the wiki lifetime, so longitudinal representations of collaborative activity were not substantially more informative that simpler representations. As a result, I simply chose to present measures of student collaborative behavior as we found them on the last date a wiki was changed or on our final occasion of measurement at 400 days after wiki creation.

Thus, in this chapter, I report the proportion of wikis in our samples containing each of the seven discursive moves included in the taxonomy of collaborative behaviors, as measured after 400 days of observation. I also report the Complex Communication subscale scores for each wiki—a scale ranging from 0 to 7 representing the number of collaborative student behaviors identified on the wiki—as measured after 400 days of observation.

Data-Analytic Strategy

To address my first research question—How do students collaborate in wiki learning environments?—I present a detailed description of the seven discursive moves identified in my taxonomy of student collaborative behaviors.

To address my second research question—To what extent do students collaborate in wiki learning environments?—I present frequency counts of each of the seven collaborative moves in my representative sample of 406 US K-12 wikis as measured after 400 days of observation. I also present the distribution of complex communication subscale scores—the sum of these seven collaborative moves, in my wiki sample. Together, these descriptive statistics provide a landscape view of how students in US K-12 settings collaborate, or not, in wiki learning environments.

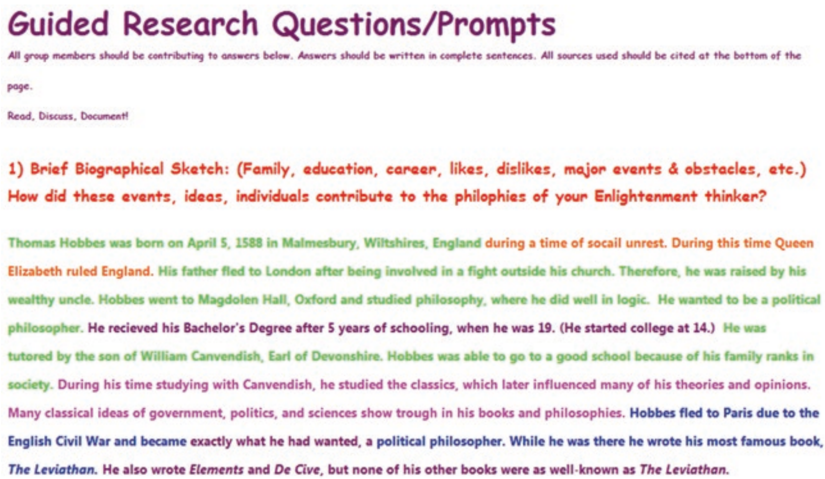
Findings

How Do Students Collaborate in Wiki Learning Environments? A Taxonomy of Collaborative Behaviors on Wikis

From the instrument development procedures described above, I identified seven different types of collaborative moves that students performed within my sample of US K-12 wikis (summarized in Table 11.1). In this section, I define each of these seven behaviors and present the proportion of wikis exhibiting each behavior.

Concatenation occurs when students post discrete content to a single page. For instance, if a team of four students was assigned to create a wiki page about trees, one student would individually write a paragraph on leaves, another on branches, another on the trunk, and the fourth on roots. They would then each add their discrete paragraphs to a common page. Concatenation might be thought of as the lowest possible level of collaborative page construction: it represents merely posting in the same place. It is the second most common form of collaborative behavior, occurring on 5.91% of US K-12 wikis in my sample.

I identified two other forms of co-writing. *Copyediting* is when students edit the grammar, spelling, or syntax of another student's contribution to a wiki page but do not make substantive changes. Copyediting occurs in 1.72% of wikis in my sample. *Co-construction* is where students substantively edit another student's contribution to a wiki page. Figure 11.1 shows a screenshot from a wiki where students co-construct a paragraph, and, conveniently for researchers, highlight each individual contribution in a different color.



Guided Research Questions/Prompts

All group members should be contributing to answers below. Answers should be written in complete sentences. All sources used should be cited at the bottom of the page.

Read, Discuss, Document!

1) Brief Biographical Sketch: (Family, education, career, likes, dislikes, major events & obstacles, etc.) How did these events, ideas, individuals contribute to the philophies of your Enlightenment thinker?

Thomas Hobbes was born on April 5, 1588 in Malmesbury, Wiltshires, England during a time of socail unrest. During this time Queen Elizabeth ruled England. His father fled to London after being involved in a fight outside his church. Therefore, he was raised by his wealthy uncle. Hobbes went to Magdolen Hall, Oxford and studied philosophy, where he did well in logic. He wanted to be a political philosopher. He recieved his Bachelor's Degree after 5 years of schooling, when he was 19. (He started college at 14.) He was tutored by the son of William Canvendish, Earl of Devonshire. Hobbes was able to go to a good school because of his family ranks in society. During his time studying with Canvendish, he studied the classics, which later influenced many of his theories and opinions. Many classical ideas of government, politics, and sciences show trough in his books and philosophies. Hobbes fled to Paris due to the English Civil War and became exactly what he had wanted, a political philosopher. While he was there he wrote his most famous book, *The Leviathan*. He also wrote *Elements* and *De Cive*, but none of his other books were as well-known as *The Leviathan*.

Fig. 11.1 Screenshot from wiki demonstrating co-construction. Contributions from different students are rendered in different colors

This behavior occurred on 4.43% of sampled wikis. It is important to note that thresholds for identifying the presence of these behaviors were quite low. While Fig. 11.1 shows an unusually extensive example of co-construction between multiple students, if one student contributed one phrase in the middle of another student's paragraph, that would also be considered evidence of co-construction. Even though our findings show very low levels of collaborative behaviors, our measures were very inclusive of even trivial forms of collaboration.

I identified two forms of student dialogue on wikis. *Commenting* is when students comment upon the work of another wiki user, student or teacher. The two most common forms of commenting behavior involved students responding to a prompt posted by a teacher and students leaving a comment evaluating the posted work of another student. In the PBworks environment, there is a defined space for comments at the bottom of every wiki page, although we also measured comments that were left in the body of a wiki page. Commenting is the most common form of collaboration, and it occurs on 6.4% of wikis in my sample. *Discussion* occurs when comments have at least four conversational turns among a group of commenters. This occurs on 2.46% of sampled wikis. To clarify the distinction between commenting and discussion: if a teacher poses a question on a wiki page and students respond directly to the question on the same page, this would be an example of commenting. If within those responses, students respond to each other's contributions, with at least four conversational turns in the process, then this would be discussion. If each student simply responds to the original prompt, then this would be commenting.

Finally, I identified two additional collaborative behaviors related to using the wiki as part of a work process. *Scheduling* occurs when students populate a list or calendar. For instance, a student might post a list of times that group members can meet, and the group members put their names next to potential times. Or a teacher might create a list of roles for a group project (such as editor, leader, proofreader, and so forth), and students sign up for those responsibilities. Scheduling is present in 1.72% of wikis in my sample.

Planning is the final collaborative move. The vast majority of student discursive moves on wikis involve creating some piece of content meant for publication and presentation. It made sense, therefore, to create a category in the taxonomy to identify moves where students were not creating content but instead planning to do something. *Planning* occurs when students use the wiki to develop plans with other students for creating work products (on the wiki or elsewhere). *Planning* occurs on 2.46% of wikis in my sample.

I considered including two additional categories related to collaborating across institutional boundaries: beyond school collaboration and international collaboration. Beyond school collaboration would be when students from two or more schools use the same wiki, and international collaboration would be when those schools are in different countries. We did not find evidence of these behaviors in our sample, so we did not include them in our taxonomy, although several well-known exemplary wiki projects, such as the Flat Classroom Project (http://flatclassroomproject.org), exhibit these behaviors (Lindsay and Davis 2012).

This taxonomy of collaborative behaviors defines and categorizes the most common discursive moves found in US K-12 wikis. This taxonomy provides a structure for systematically analyzing the distribution of collaborative behaviors in these wikis.

To What Extent Do Students Collaborate While Using US K-12 Wikis?

Student collaboration is rare in US K-12 wikis. In Table 11.2, I show the distribution of student collaborative behaviors in our sample of 406, US K-12 wikis, as measured after 400 days of observation. Notice that the

Table 11.2 Distribution of collaborative behaviors in 406 US K-12 wikis, as measured after 400 days of observations

	Percentage	*Frequency count*
Concatenation	5.91	24
Copyedit	1.72	7
Co-construction	4.43	18
Comment	6.4	26
Discussion	2.22	9
Planning	2.46	10
Scheduling	1.72	7

most common forms of collaboration—concatenation and commenting—occur in only 5.9% and 6.4% of wikis, respectively. These most common collaborative moves are also the simplest. Indeed, these forms of "collaboration" do not require any real interaction between students at all, but instead represent individual contributions that co-occur in the same virtual space.

In analyzing these percentages, it is also important to remember that the decision rules defining each of these seven behaviors were designed to be broadly inclusive of a wide variety of behaviors. If a student posts "This is stupid" or "Good job" at the bottom of a page, even these trivial moves would be counted as comments. If a student corrects a single misspelling or adds a single comma, that wiki would be designated as including "Copyediting" behavior. So even with our broadly inclusive measures, student collaboration on wikis is infrequent.

Another way to evaluate the distribution of collaborative behaviors is to count the number of identified behaviors occurring on each wiki. In Table 11.3, I show distribution of the number of collaborative behaviors found in my sample of 406, US K-12 wikis as measured after 400 days of observation. The striking finding from this table is that 89% of wikis have no identifiable student collaboration at all. Another 6% of wikis have only one identifiable form of collaboration, and 5% of wikis have between two and seven collaborative behaviors. If Table 11.2 shows that each individual collaborative behavior is rare, then Table 11.3 demonstrates that wikis that include multiple forms of collaboration are also quite rare, even given our low standards for what can be considered collaborative behaviors.

Table 11.3 Distribution of complex communication subdomain scores in 406 US K-12 wikis, as measured after 400 days of observation

Complex communication score	*Percent*	*Frequency count*
0	88.92	361
1	6.40	26
2	1.48	6
3	.25	1
4	1.48	6
5	.74	3
6	0	0
7	.74	3

Discussion

With these empirical findings concerning the distribution of collaborative behaviors in US K-12 wikis, I can now return to a discussion of the Glassman and Kang (2011) and Dohn (2009) debate about the promise and potential of wikis. The evidence presented in this paper is much stronger warrant for Dohn's pessimistic position than Glassman and Kang's more hopeful view of the potential of wikis. On the whole, most wikis are individual constructions, and when students do engage in collaborative behaviors, students tend to be just posting in the same place rather than participating in intensively collaborative knowledge-building.

The patterns of collaborative behaviors presented above also cohere with Dohn's arguments about the power of institutional conditions and conditioning to foster a strong sense of individual ownership of text. Consider the three forms of cooperative writing that I define: concatenation, copyediting, and co-construction. On first glance, it appears that co-construction is a more sophisticated form of collaboration than copyediting; fixing commas is less challenging than fixing meaning. One might hypothesize, therefore, that copyediting would be more frequent than co-construction since modest changes to grammar, syntax, and spelling are simpler than more substantive co-writing.

It turns out, however, that copyediting is one of the least frequent collaborative practices. My hypothesis is that while copyediting is technically simpler, it involves the deletion of someone else's text, and therefore is actually perceived by students as more invasive than co-construction, which can be accomplished by threading additional phrases and sentences onto the writings of others without ever deleting anything. My quantitative findings align with the anthropological perspective on student's strong feelings about individual ownership of text presented in Grant's (2009) "I DON'T CARE DO UR OWN PAGE." Both of these studies lend different forms of evidence to support Dohn's position that the structural and cultural features of schooling are inhospitable to peer-production practices in institutionalized school settings.

My findings do not necessarily contradict Glassman and Kang's position on the theoretical possibilities of wikis; I found a small handful of highly collaborative wikis within my representative sample. To some extent, Glassman and Kang are making an argument about the possibility space for Dewey-inspired education enabled by wikis. It could be argued, therefore, that this study shows that collaborative wiki learning communities on the progressive edges of that possibility space can be found in representative samples of typical wikis drawn from huge populations.

My reading of Glassman and Kang, however, is that they argue that knowledge-building, content co-creation, and communities of investigation are not merely made theoretically possible by wikis, but that educators should understand wikis as places where these advanced learning behaviors can emerge with some regularity, indeed, enough regularity to inspire a revolution. The evidence presented here suggests that these particular arguments should be tempered with the caveat that, in practice, most wikis are individually produced platforms for content delivery, more often created by teachers than by students.

As with all social science debates, this one study certainly does not "settle" any issue, and of course the revolution predicted by Glassman and Kang could indeed be right around the corner. I am currently conducting several follow up studies on samples of wikis collected in 2010 to evaluate whether collaborative patterns have changed over time. If Dohn is correct, then the fact that teachers will have several more years of experience with wikis and peer-production tools will prove to be, in the main, irrelevant for the advancement of richer collaborative practices, since the institutional and culture barriers to social practice and knowledge-building remain unchanged. If I find growth in the distribution of collaborative practices, especially the more intensive forms of collaboration, then the Glassman and Kang, and Dohn debate will need to be reexamined through these new data.

Situating Case Studies in the Landscape of Wiki Practices

In the absence of broad, generalized, contextual data about practices with emerging technology and pedagogy, it can be very difficult to ascertain how a particular learning environment compares to other learning environments employing similar tools or design principles. For instance, the signature event in Grant's (2009) "I DON'T CARE DO UR OWN PAGE" is when a student logs in to edit another student's wiki page and makes a few modest changes, and she is strongly rebuked by the original creator of the page for attempting to make edits. Grant presents the case study as an example of the failure of a new technology to foster the development of new collaborative practices. In reference to the standards for collaborative behaviors explicitly set by the teacher and implied by the researcher, the project fails.

A somewhat different picture emerges by comparing the practices identified in Grant's (2009) case study to the taxonomy of collaborative behaviors presented in this study. In the article, Grant shows clear evidence of at least three of the seven collaborative moves from the taxonomy—concatenation, copyediting, and commenting—occurring on the wiki being studied. The article text suggests there may have been co-construction as well. If this wiki does in fact have evidence of four types of collaborative moves by students, then it has more collaborative moves than 96% of US K-12 wikis. Seen from this perspective, it is perhaps more remarkable that students were even willing to attempt invasive collaborative moves than the fact that those moves were so sharply rebuked. From its own internal frame of reference, Grant's case study appears to be a story of failing to meet expectations. With a larger perspective, it might be possible to revisit Grant's case to identify what factors enabled the relatively high (if ultimately disappointing) levels of collaboration that the learning environment did manage to foster.

A similar kind of reframing might occur in reference to the two other case studies mentioned early, by Forte and Bruckman (2009) and Pifarre and Staarman (2011). Set against the backdrop of the distribution of student collaborative behaviors in US K-12 schools, it becomes clearer that these particular cases are examples involving very high degrees of student collaboration and they are examples of very atypical situations. Within this frame of reference, Forte and Bruckman's case might be positioned, like Grant's case, as less a story about the barriers to collaborative practice that the students and educators failed to overcome, and more about the remarkable degree to which they fostered any collaborative activity at all. Pifarre and Staarman's case is one of the few design research studies presented in the literature as a more or less unqualified success, and the efficacy of their example appears much more remarkable in comparison to the very low levels of collaboration found in US K-12 wikis broadly.

The data presented in this study allow readers and authors of case studies to situate these individual classroom cases within a larger landscape of wiki usage. In particular, these findings help highlight the atypical nature of those wiki learning environments that foster any degree of student collaboration. From this perspective, it becomes apparent that the research literature on classroom wikis consists almost exclusively of cases at the tail of the distribution of collaborative behaviors, potentially biasing conclusions about classroom wikis drawn from this literature. Case studies that explore the reasons why teachers use wikis as sites for individual production may be as useful for understanding how to advance teacher practice as those that examine more collaborative approaches.

Beyond Wikis, the Challenges of Peer Production in Education

Wikis provide an example of a platform designed for peer production, though in K-12 education settings they are primarily used for individual production. An emerging set of studies of other peer-production platforms within and beyond education suggests that this pattern is typical of peer-production platforms. Acknowledging this widespread pattern of individual production in collaborative environments requires raising difficult questions about designing learning experiences using these platforms.

Scratch (Resnick et al. 2009) is an online platform (http://scratch.mit.edu) where students can program games, simulations, and animations using an open-source visual programming language. Any participant can build their own project, but they can also edit and remix any project shared within the Scratch community. Hill and Monroy-Hernandez (2013) studied all 536,245 projects created in a one year period in 2010 on the Scratch platform. They found that only 7% of these projects were remixed within one year of their creation, and only a tiny percentage of Scratch projects were ever remixed after one year. The vast majority of Scratch projects are individual productions. As with wikis, Scratch makes collaboration possible, but most Scratchers choose to work alone.

Hunt (2011) analyzed the activity from a district installation of a blogging platform, and he found similar patterns of production. First, as with wikis, blogs were primarily tools for teacher communication. Even though students outnumber staff five to one in the district, teacher posts on blogs outnumber student posts two to one. Moreover, blogs were primarily individual productions: 80% of posts had no comments at all. Among the 20% of posts with comments, most comments were mandated responses to teacher questions without any real discussion ("comments" instead of "discussion" in the parlance of my taxonomy of collaborative behaviors), evaluation of student work by teachers, or trivial responses by students to other students (e.g. "good job."). As Hunt writes, "If the purpose of the blogging engine was and is to provide students and staff access to each other for the purposes of being in conversation about teaching and learning, then the blog engine is a gross failure" (p. 48).

As an example from outside the education space, Sourceforge is an extensively researched platform for the development of open-source software projects with a robust infrastructure for collaboration. As with educational wikis, most Sourceforge projects have been created and developed by individuals. Data show that 70% of Sourceforge projects have only one developer, 14% of projects have two developers, and only 2% of projects have more than ten developers. (Hill 2011; Schweik and English 2007). Leveraging collaborative platforms for individual production, therefore, does not seem to be limited to educational environments.

K-12 wikis, blogs, Scratch projects, and Sourceforge projects all display a Pareto distribution of collaborative behavior, where most projects on peer-production platforms are individually produced and a small fraction are actually collaborative. One simple design principle that I adduce from analyzing these patterns is that the introduction of a new peer-production platform into a particular learning environment or into the ecology of schools more broadly is very unlikely to, in and of itself, bring about more collaborative behaviors. That point is perhaps obvious, but it is still worth emphasizing.

However, the claim made by Dohn (2009), and to some extent Grant (2009) and Forte and Bruckman (2009), is that what curtails that development of collaborative practices in educational settings is the logics and culture of individual assessment in schools. One possible line of argument following from that premise is that educators interested in supporting collaborative learning need to change the organization and cultures of schools and classrooms to make collaborative learning viable. The comparison with Sourceforge, however, suggests that barriers to collaboration in peer-production environments may not be particular to educational institutions. If this is the case, mitigating barriers to collaboration inherent in the design of schools may not be sufficient to ameliorate the barriers to collaboration that appear to exist more broadly in wider society. Getting people to collaborate online may be hard even without including the special challenges faced in educational environments.

If it is indeed the case that most peer-production platforms primarily support individual rather than collaborative activity, then this raises serious questions about the ethical and pedagogical responsibilities of educators who might introduce peer-production tools. Probabilistically, it is unlikely that an average educator's typical effort will yield high-quality collaborations. Should educators avoid introducing peer-production tools until the organizational structures of school change sufficiently to make them more viable pedagogical options? Should educators produce learning designs that anticipate failed efforts at collaboration, such that individual productions can still yield meaningful learning opportunities? Should educators produce learning designs that anticipate failed efforts at collaboration for the specific purpose of analyzing why they fail, as Grant (2009) and Forte and Bruckman (2009) suggest? Is it reasonable to have students engaged in a learning activity where the desired results are unlikely to be achieved? These are vital questions to address in learning designs involving peer-production platforms, and theories of technology-mediated collaborative learning need to pay closer attention to the difficulties implied by these questions.

The data presented in this study, and the studies of blogs, Scratch, and Sourceforge, suggest that these questions are not particular to certain kinds of classroom or educational settings, but universal challenges across diverse environments for collaborative learning. Even when teachers put collaborative online environments in the hands of "digital natives" (Palfrey and Gasser 2008; Prensky 2010) who are members of a "participatory culture," (Jenkins 2009) most work is completed individually or assembled from the discrete contributions of individuals: students just posting in the same place. One of the signature challenges of the technology-mediated learning in the decades ahead will be to reshape these power curves and develop the design principles that enable peer-production tools to support meaningful collaborative learning at scale in online settings. Confronting the paucity of collaborative behaviors currently found in these peer-production environments will be an essential part of that challenge.

Acknowledgments This research was supported in part by a grant from the William and Flora Hewlett Foundation's Open Education Resources initiative.

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O. O. Adesope, A. G. Rud (eds.), *Contemporary Technologies in Education*, https://doi.org/10.1007/978-3-319-89680-9