Digital learning environments, the science of learning and the relationship between the teacher and the learner

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Abstract

The relationship between teachers and their students is being increasingly mediated via educational technologies. This increased use of technologies has implications for all levels of education, perhaps most evident in a higher education context where students are spending less time on campus and more time online than they did in the past. The flexibility afforded by educational technologies is evident in the emergence of 'flipped classes', massive open online courses and a growing number of programs being offered by institutions online. Data, analytics, artificial intelligence and machine learning are also all poised to substantially influence the adaptability and capacity for personalisation of educational technologies. These trends necessitate an ongoing adjustment of the role of teachers and their relationship with students. As the relationship changes, there is a pressing need to ensure that what is understood about quality student learning remains the primary consideration. In this chapter, we will examine how research findings from the science of learning might be best used to help support learning as the relationship between teachers and learners evolves into the future.

Introduction: Educational technologies in the 21st Century

Educational technologies are increasingly commonplace and expected in formal learning environments. In addition to traditional multimedia like videos and audio, these technologies now allow for students to interact with these environments, providing much richer learning experiences (for overview, see Freina & Ott, 2015). As these technologies continue to evolve and become more sophisticated, it will have profound implications for formal education environments. One of the most pressing of these implications is what these technologies will mean for the relationship between the student and the teacher. As technology continues to impact on the ways in which students learn, it is also, and will continue to impact on the ways in which teachers and students interact with each other and with content. In this chapter, we provide an overview of the impact of these technologies, particularly on higher education, and discuss the implications of emerging educational technologies for the student-teacher relationship. Specifically, this discussion is aligned with research from the science of learning. The implications of emerging trends and understanding how these technologies can be best deployed to enhance student learning need to be built on a foundation of research on how students learn. We offer suggestions for emerging priorities for science of learning researchers and educators.

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There are obvious signs that learning, both within formal education environments and beyond, is increasingly being mediated via technology. Mobile devices now mean that there is potential to access a wealth of information at anytime and anywhere with a network connection. One of the clearest examples of the impact this availability of networked devices has had is to fundamentally alter how people go about developing certain kinds of knowledge. In order to see how to bake a pavlova or to erect a fence, many people will now go to online videos as a first option in order to see the process in action. Videos are particularly well-suited to this form of procedural learning (Lee & Lehto, 2013). The availability of networked devices and multimedia allows for easy access to demonstrations of almost any procedural task imaginable. The ease of access to this kind of resource raises questions about how teachers and educational institutions adapt to a world where information and knowledge are available on demand.

The emergence of new technologies has raised questions about what the impact on education will be since the invention of the printing press (see Moodie, 2016). What is perhaps different about the trends emerging in the 2000s and 2010s is that information and knowledge are no longer predominantly the domain of institutions. Even after the Gutenberg's invention made books available to the masses, the majority of these books were still to be found within university, monastery, or library walls. It was also only possible to carry a certain number of books around, as anyone who attended school in the 20th Century can attest. The capacity to both access and store vast (practically limitless) information in mobile devices is a change that is fundamentally different to those that have come before. Students in higher education contexts are constantly connected and are interacting with each other and with content using mobile devices (Gikas & Grant, 2013). These trends raise questions about how these devices influence the ways in which students acquire, store, update, and use information and knowledge. Under what conditions do these technology tools lead to the most effective learning experiences? Do they serve as a distraction if not deliberately integrated into learning activities? When these devices are incorporated deliberately into learning activities, how are students using them to make sense of ideas and apply them in practice? There is a significant role for the science of learning in exploring and understanding these trends and unpacking the implications for students and teachers.

While the growing use of educational technologies is evident in all levels of formal education, it is perhaps in higher education that some of the most profound changes are taking place. Students are increasingly engaging in their studies in 'blended', 'flipped', or online modes with significant proportions of the learning activities they undertake occurring in digital environments (Siemens, Gasevic, & Dawson, 2015). In particular, students increasingly engage in acquiring information and developing knowledge online. Some commentators have suggested that the impact of these new practices heralds the end of higher education as we know it (e.g. Christensen & Eyring, 2011). However, as we outline in this chapter, established and emerging research paints a far more complex and nuanced picture than a simplified dichotomous tension between traditional and digitally-mediated educational offerings. There are advantages and disadvantages to learning in both physical and virtual settings, with teachers needing to employ different strategies and tactics in diverse environments.

Data, analytics, and their impact on learning and learning environments

The growing use of data, sophisticated algorithmic work and increasingly accessible and cost effective adaptive environments are resulting in an evolution in digital and emerging technologies. Data and analytics are being used in ever more sophisticated ways to track students' progress, predict their learning trajectory and inform interventions. These developments have allowed much more targeted and personalised learning experiences which support the development of learning complex concepts and ideas, not just procedures and declarative facts.

The field of learning analytics, for example, has grown rapidly since the first *Learning Analytics and Knowledge* (LAK) conference in 2011. Learning analytics innovations are focussed on collecting and analysing data generated about, for and from students about various aspects of their learning (Sclater, 2017). This includes audit trail data generated as students interact with digital environments, personal data about who they are, what their preferences might be and data about their knowledge and abilities generated through assessment. There are significant ethical implications associated with the collection and analysis of these data (Slade & Prinsloo, 2013). There are, at the same time, significant opportunities to better understand how students learn broadly and to gain insight into how individual students learn (Lodge & Corrin, 2017; Siemens et al., 2015). These findings can then be used in order to provide personalised feedback and other interventions.

The initial focus for the field of learning analytics broadly was to find indicators that students in higher education were potentially at risk and failing or withdrawing (e.g. Macfadyen & Dawson, 2010). There were, however, also earlier attempts to draw on audit trail data to gain insight into student learning processes (e.g. Kennedy & Judd, 2004). These studies laid a foundation for exploration of the use of 'big data' and analytics to help understand how students are learning in digital environments. In the years since the first LAK conference, there has been increased interest in how these data might contribute to an understanding of student learning. Aligned with this has been a trend towards integrating learning analytics with design (e.g. Lockyer, Heathcote & Dawson, 2013) and with ideas and methods from educational psychology (e.g. Gašević, Dawson, & Siemens, 2015). This trend was particularly apparent at the 2018 LAK conference where the most cited articles in the proceedings were from the educational psychology literature and not from technical domains that had, up until that point, dominated the discussion about big data and analytics in education.

It is always difficult to predict future trends but there is reason to believe that some recent emerging technologies, such as machine learning and artificial intelligence (AI) could follow a similar trajectory to that of learning analytics. These technologies are poised to have a significant effect on education in the near future, as in other domains (Jordan & Mitchell, 2015: Luckin, 2018). Luckin (2017), for example, argues that artificial intelligence systems can and will fundamentally change the way assessment is carried out in education. AI-based systems will allow for continuous assessment and real-time feedback that aligns much more closely with what is understood about quality learning and feedback. There is some conjecture about what counts as artificial intelligence and what role it will play in education (Roll & Wylie, 2016). What is less controversial, however, is that it is likely that the advanced processing and adaptability provided by AI platforms will contribute, as is learning analytics, to our understanding of how students learn. There are, in parallel, also great possibilities for drawing on the science of learning to provide personalised interventions including through feedback, prompts and tailored learning pathways in digital environments using these same technologies (e.g. Pardo, 2018). These trends suggest the coming to fruition of the promise of multimedia learning; adaptability in real time and personalisation built on data mining and predictive algorithms. It is difficult to see how the potential of these technologies will be fulfilled without drawing on the science of learning to provide a foundational knowledge base describing how students learn.

The realisation of the full potential of learning analytics, machine learning and AI in education may still be a work in progress, however, there have been significant advances to date. There are already advanced, adaptive environments available that are being used for both research and educational purposes. Some of these systems have been in use for some time. For example, there are already sophisticated simulation environments for training pilots (Huet et. al., 2011), surgeons (Piromchai et al., 2017), and dentists (Perry, Bridges & Burrow, 2015). What these environments share though is a focus on procedural tasks. It is much more complicated and difficult to develop an environment that can facilitate learning in complex conceptual domains. These domains include biological systems, climate, social and political phenomena as examples. These are all phenomena that require complicated mental structures or schema in order to understand them, which, in turn rely on or are inhibited by prior knowledge (Carey, 2009). Understanding these concepts is difficult even without considering the additional complexity that comes with the application of this knowledge, which adds a further set of complexities. Focussing on the acquisition and updating of complex concepts of this kind, Dalgarno, Kennedy and Bennett (2014), for example, found that people adopt a variety of strategies when working through simulations to help them understand complex biological and meteorological concepts. The challenge with facilitating the learning of these more complex ideas is that it requires some understanding or assessment of how each individual makes sense of the concept to begin with. As the vast literature on conceptual change has demonstrated, there are many different reasons why an individual student might misunderstand a concept (Amin & Levrini, 2017). Each student constructs meaning in their own way (as per Bruner, 1962). Therefore, while adaptive systems have taken some forward leaps, there is still some way to go before these environments can cope with the significant diversity in how individual students make sense of complex ideas.

Taken together, developments in machine learning, AI, and learning analytics point to a situation where it will be possible to acquire even complex conceptual ideas in digital environments. However, adapting these environments on the basis of how each individual constructs meaning and develops mental schema remains a significant challenge. For example, it is relatively easy to see when a student might reach an impasse in a digital environment based on their activity within the environment. It is much more difficult to make a prediction about why (Arguel, Lockyer, Lipp, Lodge & Kennedy, 2017). Chi's (2013) categorisation of misconceptions partly explains what the difficulty is. Depending on how students structure related ideas in their mind, that structure will limit the way in which new information can be incorporated. So, one individual may see a very large dog and assume it is a horse, hence placing the example of the dog into the wrong conceptual schema (horse). Another may see a horse and assume it is a very large dog if they do not have a pre-existing conception of 'horse'. The problem with providing personalised instruction in a digital environment is therefore not just about what the overall level of prior knowledge is but how that knowledge is structured in students' minds.

Helping students develop their conceptual understanding is therefore a key challenge for developers of adaptive digital learning environments. Given the need to be able to predict not just overt behaviour but the ways in which each student is making sense of both the ideas they are being exposed to and developing their capacity to monitor and update their own understanding. The research in the science of learning examining how students acquire concepts (e.g. Schoor & Bannert, 2011), how they change their conceptual understanding (e.g. Amin & Levrini, 2018), how they make judgements about what they know and think they know (e.g. Lodge, Kennedy & Hattie, 2018) and how they self-regulate their learning (e.g. Broadbent

& Poon, 2015) are all critical for informing the development of these technologies. Integrating what is known about how students learn is required here in order to make better predictions about what students are having trouble with and provide appropriate interventions. Research on these fundamental processes are all critical if digital environments are to be fully responsive to student needs and learning trajectories.

Technologies that are and will continue to impact on education need to be built on a foundation that includes a deep understanding of how students learn. Without this, the kinds of technologies available will struggle with facilitating learning beyond procedural domains or simple adaptations that treat all students as the same on the basis of observable behaviour rather than the underlying cause. It will also be difficult to determine what role the teacher will need to play working alongside these environments. The science of learning will contribute here in two ways. First, the capacity for conducting laboratory-based experiments leads to increased confidence that different kinds of conditions and interventions cause specific outcomes. Second, and perhaps more importantly, if these technologies are to fulfil their potential, the science of learning will help to better understand individual differences. With learning scientists, designers, data scientists and developers working together with teachers, it is possible that the potential of adaptive educational technologies will finally be realised after what seems like decades of promise (e.g. Wenger, 1987).

Teacher and student relationships in the digital world

With machine learning and AI evolving rapidly and being used in new domains, it is tempting to think that there will be soon be sophisticated programs and platforms that can replace teachers altogether. One of the strongest indicators of how difficult this is likely to be comes from a study conducted by Koedinger, Booth and Klahr (2013). Using a modelling approach, these researchers attempted to map out the total possible number of ways in which instruction can be delivered. This 'teacher model' included factors such as how and when feedback should be delivered, how examples are used, and a multitude of other instructional factors. It quickly became apparent that teachers are constantly navigating a decision set that is practically infinite. The researchers abandoned the model building process about half way through coding in all the factors with the number of possible instructional options already well over 200 trillion. The model also did not take into account content, context, or the variability that is brought to educational environments by students and teachers. This exercise shows how complex the task of teaching is. It also suggests that, even when the critical social elements of teacher-student interaction are removed, the number of decisions required to effectively deliver instruction makes the task of teaching extraordinarily complex.

It is unlikely that technologies will be able to replace teachers or teaching in the short term given the complexity teachers deal with in practice. However, the 4th industrial revolution is here and digital technologies are here to stay in our virtual and physical classrooms (Aoun, 2017). The question becomes one of when and how technologies can be most effectively used, for what, and understanding what implications this has for the teacher-student relationship. The science of learning points to vital elements teachers bring to educational environments that are difficult to simulate digitally. Beyond just what students know (epistemology), modelling of knowledge and professional ways of being (ontology) are critically important to quality higher education (Dall'Alba & Barnacle, 2007). To date, it is difficult to simulate this modelling of professional ways of being virtually or digitally (e.g. Cunningham, 2015; Mastel-Smith, Post & Lake, 2015). The extensive research on the contributions of social cognition to learning across many domains (Blakemore, 2010) is one example of the importance of the interactions between students and teachers. Many of the subtle nuances of applying knowledge in practice in professional contexts, as explained by social cognition, require seeing these processes in action and that means seeing them demonstrated by a teacher. Additionally, when it comes to the direct relationship between students and their teachers, there is also great difficulty in simulating the ability of a teacher to read and respond to student emotions. Although affective technologies are developing rapidly (see Calvo, D'Mello, Gratch & Kappas, 2015), they do not come close to replicating the capacity a teacher has for seeing when a student is confused or frustrated and adequately intervening. For example, our research suggests there is potential in further exploring how confusion can be identified and managed in digital environments (e.g. Arguel et al., 2017). However, it will be some time before these environments can be built to operate at a capacity nearing that of a human teacher in a face-to-face setting. What is critical in the meantime then is to better understand how best to build environments that can respond to students in productive ways.

The changing student-teacher dynamic in higher education

Partly in response to broader trends associated with the ubiquity of technologies, there are already signs of significant change in policy and practice across higher education settings. While debateable, some (e.g. Lai, 2011) have argued that the core teaching approach in universities has not changed for centuries. In other words, while there has been some movement away from traditional pedagogical approaches, the relationship between students and their teachers has been predominantly through the lecture or other didactic approaches. Essentially academics have broadcast what is in their minds to students. Mounting evidence over an extended timeframe about the value of active learning (e.g. Bell & Kozlowski, 2008; Freeman & Eddy, 2014), underpinned by constructivist learning theories and instructional frameworks, has put increasing pressure on the lecture as a viable means of teaching students in universities (French & Kennedy, 2017). A substantial proportion of this evidence can be traced back to the science of learning. For example, Bell and Kozlowski (2008), examined how the emotional, cognitive and motivational aspects of active learning contribute to long-term learning and transfer. They found that a complex mix of factors including goal orientation and capacity for metacognition influence the success of active learning activities. An overview of how research such as this is impacting on education, including in universities, has been provided by Yates and Hattie (2013). Thus, the science of learning has already had significant impact on notions of effective teaching in higher education.

Lecturing as the key pedagogical approach in higher education has also come under scrutiny over several decades due to changes in the availability of information and knowledge, as we have previously outlined (see also Laurillard, 2002). In tandem, there has been pressure placed on universities through increases in student numbers and a diversification of student cohorts, often without commensurate increases in government funding for higher education (Marginson, 2016). There has therefore been an ongoing need to enrol students in large classes of various kinds to accommodate the growth in numbers. A tension emerges here because the continued move from elite to mass higher education globally has meant, economically at least, lectures have remained a central approach (French & Kennedy, 2017). Easy availability of high quality learning resources outside the university combined with the greater understanding of the value of active learning has created demand for more meaningful and interactive pedagogical approaches on campus (Boys, 2015). From a student perspective, there is also demand for more flexible learning experiences as students lead increasingly demanding lives and have work, carer and other responsibilities competing with their studies for time and attention (Baik, Naylor & Arkoudis, 2015).

These forces are leading to slow but fundamental change in the ways in which higher education is being delivered. With high quality resources now freely available online and an ability to acquire information anytime, there is a need to refocus on the value of the campus experience (Boys, 2015; French & Kennedy, 2017). In particular, the value of interaction between students and between students and academic teaching staff takes on a new level of importance. Sfard's (1998) two metaphors for learning are important here. The critical argument Sfard makes is that there are two central narratives about what learning is. The first, acquisition, is vital but the second, participation, is even more powerful for learning. Participation means not just accumulating knowledge but using it in meaningful ways in collaboration with others and in varying contexts. As technology currently stands, participation of this kind is still more difficult in a virtual or digital environment than on campus (Kebritchi, Lipschuetz & Santiague, 2017). Accessing opportunities for using knowledge in meaningful ways (i.e. application) has improved through increased use of webinars, wikis and other collaborative tools. However, the capacity to interact with qualified experts and see them model the processes of applying knowledge is difficult to capture in a video. This modelling is highly valuable and necessary in many instances, for example when clinical reasoning is carried out in a medical setting (e.g. Eva, 2005). Similarly, watching a video of an experienced nurse go about their practice is not quite the same as seeing this same practice first hand in a live classroom setting or hospital (Mastel-Smith et al., 2015). In addition to having opportunities to use knowledge in meaningful ways, as in active learning, immersive participation and interaction with experts is not something that can easily be recreated in a virtual or digital setting beyond procedural tasks, yet. Digital simulations, virtual roleplays and virtual reality environments are beginning to bridge this gap. How much these environments can and do emulate the application of knowledge and/or provide access to expert application of knowledge remains an open question.

Within this changing context, it is not straightforward to take findings from experimental studies and apply them to such complex and dynamic conditions (Horvath & Donoghue, 2016) in order to understand how student-teacher interaction will change and can be enhanced. However, there are some key areas in which the science of learning can and is having an impact on informing the future of higher education (Lodge, 2016). Research on the effective design of video resources (e.g. Carpenter, Wilford, Kornell & Mullaney, 2013; Muller, Bewes, Sharma & Reimann, 2007) is one example of a relatively straightforward translation process from laboratory to classroom. The research of Muller and colleagues (2007) demonstrates that it is useful to use dialogue and focus on common misconceptions in instructional videos, which proves effective in the design of effective videos for 'flipped' and blended approaches. Along similar lines, Verkade et al. (2017) have highlighted the development of instructional strategies that are focussed on addressing student misconceptions that have a grounding in the extensive literature on conceptual change. Both of these evidence-informed approaches incorporate modifications to the way in which teachers mediate the interaction between students and concepts. There are therefore already numerous examples of how the science of learning may be used in understanding and enhancing student-teacher interaction as technology increasingly impacts on policy and practice. These same approaches will continue to prove useful and informative as the nature of student-teacher relationships continues to evolve.

Key priorities for the science of learning

Within this broader context of rapidly evolving technologies and a rethinking of traditional approaches to education, there are several key areas in which the science of learning is and will continue to contribute. We have already discussed the ways in which the science of learning is providing a foundation for the design and use of cutting edge technologies such as data-driven adaptive learning environments and how these environments might continue to shape the student-teacher dynamic in education. There are also several other key areas, particularly associated with the evaluation of new technologies, helping students to work with technologies and how these technologies can be best deployed to function alongside teachers. We will touch on these areas below.

Informing the development of and evaluating new technologies

Given it is seemingly inevitable that there will continue to be improvements in the capabilities of digital technologies for facilitating learning, there will be a parallel need for informing these developments and determining their effectiveness. This will not only be needed to better understand how teachers and machines will work together to enhance student learning but also to determine the effectiveness of these technologies themselves in a comprehensive way. One of the major issues with the development of educational technologies is that the research examining the effectiveness of the tools lags well behind the spread of their use (Lodge & Horvath, 2017). In other words, new technologies are created and enter into widespread use often before the educational implications of the technologies are fully understood. As highlighted by Luckin (2017), there is great potential for continuous forms of assessment and feedback beyond the procedural domains such as dentistry where simulations incorporating continuous assessment and feedback are common. Development of these technologies will inevitably rely on a sound understanding of the learning process and evaluation approaches that are specifically designed to determine the impact on learning.

Alongside the overall need for the science of learning to help underpin the development of new instructional technologies, this is a clear need to draw on principles of quality student learning to determine how best to effectively combine the expertise of teachers and power of machines. As the student-teacher dynamic evolves, it will be important to monitor and obtain rigorous data on the best ways to deploy technologies and to set up activities and curricula designed specifically to maximise the benefits of the tools and the teacher. Simplified dichotomies will not sufficiently capture the complex nature of the three-way interaction of students, teachers and machines. It would seem that the science of learning is well placed to conduct this ongoing monitoring in concert with teachers and educational designers.

Helping students to work with technologies

Alongside a better understanding of how teachers and machines can work together to help students, there is an ongoing need to help students to work with technologies themselves. As it is likely that more of the acquisition side of learning, as per Sfard's (1998) two metaphors, is carried out by students in digital environments, there will be a need to understand how this is occurring and to help enhance it. Students will increasingly be asked to self-regulate their own learning in these contexts. That is, without the nuanced intervention strategies that teachers employ in a classroom, students, in the short to medium term at least, will need to be selfdirected in their learning. This includes making sound judgements about how much they know compared to how much they need to know, how they are progressing towards completing quality work and whether or not they need to shift strategies if the approach to their learning is not as effective as it could be. It is critical to determine how best to support students to do so in the absence of a teacher to help with this. The science of learning will play a key role in both understanding how students learn with and adapt to emerging technologies and determining how best to equip them with the right knowledge and skills to get the most out of these environments until such time as these environments are as sophisticated in their intervention strategies as a live teacher is in a classroom. With teachers seemingly likely to play less of a role in acquisition and more of a role in facilitating participation, it is critical to understand what the implications are for student learning.

Determining how technologies can best facilitate teaching and learning

A further area in which the science of learning will assist in understanding the changing student-teacher dynamic in education is through the implications on broader policy and practice. Much of what we have focussed on in this chapter has been the operational aspects of the teacher-student dynamic. Beyond this, there are implications for schools and universities, as well as policy making bodies and government as technology increasingly encroaches on education. The increased use of these technologies in classrooms must be driven by what is known about quality learning and not about financial or political motives. The history of educational technologies is littered with examples of technologies that have been implemented for reasons other than what is best for facilitating learning (Watters, 2014). The science of learning has a critical role to play in providing the evidence base for what works to counter they hype so often accompanying the development and spread in the use of technologies in education (see also Lodge & Horvath, 2017).

Conclusions

Developments in emerging educational technologies are already significantly impacting on education. This is apparent through the changing student-teacher dynamic in all levels of education. While it is most obvious in higher education, it is increasingly clear that teachers will be working alongside sophisticated machine learning and AI systems to help facilitate student learning. The science of learning has and will continue to play a pivotal role in providing a foundation underpinning these technologies and for determining how best the combination of teachers and machines can be deployed to enhance learning. While it has perhaps not received the attention that other implications of emerging technologies have, we have highlighted what these technologies mean for how students and teachers work together and in combination with machines. The complex, social environment of the physical and virtual classroom will continue to raise issues and problems that will necessitate investigation. As has become apparent in the field of learning analytics, these investigations cannot rely on technical solutions alone but must be driven through a fundamental understanding about how students learn. So, while teachers seem unlikely to be replaced by robots anytime soon, it seems unlikely that researchers in the science of learning will either.

References

Amin, T. G., & Levrini, O. (Eds.). (2017). *Converging perspectives on conceptual change: Mapping an emerging paradigm in the learning sciences*. Abingdon, UK: Routledge.

Aoun, J.E. (2017). *Robot-proof: Higher education in the age of artificial intelligence*. Cambridge, MA, US: MIT Press.

Arguel, A., Lockyer, L., Lipp, O., Lodge, J. M., & Kennedy, G. (2017). Inside out: ways of detecting learners' confusion for successful e-learning. *Journal of Educational Computing Research, 55* (4), 526-551. DOI: 10.1177/0735633116674732

Baik, C., Naylor, R., & Arkoudis, S. (2015). *The first year experience in Australian universities: Findings from two decades, 1994–2014*. Melbourne: Melbourne Centre for the Study of Higher Education, The University of Melbourne.

Bell, B. S., & Kozlowski, S. W. (2008). Active learning: effects of core training design elements on self-regulatory processes, learning, and adaptability. *Journal of Applied Psychology*, *93*(2), 296.

Blakemore, S. J. (2010). The developing social brain: implications for education. *Neuron, 65* (6), 744-747.

Boys, J. (2015). *Building better universities: Strategies, spaces, technologies*. Abingdon, UK: Routledge.

Broadbent, J., & Poon, W. L. (2015). Self-regulated learning strategies & academic achievement in online higher education learning environments: A systematic review. *The Internet and Higher Education*, *27*, 1-13.

Bruner, J. S. (1962). *A study of thinking*. New York, NY: Science Editions, Inc.

Calvo, R., D'Mello, S. K., Gratch, J., & Kappas, A. (Eds.). (2015). *The Oxford handbook of affective computing*. New York, NY: Oxford University Press.

Carey, S. (2009). *The origin of concepts*. Oxford, UK: Oxford University Press.

Carpenter, S. K., Wilford, M. M., Kornell, N., & Mullaney, K. M. (2013). Appearances can be deceiving: instructor fluency increases perceptions of learning without increasing actual learning. *Psychonomic Bulletin & Review*, *20*(6), 1350-1356.

Chi, M. T. H. (2013). Two kinds and four sub-types of misconceived knowledge, ways to change it, and the learning outcomes. In S. Vosniadou (Ed.), *The international handbook of conceptual change* (2nd ed., pp. 49–70). New York: Routledge.

Christensen, C. & Eyring, H. (2011) *The innovative university: Changing the DNA of higher education from the inside out.* San Francisco: Jossey-Bass.

Cunningham, J. M. (2015). Mechanizing people and pedagogy: Establishing social presence in the online classroom. *Online Learning*, *19*(3), 34-47.

Dalgarno, B., Kennedy, G. & Bennett, S. (2014): The impact of students' exploration strategies on discovery learning using computer-based simulations, *Educational Media International*, *51*(4), 310-329. DOI: 10.1080/09523987.2014.977009

Dall'Alba, G., & Barnacle, R. (2007). An ontological turn for higher education. *Studies in Higher Education*, *32*(6), 679–691. http://doi.org/10.1080/03075070701685130

Eva, K. W. (2005). What every teacher needs to know about clinical reasoning. *Medical Education*, 98–106.

Freeman, S., & Eddy, S. L. (2014). Active learning increases student performance in science, engineering, and mathematics. *Proceedings of the National Academy of Sciences*, *111*(23), 1–6. http://doi.org/10.1073/pnas.1319030111

Freina, L. & Ott, M. (2015). A literature review on immersive virtual reality in education: state of the art and perspectives. in *Proceedings of eLearning and Software for Education (eLSE), 2015 April 23–24*. Bucharest.

French, S., & Kennedy, G. (2017). Reassessing the value of university lectures. *Teaching in Higher Education, 22*(6), 639-654. DOI:10.1080/13562517.2016.1273213

Gašević, D., Dawson, S., & Siemens, G. (2015). Let's not forget: Learning analytics are about learning. *TechTrends*, *59*(1), 64-71.

Gikas, J., & Grant, M. M. (2013). Mobile computing devices in higher education: Student perspectives on learning with cellphones, smartphones & social media. *The Internet and Higher Education*, *19*, 18-26.

Horvath, J. C., & Donoghue, G. M. (2016). A bridge too far – revisited: Reframing Bruer's neuroeducation argument for modern science of learning practitioners. *Frontiers in Psychology*, *7*(429), 71–12. DOI: 10.3389/fpsyg.2016.00377

Huet, M., Jacobs, D. M., Camachon, C., Missenard, O., Gray, R., & Montagne, G. (2011). The education of attention as explanation of variability of practice effects: Learning the final approach phase in a flight simulator. *Journal of Experimental Psychology: Human Perception and Performance*, *37*(6), 1841.

Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science*, *349*(6245), 255-260.

Kebritchi, M., Lipschuetz, A., & Santiague, L. (2017). Issues and challenges for teaching successful online courses in higher education: A literature review. *Journal of Educational Technology Systems*, *46*(1), 4-29.

Kennedy, G. E., & Judd, T. S. (2004). Making sense of audit trail data. *Australasian Journal of Educational Technology*, *20*(1), 18-32. DOI: 10.14742/ajet.1365

Koedinger, K. R., Booth, J. L., & Klahr, D. (2013). Instructional complexity and the science to constrain it. *Science*, *342*, 935–937.

Lai, K. W. (2011). Digital technology and the culture of teaching and learning in higher education. *Australasian Journal of Educational Technology*, *27*(8).

Laurillard, D. (2002). *Rethinking university teaching* (2nd ed.). Abingdon, UK: Routledge Falmer.

Lee, D. Y., & Lehto, M. R. (2013). User acceptance of YouTube for procedural learning: An extension of the Technology Acceptance Model. *Computers & Education*, *61*, 193-208.

Lockyer, L., Heathcote, E., & Dawson, S. (2013). Informing pedagogical action: Aligning learning analytics with learning design. *American Behavioral Scientist*, *57*(10), 1439-1459.

Lodge, J. M. (2016). Do the learning sciences have a place in higher education research? *Higher Education Research & Development, 35* (3), 634-637. DOI: 10.1080/07294360.2015.1094204

Lodge, J. M. & Corrin, L. (2017). What data and analytics can and do say about effective learning. *Nature: npj Science of Learning*, *2* (1), 4-5. DOI: 10.1038/s41539-017-0006-5

Lodge, J. M. & Horvath, J. C. (2017). Science of learning and digital learning environments. In J. C. Horvath, J. M. Lodge, & J. A. C. Hattie (eds.). *From the laboratory to the classroom: Translating learning sciences for teachers.* Abingdon, UK: Routledge.

Lodge, J. M., Kennedy, G. & Hattie, J. A. C. (2018). Understanding, assessing and enhancing student evaluative judgement in digital environments. In D. Boud, R. Ajjawi, P. Dawson & J. Tai (Eds.) *Developing evaluative judgement in higher education: Assessment for knowing and producing quality work.* Abingdon, UK: Routledge.

Luckin, R. (2017). Towards artificial intelligence-based assessment systems. *Nature Human Behaviour*, *1*(0028). DOI: 10.1038/s41562-016-0028

Luckin, R. (2018). *Machine learning and human intelligence*. London: UCL Institute of Education Press.

Macfadyen, L. P., & Dawson, S. (2010). Mining LMS data to develop an "early warning system" for educators: A proof of concept. *Computers & Education*, *54*(2), 588-599.

Marginson, S. (2016). *Higher education and the common good*. Melbourne: Melbourne University Press.

Mastel-Smith, B., Post, J., & Lake, P. (2015). Online teaching: "are you there, and do you care?". *Journal of Nursing Education*, *54*(3), 145-151.

Moodie, G. (2016). *Universities, disruptive technologies, and continuity in higher education: The impact of information revolutions*. New York: Palgrave Macmillan.

Muller, D. A., Bewes, J., Sharma, M. D., & Reimann, P. (2007). Saying the wrong thing: improving learning with multimedia by including misconceptions. *Journal of Computer Assisted Learning*, *24*(2), 144–155. DOI: 10.1111/j.1365-2729.2007.00248.x

Pardo, A. (2018). A feedback model for data-rich learning experiences. *Assessment & Evaluation in Higher Education*, *43*(3), 428-438.

Perry, S., Bridges, S. M., & Burrow, M. F. (2015). A review of the use of simulation in dental education. *Simulation in Healthcare*, *10*(1), 31-37.

Piromchai, P., Ioannou, I., Wijewickrema, S., Kasemsiri, P., Lodge, J. M., Kennedy, G., O'Leary, S. (2017). The effects of anatomical variation on trainee performance in a virtual reality temporal bone surgery simulator – a pilot study. *The Journal of Laryngology & Otology, 131* (S1), S29–S35. DOI: 10.1017/S0022215116009233

Roll, I., & Wylie, R. (2016). Evolution and revolution in artificial intelligence in education. *International Journal of Artificial Intelligence in Education*, *26*(2), 582-599.

Schoor, C., & Bannert, M. (2011). Motivation in a computer-supported collaborative learning scenario and its impact on learning activities and knowledge acquisition. *Learning and Instruction*, *21*(4), 560-573.

Sclater, N. (2017). *Learning analytics explained*. Abingdon, UK: Routledge.

Sfard, A. (1998). On two metaphors for learning and the dangers of choosing just one. *Educational researcher*, *27*(2), 4-13.

Siemens, G., Gasevic, D., & Dawson, S. (2015). *Preparing for the digital university: A review of the history and current state of distance, blended, and online learning*. Report Commissioned by the Bill & Melinda Gates Foundation. Retrieved on 15 April, 2018 from http://linkresearchlab.org/PreparingDigitalUniversity.pdf

Slade, S., & Prinsloo, P. (2013). Learning analytics: Ethical issues and dilemmas. *American Behavioral Scientist*, *57*(10), 1510-1529.

Verkade, H., Mulhern, T. D, Lodge, J. M., Elliott, K., Cropper, S., Rubinstein, B., Horton, A., Elliott, C., Espiñosa, A., Dooley, L., Frankland, S., Mulder, R., and Livett, M. (2017). *Misconceptions as a trigger for enhancing student learning in higher education: A handbook for educators*. Melbourne: The University of Melbourne.

Watters, A. (2014). *The monsters of education technology*. Seattle, WA: Amazon.

Wenger, E. (1987). *Artificial intelligence and tutoring systems*. Los Altos, CA: Morgan Kaufmann.

Yates, G. C., & Hattie, J. (2013). *Visible learning and the science of how we learn*. Abingdon, UK: Routledge.