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Psychological foundations of emerging technologies for teaching and learning in higher education

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As the research on the use of educational technologies increases, greater focus is being placed on the psychological processes underlying teaching and learning with these tools. In this research review, we examine six contemporary technologies identified in the 2020 edition of the Horizon Report through the lens of educational psychology theory. Specifically, we highlight the educational, cognitive, and social psychological processes that unfold during teaching and learning with each technology and illustrate how considering these processes can inform study and use of educational technologies and subsequent learning outcomes.

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Current Opinion in Psychology 2020, **36**:xx–yy

This review comes from a themed issue on **Cyberpsychology**

Edited by **Jon Elhai** and **Dmitri Rozgonjuk**

https://doi.org/10.1016/j.copsyc.2020.04.011

Introduction

As research on educational technologies increases in volume and rigor, greater focus is being placed on the psychological processes underlying teaching and learning with these tools [1,2••,3]. Features of technologies that are designed to promote more effective learning typically aim to scaffold psychological processes known to be critical to learning and that have been shown to produce targeted academic outcomes [4••]. The purpose of this review is to consider a set of contemporary technologies employed in higher education settings through the lens of educational psychology theory, highlight the educational, cognitive, and social psychological processes that unfold during teaching and learning with each technology, and illustrate how a focus on those processes can lead to better educational technologies and subsequent learning outcomes.

A variety of technologies are being used for educational purposes, such as robots [5], mobile devices [6,7], and social networking tools [8,9]. The 2020 edition of the *Horizon Report* — an annual publication that documents contemporary learning technologies and forecasts future ones — delineated a set of emerging technologies and practices [10]. Using a Delphi method, which involves expert panelists who conducted multiple rounds of commenting and voting to achieve consensus on six technologies that are likely to have a high impact on future teaching and learning in higher education. These include 1) Adaptive learning technologies, 2) Artificial intelligence (including machine learning-based education applications), 3) Analytics for student success, 4) Elevation of instructional design/learning engineering and user experience (UX) design in pedagogy, 5) Open educational resources, and 6) X-Reality (XR) technologies. Each of these technology classes spans a wide range of products with differing features, applied in differing educational contexts, to support teaching and learning in a variety of academic domains. Here, we provide a general definition of each learning technology, summarize its purpose and features, and consider the psychological processes required to engage in a corresponding educational task the technology is meant to support.

Adaptive learning technologies

Adaptive learning technologies are distinguished by interactive features that allow learning content and learning resources to be personalized based on individual student responses [11]. These technologies analyze a student's performance in real time and then select and modify 1) learning methods, 2) content, and 3) feedback and support to fit the learner's needs. Adaptive learning platforms include Khan Academy [12] and more elaborated *intelligent tutoring systems* (ITSs; e.g. MATHia [13], which are particularly well-studied. Researchers design ITSs by engaging expert and novice math learners in *cognitive task analysis* [14] to understand how they solve math problems. They trace problem-solvers' cognitions as they correctly and incorrectly complete problem steps and engage in metacognitive processes such as evaluating their prior knowledge and answer correctness. Psychologists and software developers then use the results of cognitive task analyses as guides to collaborate and improve ITSs' ability to diagnose learner misconceptions and provide timely and precise feedback that improves *learning efficiency* [15]. Researchers have shown that ITSs built on educational and cognitive psychology principles can match the effects of human tutors, at much larger and more feasible scales [16].

Analytics for student success

Learning analytics is the "measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" [17]. When technologies such as learning management systems (LMSs) are used to house digital learning objects including textbook passages and notes on course topics, students can engage cognitively with course content in ways that can be accurately captured at fine-grained levels of detail [18]. When instructors further supplement these materials with interactive resources like quizzes that test student knowledge and provide feedback, these systems can capture the presence or notable absence of powerful cognitive strategies that promote learning [19] including retrieval practice [20] and self-explanation [21]. Analytics can also trace student use of resources design to support metacognitive aspects of self-regulation [22] such as planning using learning objectives and syllabi, monitoring of learning using feedback on performance after study, and adaptation in strategy use to improve learning [23]. These data can be used to identify and support students who would otherwise struggle, often unnoticed, in such courses [24].

AI education applications

Artificial intelligence (AI) has been discussed since the 1950s, with theoretical underpinnings influenced by mathematics, linguistics, biology, chemistry. However, the definition is widely disputed due to the changes in the political, psychological and philosophical concepts of intelligence. Based on existing definitions of AI and what is known at this current time, AI are "computing systems that are able to engage in human-like processes such as learning, adapting, synthesizing, self-correction and use of data for complex processing tasks" [25]. AI solutions in higher education often rely upon learning analytics (described above) to provide traces of students' cognitions and metacognitions, which become the key features submitted to algorithms that leverage AI to predict and support student success. By observing early learning events of high and low performers, educational psychologists and computer scientists can develop algorithms informed by theories of cognition and metacognition that accurately identify students who will perform poorly in a course [e.g. 26]. These algorithms can trigger adaptive support to train students' cognitive strategy use and monitoring of their learning [e.g. 27•]. This is but one example of the use of AI in higher education. In a systematic review of the use of AI in medical education in the higher education context, Chan and Zary [28] found that AI was used for learning support, student assessment, and curriculum review. Furthermore, AI equipped robots were used to simulate patients [29], and in another study AI was used to provide students with a guided learning pathway and personalized feedback [30]. Such AI systems allow for individualized scaffolding (i.e. diagnosis, support, and then fading of that support [31]; at scales infeasible with human instructors.

Elevation of instructional design learning engineering, and UX design

With the rapid expansion of technological tools for teaching and learning, the role of instructional design has made concomitant leaps in course design and development. New titles have emerged for this role, such as learning experience designer (LXD) and learning engineers [10]. These LXDs focus on user experience (UX), integrated course design and how students learn. The University of Waterloo [32] introduced a user experience design for learning (UXDL), called the UXDL Honeycomb. This Honeycomb framework has seven criteria: usable, useful, desirable, valuable, findable, creditable, and accessible. As the LXDs develop curriculum content, each of these seven criteria inform design. Such design initiatives align with research on cognitive load [2••], and how multimedia learning must take into account the affordances and limitations of human cognitive architecture [33]. In particular, psychological research has demonstrated the importance of maximizing working memory capacity by varying modality of input (e.g. visual and verbal stimuli) rather than overloading a single model (e.g. all visual input).

Open educational resources

Open Educational Resources (OER) are teaching and learning materials with open licensing that permit users to use, reuse, revise, remix, and retain that material for educational purposes [34]. OER materials offer educators the ability to adapt the resources to the specific needs of the students [35]. In a study on the use of OER in higher education, Baas *et al.* [36], revealed that educators may use the resources as-is, or as a source for inspiration. Such resources can be used to democratize information for equity goals but also require that educators and learners have the knowledge, skills, and dispositions to critically consume, integrate, and use such material [37]. The epistemic cognition underlying such skills [38] provides a critical bridge between the individual conceptions of knowledge and what it means to know with the disciplinary norms and practices used to make contributions to human knowledge [39]. Open educational resources can drive innovation and inspiration but the learning that results is dependent upon educators' ability to curate those resources into reliable sources of knowledge and learners' ability to enact their own epistemic cognition using those resources [40].

XR (AR, VR, MR) technologies

X-Reality (XR) are the systems that involve mixing real and virtual worlds to include augmented, virtual, mixed reality systems and haptic systems [41,42]. Each of these are explained in Table 1.

Table 1

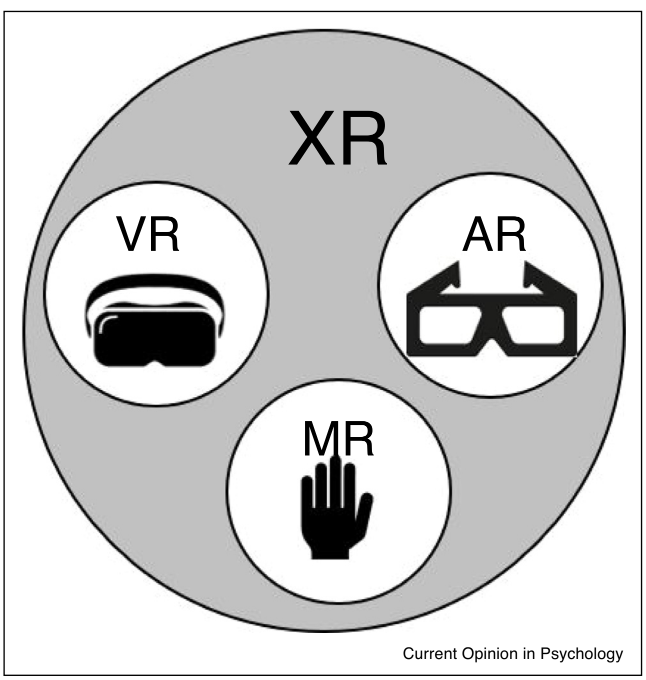
XR systems

System name	System description
Virtual Reality (VR)	Virtual reality is an immersive experience as the user has a headset that generates images and sounds similar to a real or imaginary world.
Augmented Reality (AR)	Augmented reality is experienced using a headset, glasses, or handset (e.g. phone or tablet) to view a live view of the physical world while elements are incorporated, such as images, video, sound or GPS data. The AR is an overlay of digital content on the real world.
Mixed Reality (MR)	Mixed reality, which is also called hybrid or extended reality is when real and virtual worlds are merged and physical and digital objects co-exist and interact in real time. For example, while seeing a digital image, a user may be able to reach out and interact with the digital overlay.

XR is the overarching term the encompasses VR, AR, and MR. Figure 1 provides a visual representation of the distinct modalities involved in Virtual Reality (fully immersive goggles), Augmented Reality (goggles displaying information with transparent lens), and Mixed Reality (affording physically interactive opportunities) technologies.

Janabi *et al.* [43] examined the use of mixed reality to improve outcome performance of novice surgeons. Using the HoloLens, users put on a head mounted display that allows the user to see the patient and move their hands as they would while preforming surgery. Real operating equipment was used to simulate realism and application to training, the user read a patient scenario and then went into the surgical simulation using the HoloLens. The study findings show that the MR device facilitated improved outcomes of performance. Basic perception is implicit and critical to all cognitive processing, but learners' perceptional processes are particularly relevant in XR contexts. Learners must be able to manage their physiological and cognitive responses while they attend to the virtual features of their environment to engage productively in learning.

Figure 1



Modalities involved in Virtual Reality.

Conclusion

A thoughtful appraisal of the emergent technologies likely to influence teaching and learning in universities requires a thorough consideration of the psychological processes that creators aim to invoke in the design of their technologies, that instructors undertake when selecting and implementing them, and that students enact when they use these technologies to learn, both individually and socially or in collaboration. Developing an understanding of students' perceptions, cognitions, metacognitions and affective and physiological responses requires that developers, instructors, and those who aim to promote effective learning engage in research on the use of emerging learning technologies. During development, designers would be wise to draw on human factors [44] and user experience [45] research design paradigms. Likewise, educational technologists should study instructors' goals and standards [46], technology integration frameworks [e.g. 47–49], and educational conditions to support the use of technology [50•], the use of technologies in higher education [e.g. 51••], and epistemic cognition [37] as they adopt, adapt, and implement technologies for learning. Finally, continued scholarly and practical progress will require that researchers make use of digital trace data produced when students learn [18], and align these to more classical trace data (i.e. think-aloud protocols [40], to more precisely investigate the psychology of learning with emerging technology in authentic educational contexts.

Conflict of interest statement

Nothing declared.

CRediT authorship contribution statement

Helen Crompton: Conceptualization, Project administration, Writing - original draft, Writing - review & editing.

Matthew Bernacki: Writing - original draft, Writing - review & editing. **Jeffrey A Greene:** Writing - original draft, Writing - review & editing.

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- • of special interest
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