Introduction

Of all areas where it is possible for the science of learning to have an impact on educational practice, it is arguably in the use of technologies where research from the laboratory can have the greatest influence. The introduction of new technologies raises profound (but also mundane) questions about education into the future. Learning occurring in digital environments also affords possibilities for personalisation and adaptive learning design that are not always possible in face-to-face educational settings. Moreover, educational technologies provide opportunities for capturing aspects of learning that are not easy to evaluate in complex, often chaotic classrooms.

In this chapter we will provide an overview of some of the main research traditions underpinning the understanding of learning in digital environments with an eye to the future. While this work has been translated to real life educational settings to some degree to date, there is substantial potential for further research to have an impact on future education. We will conclude with guidance to teachers about how best to conceptualise and use educational technologies in their practice.

The Trouble with Technology

The exponential growth in power and affordability of technologies has changed numerous aspects of modern life. While there is some conjecture as to the extent of the impact these developments have had on education (e.g. Selwyn, 2013), what is uncontroversial is that it is now easier and more efficient to access information than it has been throughout history. Information is no longer limited to particular sources or locations; it is now possible to access information about almost any topic at any time from anywhere so long as you have a device and some means for accessing the Internet. The development of smaller, more mobile, more powerful devices means that it is common for many people throughout the world to have this persistent access to information.

As educational practices are notoriously difficult to change, these fundamental transformations of the relationship between students and information are yet to be integrated into most educational environments. One of the most obvious examples of this is in higher education where the traditional lecture is still dominant on many campuses, despite it being more suited to an era where information was scarce and difficult to obtain (Friesen, 2011). This slow rate of change is occurring despite pressure being placed on universities by
numerous innovations and global competition. Not only are mobile devices changing the way that students interact with knowledge on campus, there is also the development of massive open online courses (MOOCs) and other innovations (such as social media) changing the way in which students interact with content, faculty, and each other. Higher education provides, perhaps, a particularly striking example of a collision between traditional teaching practices and new technologies; however, the same forces are evident in all levels of education (Ertmer, Ottenbreit-Leftwich, & Tondeur, 2015).

While there is undoubtedly potential in the use of new, networked technologies for providing access to knowledge and educational opportunities, there is some caution required until these innovations reach their full potential. Educational technologies are particularly prone to hyperbole and myth (see De Bruyckere, Kirschner, & Hulshof, 2015). Technology and its potential for use in society (broadly) and in education (specifically) is evolving at a pace that far outstrips the capacity for researchers to determine what impact (if any) new devices or innovations have on learning. The situation is worsened by the overly optimistic and closed attitude taken by many researchers in the educational technology community (Selwyn, 2011). In fact, many practitioners and policy makers are surprised to learn that educational technologies appear to have a negligible effect on the enhancement of student learning (Hattie, 2009). Reeves and Reeves (2015), in particular, have been vocal in lamenting the inability of rigorous research into these technologies to find statistically significant differences across and between media platforms. Clark has further argued that different media used in education are “mere vehicles that deliver instruction but do not influence student achievement any more than the truck that delivers our groceries causes changes in our nutrition” (1983, p. 445)

These critiques of research on educational technology (and, particularly on rigorous, controlled studies on the use of these technologies) have some merit. That is not to say that these views are held unanimously (see Butler, Marsh, Slavinsky & Baraniuk, 2014; Lodge, in press). What these diverse views do suggest, however, is that there is still work to be done to determine if and how technologies impact on student learning.

The lack of research that demonstrates clear benefits of particular technologies is problematic for providing teachers and policy makers with the evidence to make sound choices about what tools and innovations to adopt in practice. The void left by the lag between the introduction of technologies and the provision of evidence about how they can be best utilised is often filled with hype and rhetoric (see: De Bruyckere et al., 2015). In some cases, these misconceptions are used in order to sell devices or software; in other cases, these myths can be unequivocally detrimental to student learning.

There are many examples of hype outpacing solid evidence in relation to educational technologies and innovations. Perhaps the most (in)famous recent example is that of massive open online courses (MOOCs). MOOCs were developed as a way of democratising higher education through the provision of free access to some of the world’s leading professors from the highest-ranking universities. MOOCs created so much hype that it led to the New York
Times to declare 2012 ‘The year of the MOOC’ (Pappano, 2012). As the hype around MOOCs grew, there were commentators claiming that MOOCs would be responsible for completely changing the way in which higher education is delivered globally and herald the emergence of a new model for the design and delivery of university education (see Daniel, 2012). In the ensuing period, it has become evident that MOOCs will not force a fundamental change in the global higher education sector. While MOOCs have raised some questions in terms of the role of the Internet in modern higher education (e.g. Porter, 2015) and the ways in which credentials are conceptualised and recognised (e.g. Lewis & Lodge, 2015), they have not had the impact that was predicted. Instead, the MOOC phenomenon has highlighted a lack of appreciation for existing work over several decades in online and distance learning (Bates, 2014).

Other examples of hype around new educational technologies include the interest around tablet computers (e.g. El-Gayar, Moran & Hawkes, 2011), brain training (e.g. Rabipour & Raz, 2012) and use of the now almost ubiquitous learning management systems (e.g. Weaver, Spratt, & Nair, 2008). In each of these instances, the hype cycle followed a similar pattern as illustrated by the widely cited Gartner Hype Cycle (Gartner Inc., 2015). In other words, an initial period of excitement about the introduction of a new technology is followed by a period of disillusionment when the reality fails to live up to the inflated expectations of the new innovation. Eventually, though, technologies and innovations find their niche in the educational landscape. The over-hyping of new innovations is particularly problematic. Technology is often seen as a panacea and is sold in such a way by vendors, who could cynically be accused of attempting to profit from the hype and lack of immediate evidence around new technologies (see also Selwyn, 2012).

While technology companies attempt to gain a foothold in the education market, there is simultaneously increasing pressure on all levels of education for institutions and schools to cut costs. Many Western countries are spending less per capita on education in relation to GDP than they have in the past (OECD, 2015; Yang & McCall, 2014). This creates pressure on schools and on individual teachers to do more with less. The outcome of these pressures is that simplified technological solutions begin to look appealing as a way of cutting costs and ostensibly providing a superior learning experience for students. The evidence, however, is far from definitive and without sufficient support from rigorous research studies into these new technologies, there is the potential that new technologies could increase costs through implementation and upgrade requirements while being detrimental to student learning. The implementation of educational technologies in practice is, therefore, mired in complex economic and political circumstances that impact on the ability for research to have impact on practice.

Technology, the Internet and Rotting Brains
The hype surrounding various technologies is not only an issue in relation to educational economics and politics, but also in relation to learning broadly. The use of technology in learning is often seen as deleterious to the basic thinking skills that have proven necessary throughout history. There are many (e.g. Brabazon, 2002; Carr, 2008; Daniel & Willingham, 2012) who argue that the use of educational technologies and the Internet is leading to students underperforming in education. This argument aligns with those claiming that the Internet is leading to a general decrease in intelligence in the population. Further to this, authors such as Susan Greenfield (e.g. 2014) claim that technology is leading to wholesale detrimental changes in the brain. As such, there are numerous examples of researchers and other commentators claiming that the Internet and associated technologies are causing harmful effects on student learning and on society more broadly. However, the evidence in support of these arguments is equivocal, at best; non-existent at worst (Loh & Kanai, 2015).

The mixture of technologies and neuroscience is particularly prone to the development and perpetuation of myths and misconceptions that have led to these sorts of negative views about technology and learning. Both are areas that have a certain intuitive appeal. In each area, discoveries are often seen as groundbreaking and at the cutting-edge of science and innovation. The inclusion of a neuro-image (e.g. McCabe & Castel, 2008) or the mention of a new technology or educational innovation (e.g. Ritchie, Chudler & Della Sala, 2012) have both been shown to lead to readers being more susceptible to believe the claims being made in the publication. Beneath the hype, there is a great need for discoveries that combine these two fields to be taken with some caution. The brain is an extremely complex organism. Similarly, the sophistication of new and emerging technologies (such as learning analytics, machine learning and artificial intelligence) are also highly complicated and designed for implementation in complex education settings. Attempting to simplify the developments in either field for blanket use in education is fraught, particularly when the two areas are combined; for example, when evidence from neuroscience is used to support the efficacy of particular innovations or technologies. What this suggests is that research aiming to determine how best to use neuroscience to inform the effective implementation of innovations in education is difficult, complex and will require substantial investments of time and resources. There will be no simple answers or quick fixes. The translation from the laboratory to the classroom is perhaps more complex here than in other areas of education, while, simultaneously, there is increased pressure to provide useful guidance to teachers and policymakers as technologies rapidly evolve.

**Theory and Evidence of Learning in Digital Environments**

The steady stream of hype around the introduction of new technologies suggests that there is a dearth of evidence about how best to use educational technologies in practice. That is, however, not the case. There is an extensive history of work that has been carried out both in laboratory and in educational settings in relation to educational technologies. These activities have tended to sit within one of three distinct paradigms or research traditions. While there
are other ways and means of evaluating the use of educational technologies (see Phillips, McNaught & Kennedy, 2012), these are the dominant approaches. Each has a different level of focus and has contributed in different ways to the overall understanding of the use of educational technology.

The first area of focus is on the technologies themselves. This research tradition has focussed closely on the technical aspects of educational technology development. Often this work is carried out by computer scientists in collaboration with educational practitioners. Perhaps the most prototypical area of research within this tradition is that associated with the development of intelligent tutoring systems. Stretching back to the pioneering work of Alan Newell (e.g. Newell, 1990), there has been a long-standing focus on the development and implementation of technologies that can interact with and adapt to student learning needs in real time. An example of these systems is that of AutoTutor (Nye, Graesser & Hu, 2014). This system has been developed and used in classroom settings in numerous studies (e.g. Craig, Graesser, Sullins & Gholson, 2004; Graesser, Chipman, Haynes & Olney, 2005). Of greater importance to the development of a more sophisticated understanding of how educational technologies can be most effectively used in practice, these systems have also been used extensively to create computational models of the student learning process (Koedinger, D’Mello, McLaughlin, Pardos & Rosé, 2015). For example, AutoTutor has been used in experimental studies examining the effect of emotion on student learning (Craig et al., 2004). This is a requirement for the evolution of intelligent tutoring systems. These systems need to have built into them a sophisticated algorithmic model for predicting the processes by which students are learning. The tradition that is the study of educational technologies from the technical viewpoint has, therefore, been useful to aid in both the evolution of the technologies themselves and in better understanding aspects like confusion that are an important part of the student learning process (see also Arguel, Lodge, Pachman, Lockyer & Kennedy, in press). We will return to the work in this area later in the chapter when we discuss the current state of the field.

Another research paradigm that has had an impact on educational technology is research that uses an approach akin to that commonly used in experimental psychology. This tradition tends to look at aspects of learning in digital environments in a controlled laboratory setting. This research is often carried out by experimental psychologists, cognitive neuroscientists and/or learning scientists and is often done in collaboration with educational practitioners and/or educational technologists. The advantage of these studies is that they are able to isolate various processes and features of technologies and enable an inference to be made about a cause and effect relationship between technologies, features of these technologies and learning. For example, Mueller and Oppenheimer (2014) conducted an experimental examination comparing handwritten note taking to note taking on a notebook computer (the handwritten notes were more effective for studying in this experiment). This tradition aligns with the established sub-discipline of the learning sciences (as discussed in the introduction of this volume). While there are advantages to using these studies for determining cause and effect relationships, laboratory studies such as those carried out in this paradigm also suffer from criticism for being difficult to generalise to practice (e.g. Reeves & Reeves, 2015). As is
the case with many of the areas of educational practice discussed in this volume, the distance from the experimental laboratory to the classroom is great. In the case of educational technologies, this distance has the potential to provide further fertile ground for the development of myths and misconceptions about the efficacy of technologies in practice, as highlighted above.

At the other end of this spectrum from highly controlled, rigorous laboratory work are studies that are conducted in real educational settings. These studies can involve the use of particular devices or applications in physical classrooms or online. These types of studies may be based on paradigms such as action research (Zuber-Skerritt, 1992) or design based research (Van den Akker, Gravemeijer, McKenney & Nieveen, 2006) and are often carried out primarily by teachers and/or applied educational researchers. The aim of these studies is to evaluate particular technologies or features of those technologies in particular educational settings. For example, Venema and Lodge (2013) investigated the use of a USB tablet and ‘digital ink’ in a live lecture setting to determine whether the use of this tool led to enhanced learning over the use of a whiteboard or other, similar tools (it appeared as though this tool did help student learning in this case). While these sorts of studies are chiefly useful for obtaining a qualitative appreciation of a tool or innovation in teaching practice, they are highly context specific. The proliferation of studies of this type that are unable to generalise broadly across educational settings has recently led the The British Journal of Educational Technology (a top ranked educational technology journal) to seek types of research beyond small sample, highly contextualised studies. Instead, the editors have made a call for more systematic and generalisable work on the use of educational technologies (Latchem, 2014).

Research investigating the use of educational technologies, therefore, spans a number of different paradigms, as does the study of education more broadly. Whether the focus is on the technologies, on cause and effect relationships or on situated practice, there are advantages and disadvantages to each approach. A source of tension in recent times is the balance between rigour and relevance in the research on educational innovations (Lodge & Bosanquet, 2014; Ross, Morrison & Lowther, 2010). Reeves (2006) suggests that a remedy to this tension is work that is conducted within the educational design research tradition. Research in this tradition is based on iterative cycles of design and evaluation that builds on approaches commonly used in instructional and educational design. Goodyear (2015) further suggests that educational design research and design thinking are critical for ‘actionable knowledge’ that can be utilised in educational practice, particularly practice involving innovation and technology. It would seem, then, that educational design research and design thinking are crucial to bridging the gap between the laboratory and the classroom and between rigour and relevance (as has been discussed in other chapters in this volume).

Multimedia Learning Theory
Of the theories and approaches that have developed from the dominant paradigms in educational innovation, it is perhaps the work of Richard E. Mayer and colleagues (e.g. Mayer, 2014) that has been most influential. Mayer’s (2009) multimedia learning theory is the most prominent example of laboratory work on educational technology that has been effectively translated and applied to practice. Multimedia learning theory is an information processing theory implying that learning occurs via the active process of filtering, organizing, and integrating information. In short, multimedia information enters the brain via different sensory channels, each of which containing limited capacity and integrative capabilities (Mayer, 2009). From this foundation, it is possible to carefully consider how information being presented in these multiple channels affects the learning process.

Multimedia learning theory has been used as the underpinning theoretical framework for the conceptualisation of much work examining the role of technologies in learning (e.g: Horvath, 2014). Several handbooks have, in fact, been developed on the basis of this work (Clark & Mayer, 2011; Mayer 2005; 2009; 2014). The success of multimedia learning theory in this context has predominantly been due to the rigour in which Mayer and colleagues have applied to the research that informed the development of the theory. It has also proven to be robust to further elaboration, particularly by Moreno (2006), who made important contributions to multimedia learning theory by incorporating aspects of motivation and emotion (Mayer, 2014a). Again, rigorous laboratory studies were used as the evidence in support of these enhancements of the theory.

One reason that multimedia learning theory has been particularly influential in the use of educational technologies in practice is that it as generated solid, simple to follow guidelines for practitioners that can be easily adapted according to environmental and contextual pressures. These guidelines are commonly referred to as ‘multimedia principles’. For example, the redundancy principle states that learning is impaired when identical (rather than non-conflicting supportive) information is presented to two sensory channels simultaneously – such as task instructions simultaneously being presented verbally (auditory) and textually (visual) (Mayer & Fiorella, 2014: we will further explore this principle later in this chapter). Thus, the real genius in the work of Mayer and colleagues is not just that they have been able to draw on rigorous research from the laboratory to develop a robust theory about how student learn with technologies, but also that they have been able to distil this work into a set of principles that provide clear, evidence-based guidance to teachers for the use of technology in their own practice (see Mayer, 2014). This process of translating from the laboratory research to basic principles that can be picked up and used by teacher is common to the emerging work in design for learning and design thinking (mentioned earlier in this chapter).

**Cutting-Edge Research on Learning in Digital Environments**

Multimedia learning theory provides a solid basis for the understanding of learning in digital environments. While it has been particularly useful in guiding the development of educational
technologies and in providing principles for teachers to apply in their practice, the work on
the use of these technologies into the future will continue and will need to grow. One example
of the constantly dynamic nature of work in this area is the emergence of the discipline of
learning analytics. This new area of research has grown out of the powerful new techniques
that are available for collecting data about and from students in various digital environments
and integrating this data for deep analysis about their learning (Koedinger et al., 2015). While
the early focus of this work was to determine which students were most at risk of falling
behind and potentially withdrawing from their university studies (e.g. see Macfadyen &
Dawson, 2010), the field has rapidly evolved to now focussing on more nuanced and
sophisticated aspects of the student learning experience (e.g. de Barba, Kennedy, & Ainley, in
press). What this rapid rise in the use of these data collection, integration and analysis
processes suggests is that there is going to be a continuing need to better understand and
conceptualise how learning occurs as both the technologies and the methods for analysing
student learning continue to evolve (Lodge & Lewis, 2012).

Perhaps the area that exemplifies the cutting-edge of work in educational technologies in the
early 21st Century is the work on intelligent and adaptive tutoring systems. The sophisticated
modelling that has now been made more powerful through the use of learning analytics has
afforded the ongoing development of these systems. There are now many examples of the
kinds of adaptive systems that were first envisaged by Alan Newell and colleagues at
Carnegie Mellon University (Newell, 1990). The critical aspect underpinning this
development is the expansion in data integration and analysis approaches. Coupled with more
powerful computing and an increase in networked devices, this has led to the development of
more adaptive systems (Nye, 2014). For example, the adaptive learning platform Smart
Sparrow can provide a personalised student learning experience that is responsive to the
student’s progress through a lesson in a digital environment (Marcus, Ben-Naim, Bain, 2011).
The combination of better data collection, integration and analysis in combination with more
powerful, connected devices are thus leading to more possibilities for personalised learning.

Another growing area of research is that under the broad umbrella of ‘affective computing’
(Picard, 2000). Researchers in this field are particularly interested in the emotional aspects of
human/computer relationships. By this is meant both the ways in which humans respond to
machines and the ways in which machines are able to detect and respond to human emotions
of interest. Under this broad field, there is a substantial focus in the use of these sorts of
technologies to provide emotionally responsive systems for student learning (D’Mello &
Graesser, 2015). For example, a system that is attuned to student confusion could be
programmed in such a way as to detect confusion and provide a targeted intervention to
ensure that the episode of confusion leads to a productive learning outcome (Lehman,
D’Mello, & Graesser, 2012).

Learning analytics, intelligent and adaptive tutoring systems and affective computing provide
elements of the research that is being conducted at the forefront of educational technologies.
In each of these cases, the work has a particular focus. For learning analytics, the work has
often (but not always) been conducted in real life settings drawing on large datasets.
Intelligent tutoring systems and affective computing research has been often conducted in the laboratory, where the complex, messy reality of the classroom can be controlled. Interestingly, there are examples where these trends have been reversed. Learning analytics have been used to look at learning in specific tasks in the laboratory (e.g. Lodge & Kennedy, 2015). Intelligent tutoring systems have similarly been deployed in school systems broadly (e.g. Koedinger, Anderson, Hadley & Mark, 1997). It is when these reversals happen that the power of some of these new innovations and research approaches become evident. This will become even more so as these fields intermingle and merge. In the more mature field of health informatics, this collaborative cross-disciplinary process has already been established (Coiera, 2015). There has similarly been a call for synthesis and integration from neuroscience, laboratory-based experimental work and large datasets in psychology for the purpose of better understanding of personality and other psychological factors. This sub-field has come to be called psycho-informatics (Yarkoni, 2012). It is reasonable to expect that a more systematic, data driven means of working from the laboratory to the classroom in education may emerge. There has indeed already been some work towards the development of educational informatics (see Ford, 2008), and this may herald a more systemic future for the investigation of learning with technology.

**Future Challenges and Possibilities**

Developments in intelligent tutoring systems, artificial intelligence, machine learning and personalised education have the potential to radically transform formal and informal education in the near future. Computers and networked digital learning environments are becoming exponentially more powerful and cheaper. There is no possible way to forecast how these advances in technology will impact education in the long term. Particularly in the case of artificial intelligence, the consequences of the creation of these possibly super intelligent systems are nearly impossible to predict (Bostram 2014). Learning analytics, adaptive learning and affective computing suggest ways in which the technology will progress. In the meantime, however, there is ongoing research that suggests possibilities for the incremental evolution of the understanding of learning in digital environments. In other words, we will continue to learn more about the human side of the human/computer interaction too.

One particular area that shows potential is the ongoing work into the experience of insight (Bowden, Jung-Beeman, Fleck & Kounios, 2005). Insight, otherwise known as a ‘eureka’ or ‘a-ha’ moments, is commonly experienced when students have crossed a threshold and developed a new, more sophisticated understanding of an issue or concept (see Topolinski & Reber, 2010). While these experiences are relatively common, they have been difficult to research because it is both hard to predict when they will occur and, once they do occur, it is hard to replicate them. Replication of a phenomenon is vital for neuroimaging and experimental studies to separate the regular activity occurring in the brain and mind from the process of interest (in this case, the process leading to insight). Similar projects are underway.
looking at how error, feedback and confidence contribute to the understanding of learning across the span from the laboratory to the classroom.

As we continue to learn more about how the brain and mind work and as technologies become more sophisticated, phenomena such as ‘a-ha’ moments and error correction will become more viable as areas of investigation. Synthesising this work with the ongoing work in data science, computer science and design for learning has the potential to create powerful new approaches for supporting student learning. As opposed to the more reactionary evaluation of new technologies as they have become available in the past, there are real opportunities for research to be at the forefront in the development of these innovations from their inception. For example, it is not difficult to see that a fuller understanding of the process of developing insight could be used to create computational model of insight in the brain. This model could then be used to develop an adaptive intelligent system that can respond to students and give them exactly the individualised support and feedback they need in real time. This system would thus help students to have the insight required to gain a more sophisticated appreciation of a concept. In this way, what we learn about these processes in the brain can have a direct impact on how students are learning in a real life educational setting, albeit a virtual setting in this example.

**From the Laboratory to the Classroom**

Technology and the introduction of new educational innovations provide unique challenges for teachers. As we have discussed in this chapter, there is an illusion that technologies can provide a panacea for student learning that rarely plays out in practice. The reality is that technologies introduce substantial complexity to what is an already complex and difficult task that is preparing students for an unknowable and increasingly unpredictable future. There is a tendency for researchers and practitioners to adopt either a strong techno-positivist or overly sceptical position in relation to technologies in education. It is, thus, an area that tends to cause polarisation with strong views for and against the use of technologies in education. This polarisation unfortunately does not help with the provision of clear guidance to teachers.

Ultimately it remains the case that teachers are often (if not, always) best placed to make informed decisions about what works for them and for their students in their own classroom setting. The lag in evidence about the efficacy of new innovations in education certainly warrants some level of scepticism until such time as better evidence is available. For teachers this means drawing on what has been shown to be effective over the longer term. In other words, technology should not be privileged over pedagogy. There are very good reasons why educational practices are taught to pre-service teachers as they are – because they have been shown to be effective. When new technologies and innovations are introduced, the same cannot be said until the research has been carried out to determine whether the same standard can be applied to these new innovations. Until such time as that occurs, teachers are best placed to make professional judgements about what happens in their class.
If an educator determines an established or novel technology suits the learning goals, there are several foundational principles grounded in the cognitive theory of multimedia learning to consider. As noted above, the first is the redundancy principle, which states that learning is impaired when identical information is presented to two sensory channels simultaneously (Clark & Mayer, 2011). In terms of learning design, what this suggests is to avoid including text-based information when identical material is being covered either visually or auditorily. For instance, when utilizing a video or animation to illustrate a learning concept, do not also include text illustrating the same concept. In this instance, the video/animation and text will compete for limited attentional resources thereby impairing comprehension and memory for each (Kalyuga, Chandler, & Sweller, 2004; Sorden, 2005; Foon Fook & Aldalalah, 2010).

A second principle to consider is the coherence principle, which states that learning is improved when extraneous material is diminished or excluded from multimedia material (Clark & Mayer, 2011). Extraneous information typically comes in three forms. The first is extraneous audio: when unnecessary music, sound effects, or auditory cues are utilized (typically in a bid to attract attention), overall comprehension and memory for the learning material has been shown to suffer (Moreno & Mayer, 2000). The second is extraneous graphics: although images outlining key concepts are useful, the inclusion of secondary, irrelevant images (typically included to sustain attention) has been demonstrated to diminish learning (Mayer, Friffith, Jurkowitz, & Rothman, 2008). The third is extraneous text: the utilization of large, dense blocks of text (typically done to allow for deeper understanding) actually impairs comprehension as compared to the utilization of short, simple keywords and phrases (Butcher, 2006).

A final principle to consider is the segmentation principle, which states that breaking down larger processes or concepts into its compositional bits and presenting these in turn improves comprehension and memory (Clark & Mayer, 2011). For instance, when teaching students how a diesel engine works, utilizing a video or animation that self-pauses at each major step along the process ensures each student has ample time to link novel information with previously obtained knowledge (Mayer, Mathias, & Wetzwell, 2002; Mayer, Dow, & Mayer 2003). Although this principle is intuitively applicable to physical processes (e.g. – tying a knot or cooking a meal), it is equally applicable to more ‘conceptual’ material (e.g. – the development of a democracy or the composition of a sentence).

These principles provide a starting point for teachers to consider the utility of technologies and different forms of media in their practice. The science of learning will continue to provide foundational knowledge about the learning process that will inform the development of new innovations in education. The increasing impact of machine learning, learning analytics, data science and design will lead to incremental enhancements to technologies that already exist and to the development of new technologies specifically designed on the basis of what we are coming to know about the brain and mind. In the meantime, it behoves teachers to continue to draw on established, evidence-based teaching and learning practice. Despite the exciting
developments occurring in neuroscience, data science, computer science and educational technology, innovation in education will be via an evolution, not a revolution.
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