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Future Teaching trends: science and technology

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Introduction

This review partners with *Future Teaching trends: education and society*, highlighting the technological trends likely to have significant implications for the future of higher education over the medium term, and those we should attend to in thinking about near future teaching. This is not a comprehensive review of technological shift, but rather a brief overview of a few areas chosen for their potential high impact.

Datafication

Datafication of
society

The datafication of society extends to all aspects of daily life and has implications for education across all sectors: the data trails we generate as digital citizens, and the surveillance regimes that feed on these; **data driven decision making** by institutions, governments and corporations; the attendant questions of privacy and ethics; the impact of data on the media and the political sphere; the building intensity of these through the **Internet of Things**; and the concentration of influence in particular algorithms and platforms. Datafication is active, systematic and continuous (Raley 2013) leaning, often, toward the prediction of future behaviour as a basis for decision making.

The datafication of our private lives has normalised a 'liquid **surveillance**' (Bauman and Lyon 2013), in which the watching of ourselves and each other facilitated by digital technologies generates continuous flows of data about individuals (Lupton and Williamson 2017). This has been amplified and monetised by social media and other corporations built according to platform models (Srnicek 2016) which depend on the extraction, profiling and commercialisation of large amounts of user data to generate profit. Such 'surveillance capitalism' might be seen as one defining characteristic of our current technological moment (Zuboff 2015).

Datafication of
education

The way that datafication has been understood in education contexts (Selwyn 2014) tends often to make the assumption that data and technology can 'solve' problems in education (teaching quality, learner support, democratisation of access, plagiarism) in an unproblematic way, justifying over-simplistic adoption models. Such '**solutionist**' assumptions often drive development within the

increasingly powerful educational technology industry (Watters 2013) and subsequent imperatives to adopt within schools, colleges and universities. Some argue that this perspective aligns with neoliberal models of the university, surfacing underlying conflicts between digital technologies and foundational ideas about the purpose of education itself (Selwyn and Facer 2013; Hoofd 2016).

Datafication in higher education can be seen as the confluence of a range of social factors running in parallel with technological change, for example: **unbundling** and privatization, changing patterns of engagement and recruitment at the global scale, the normalisation of ubiquitous surveillance, massification of higher education and subsequent effects on staff workload, academic precarity and public perception of the value of universities (see the companion review *Future Teaching trends: society and education*). Universities are working with an ever-diminishing pool of government resources, a culture driven by the introduction of market values to higher education, a move toward increasing quantification and metrics-driven ways of evaluating quality of teaching, and a growing imperative for data-driven decision making. Systems are increasingly engineered towards **compliance** data as a means of establishing accountability in the wake of increased scrutiny. One outcome of these accountability reforms has been the increased production, analysis and comparison of what Selwyn et al (2015) characterise as ‘compliance data’, as opposed to ‘useful data’ (Roberts-Holmes and Bradbury 2016). Emblematic of this, high-stakes national assessments, REF, KEF, and TEF act as a ‘meta-policy’, steering pedagogy and policy further toward datafication.

Data and educational technology

With sensor and device-based tracking of individuals technically possible, **location analytics** have potential – should universities wish it – for data-enabled student tracking, attendance and ‘engagement’ monitoring (JISC 2017), albeit with legal restrictions provided by data protection regulation. Data generated manually by student use of learning management systems and access to library and other services can be subjected to **learning analytics** designed to map engagement and – in some cases – to aid **prediction** of student success or failure. Application and progression datasets being combined to predict patterns of admission and withdrawal, and analytics designed to identify students at risk for targeted support are already well-used in universities, with some claiming benefits for retention (see Dawson et al 2017). Others (e.g. Wilson et al 2017) criticise learning analytics for over-simplifying and undertheorizing the complexities of how students learn.

Quantification in education promises in the near future to extend to **neurotechnological** ways of understanding learning, with commercial educational technology initiatives promising new brain–computer interfaces, cognitive training tools and electronic neurostimulators. For example, headsets for students which track real-time student attention levels, feeding live engagement reports to teachers and using student brain data as training sets for machine learning are already under development (Williamson, 2018). Facial and **emotion recognition** technologies as means of mapping, tracking and recording

student engagement are already available and used by a small group of universities. Fundamental questions emerge from this concerning the ownership of data, its ethical uses, permanence, the risks of reproducing discrimination, and implications for the mental privacy and cognitive liberty of students and academics (Ienca and Andorno 2017).

This trend towards accelerating production, harvesting and analysis of data will continue, within changing frameworks of governance, ethics and privacy protection. With increasing **urbanisation**, the datafication of cities and campuses is likely to accelerate with new forms of 'data exhaust' offering wide opportunities for building new kinds of data-rich education, alongside risks for pulling universities into new forms of normalised, politicised, data-driven surveillance and monitoring.

Artificial Intelligence (AI) and education

Perspectives on AI

To a large extent reliant on the datafication described above, advancements in artificial intelligence (AI) and automation have profound implications for education. There is a growing commercial infrastructure to mainstream AI in a variety of domestic domains, from Apple's Siri to Google Home and Amazon's Alexa. More and more of our interactions with the internet itself are governed through AI and IoT (Internet of Things) technology, a trend that will likely accelerate in the coming years.

To date, most AI currently services limited fields: speech recognition, visual recognition, and some limited dialogue-based response. However, recent advancements suggest a near future in which AI moves further into **affective** domains, systematically identifying and responding to human emotions. Limitations in current AI are being tested through functionality that allows AI to generate its own responses rather than relying solely on what is extracted from large datasets or past experience (Lu et al 2017), while 'neuromorphic computing' (or the 'silicon brain') promises the ability to artificially mimic human brain neural processing resulting in more efficient, and more human AI (Reardon 2017).

Intelligent tutoring systems

All of these developments have relevance to higher education teaching and learning. For example Intelligent Tutoring Systems (ITS) use AI techniques to simulate **one-to-one human tutoring**, promising the ability to map learning activities directly to individual student need alongside timely, targeted **feedback**, without the need for a human teacher (Luckin et al 2016). These AI adaptive tutors for individual students could conceivably model learners' cognitive and affective states, use dialogue to engage the student, include open learner models to promote reflection and self-awareness, provide dynamic help to increase learner motivation and engagement, and more.

AI can already provide instructional capacity by way of intelligent tutoring in certain course contexts. Current uses include Georgia Tech's Jill Watson, built on IBM's Watson platform to provide **responsive tutor support** to large groups of

students (Goel and Joyner 2017), and **campus-wide AI** for enhancement of student experience at Deakin University (Popenici and Kerr 2017).

It also has potential to provide intelligent support for collaborative learning through the use of **adaptive group formation**, expert facilitation and **virtual agents**. AI can be fitted to use machine learning and shallow text processing to analyse and summarise discussions in group forums, enabling a human tutor to more easily guide students towards effective collaboration. Human tutors can receive alerts if atypical or off topic activity is taking place (such as repeating misconceptions) that might require their engagement (De Laat, Chamrada, and Wegerif 2008).

Opinion within the field of education is split between those who see AI as having positive potential to augment teaching (Popenici and Kerr 2017) or open it to new ways of understanding productive human/machine co-teaching (Bayne 2015), and others who suggest that automation of teaching through AI is only feasible if education is already impoverished by the reduction of teaching, and teacher professionalism, to performative, routinised work (Shank 2016).

Neuroscience and cognitive enhancement

Neuroscience, and its insights into the embodied and physiological aspects of learning, promise to impact in new ways on teaching. Relevant initiatives include the US BRAIN Initiative and the EU Human Brain Project, which promise to develop and apply methods for at-scale monitoring of neural activity, and to discover ‘how dynamic patterns of neural activity are transformed into cognition, emotion, perception, and action’ (NIH, 2014).

Educational
neuro-tech

Such initiatives promise developments for cognitive enhancement which have significance for higher education teaching. Commercial developments promising new **brain-computer interfaces**, cognitive training tools and electronic neurostimulators designed to ‘enhance’ learning have been dubbed ‘educational neurotech’ (Williamson 2017). For example, transcranial direct current simulation – ‘a portable, cheap, low-tech procedure that involves sending a low electric current to the brain’ (Batuman 2015) – has been shown to have positive effects on reading efficiency and memory, while IBM has invested in developing ‘neurosynaptic brain chips’ and scalable ‘neuromorphic systems’ to further develop its cognitive supercomputing system Watson (Williamson 2016).

Cognitive
enhancement
drugs in
education

Enhancement through new kinds of brain-computer device is accompanied by the promise of advanced cognitive enhancement drugs designed to improve memory, creativity or motivation. Modafinil typifies these cognitive enhancers in its benefits linked to learning: increased memory, decision making and creativity. The longer and more complex the learning task is, the more consistently Modafinil confers cognitive benefits such as enhanced attention, executive functions, and overall learning outcomes, and largely does so without evidence of side effects or mood changes (Battleday and Brem 2015).

Use of such drugs is already present in higher education: a recent study based largely on self-reported survey data found that ‘on-going use’ of cognitive drugs among students at Cambridge and Oxford is 15% and 18%, respectively (Vagwala et al 2017). Students – and academics – take these drugs for the cognitive edge they can bring to study, examination and writing performance (Porsdam et al 2018). Others are ‘disadvantaged’ by being unable to afford them. Some academics have called on higher education to consider developing policy and adopting measures such as drug testing to offset the use of cognitive enhancers in universities (Marsh 2017).

The impact that these developments might have on teaching in higher education are considerable, particularly in their potential to negatively affect the health of individuals, but also in uneven distribution of access to them: widespread use of cognitive enhancement drugs and educational neurotechnologies in the future could bring with them new patterns of **exclusion**. The intersections of neuroscience, technology, and health are likely to require institutions to develop interventions and policy for managing artificial cognitive enhancement, ‘**bio-distress**’ and the impact of these on assessment, learning and scholarship (Knowledge Works 2008).

Virtual and augmented realities

Virtual and augmented realities are becoming sufficiently mature to have meaningful impact on higher education practice. Virtual reality is often used as a generic term for distinct types of immersive experiences including augmented reality (technology that enhances a physical environment), and mixed reality (technology that uses a combination of both virtual and augmented realities). The recent commercial success of augmented reality (AR) games, moves by Apple to develop AR headsets (Gurman 2017), and Facebook to generate VR content coupled with their purchase of Oculus Rift, suggests that these technologies are mainstreaming. Recent content initiatives by commercial enterprises further suggest the sustainability of virtual and augmented realities – *The Guardian* VR (2018) has generated immersive virtual reality content to explore life as an autistic teen, or as a one-year old child, or a forensic trainee trying to solve a murder.

VR in education

Stanford University’s Virtual Human Interaction Lab has several projects exploring empathy and embodiment through VR. ‘Examining Racism with Virtual Reality’ uses immersive virtual reality (IVR) to create a ‘virtual shoes’ experience through which a participant can encounter mediated forms of racism; additional projects explore empathy at scale, and the limits of immersion and presence in virtual reality (2016). These types of projects foreground a type of immersion that allows embodied experience to take place relatively free of implications for the individual user (Shin 2018). Critics have suggested such experience is little more than ‘**identity tourism**’ (Nakamura 2002), perhaps best typified by Facebook’s much criticised virtual reality tour through hurricane-ravaged Puerto Rico featuring cartoon avatars of Zuckerberg (Solon 2017).

The teaching applications of these virtual and augmented realities are potentially varied and rich however. In **medicine**, there has been use of virtual reality for developing competency in high-risk scenarios largely through simulation (Aïm et al 2016). Virtual reality can simulate anatomy, and can record, compare and analyse performance; such simulations are permanently available, the presence of an expert teacher is potentially unnecessary, and unrestricted task repetition is possible (2016). Beyond mitigating risk in working on human subjects, the results from these types of learning simulations are generally positive in terms of surgical skills acquisition and the speed at which those skills could be applied in real surgeries (Cannon et al 2014; Valdis et al 2015). Virtual reality data analysis has been identified as potentially beneficial to **data science** (Donalek et al 2014), offering possibilities for immersion in data, which can be presented inside a 3D canvas which wraps around the user, with data points distinguished by size, colour and transparency, as well as direction and velocity of movement (Marr 2017). Commercial virtual reality data services continue to emerge.

New forms of value

A final technological development we wish to cover briefly concerns the way in which value is likely to be measured and exchanged through new distributed ledger technologies. Blockchain, currently the most well-known of these, organises data into linked 'blocks', using individual computers to record, share and verify transactions in a **distributed** network, rather than in a centralized, traditional ledger. Such technologies promise a new 'internet of value' capable of recording and transferring value peer-to-peer without the need for a trusted central authority or institution.

Blockchain and distributed ledgers

The blockchain organises data in value blocks which might consist of any asset from money, land titles and health information to accredited learning and qualifications. Claimed to be incorruptible and self-auditing, the blockchain is argued to enable new configurations of trust to be built between peers, and tighter ownership of assets, identity and reputation by individuals, in the process diminishing reliance on **institutional gatekeepers** of value like universities.

Implications of distributed ledger technologies for education include the potential to digitise and automate the award and transfer of credit, opening up ways of recording all an individual's formal and non-formal educational achievements in a form that can be trusted and verified through the ledger (Grech and Camilleri 2017). Accumulation of credit from across an individual's life course may prompt new ways of defining qualification and expertise. It might in doing so help open up accreditation to new industry and government providers, while giving individuals greater control over the recording and transfer of their educational data (Sharples et al 2016).

Smart contracts

Smart contracts enabled by the blockchain could also make it possible for teachers and students to connect directly without universities as mediator. Woolf University, a speculative blockchain university created by a group of Oxford academics offers a cryptocurrency ('Woolf tokens') which students can use to create smart contracts directly with academics, the stated aim being to 'reduce university bureaucracy, lower student fees, and ensure better salaries for academics' (Brogi et al 2018).

While the potential implications of distributed ledger technology have been much hyped, its actual uses within education are still speculative and unproven. Some critics foreground its decentralising, individuating reduction of all learning to exchangeable value, aligning it with the ideologies of 'neoliberalism, libertarianism, and global capitalism' (Watters 2016). Others challenge its vast carbon footprint (Holthaus 2017), and some see it merely as a solution in search of a problem.

This brief review should be read alongside the companion piece *Future Teaching trends: education and society*, which expands on some of the broad social issues underpinning the trends described here.

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References

Aïm, F., Lonjon, G., Hannouche, D., & Nizard, R. (2016). Effectiveness of virtual reality training in orthopaedic surgery. *Arthroscopy: The Journal of Arthroscopic & Related Surgery*, 32(1), 224-232.

Battleday, R. M., & Brem, A. K. (2015). Modafinil for cognitive neuroenhancement in healthy non-sleep-deprived subjects: a systematic review. *European Neuropsychopharmacology*, 25(11), 1865-1881.

Batuman, E. (2015, April). Electrified: Adventures in transcranial direct-current stimulation. *New Yorker*, 6 April 2015. Available at: <https://www.newyorker.com/magazine/2015/04/06/electrified>.

Bauman, Z., & Lyon, D. (2013). *Liquid surveillance: A conversation*. Hoboken: John Wiley & Sons.

Bayne, S. (2015). Teacherbot: interventions in automated teaching. *Teaching in Higher Education*, 20 (4), 455-467.

Broggi, J.; Lilly, J.; & Duquette, J. (2018). Woolf Building the first Blockchain University Token Paper. Available at: <https://woolf.university/#>

Cannon, W.D., Garrett, W.E., Jr, Hunter, R.E., Sweeney, H.J., Eckhoff, D.G., Nicandri, G.T., Hutchinson, M.R., Johnson, D.D., Bisson, L.J., Bedi, A., Hill, J.A., Koh, J.L. & Reinig, K.D. (2014). Improving residency training in arthroscopic knee surgery with use of a virtual-reality simulator. A randomized blinded study. *The Journal of Bone and Joint Surgery*, 96(21): 1798-1806.

Dawson, S., Jovanovic, J., Gasevic, D., Pardo, A. (2017) From prediction to impact: evaluation of a learning analytics retention program. In *Proceedings of the Seventh International Learning Analytics & Knowledge Conference*, 474-478.

De Laat, M., Chamrada, M., & Wegerif, R. (2008). Facilitate the facilitator: Awareness tools to support the moderator to facilitate online discussions for networked learning. In *Proceedings of the 6th International Conference on Networked Learning*, 80–86.

Donalek, C., Djorgovski, S. G., Cioc, A., Wang, A., Zhang, J., Lawler, E., and Davidoff, S. (2014, October). Immersive and collaborative data visualization using virtual reality platforms. In *Big Data (Big Data), 2014 IEEE International Conference*, 609-614.

Goel, A. K., & Joyner, D. A. (2017). Using AI to Teach AI: Lessons from an Online AI Class. *AI Magazine*, 38(2).

Grech, A. and Camilleri, A.F. (2017). Blockchain in Education. In A. dos Santos, (Ed.) *Science for Policy report by the Joint Research Centre (JRC)*. Available at:

[http://publications.jrc.ec.europa.eu/repository/bitstream/JRC108255/jrc108255_blockchain_in_education\(1\).pdf](http://publications.jrc.ec.europa.eu/repository/bitstream/JRC108255/jrc108255_blockchain_in_education(1).pdf)

Guardian (2018). Virtual Reality Studio. *The Guardian*, 29 March 2018. Available at: <https://www.theguardian.com/news/series/virtual-reality-studio>

Gurman, M. (2017). Apple Is Ramping Up Work on AR Headset to Succeed iPhone. *Bloomberg*, 8 November 2017. Available at: <https://www.bloomberg.com/news/articles/2017-11-08/apple-is-said-to-ramp-up-work-on-augmented-reality-headset>

Holthaus, E. (2017, December). Bitcoin Mining Guzzles Energy—And Its Carbon Footprint Just Keeps Growing. *Wired*, 16 December 2017. Available at: <https://www.wired.com/story/bitcoin-mining-guzzles-energyand-its-carbon-footprint-just-keeps-growing/>

Hoofd, I. (2016). *Higher Education and Technological Acceleration*. London: Palgrave Macmillan.

Ienca, M., & Andorno, R. (2017). Towards new human rights in the age of neuroscience and neurotechnology. *Life sciences, society and policy*, 13(1), 5.

JISC (2017). The smart home reloaded - welcome to the intelligent campus. *JISC*, 27 July 2017. Available at: <https://www.jisc.ac.uk/blog/the-smart-home-reloaded-welcome-to-the-intelligent-campus-27-jul-2017>

Knowledge Works (2008). *2020 Forecast: Creating the Future of Learning*. Available at: http://www.iftf.org/uploads/media/IFTF_SR-1165A_RemakingLearningForecast.pdf

Lu, H., Li, Y., Chen, M., Kim, H., & Serikawa, S. (2017). Brain intelligence: go beyond artificial intelligence. *Mobile Networks and Applications*, 23(2), 368-375.

Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). *Intelligence unleashed: An argument for AI in Education*. Available at: <http://oro.open.ac.uk/50104/1/Luckin%20et%20al.%20-%202016%20-%20Intelligence%20Unleashed.%20An%20argument%20for%20AI%20in%20Education.pdf>

Lupton D. & Williamson, B. (2017). The datafied child: The dataveillance of children and implications for their rights. *New Media & Society*, 19(5), 780-794.

Marr, B. (2017). How VR And AR Will Change How We Visualize Data. *Forbes*, 31 August 2017. Available at: <https://www.forbes.com/sites/bernardmarr/2017/08/31/how-vr-and-ar-will-change-how-we-visualize-data/#50905bf81cac>

Marsh, S. (2017, May). Universities must do more to tackle use of smart drugs, say experts. *The Guardian*, 10 May 2017. Available at: <https://www.theguardian.com/education/2017/may/10/universities-do-more-tackle-smart-drugs-say-experts-uk-exams>

Nakamura, L (2002). *Cybertypes: Race, Ethnicity, and Identity on the Internet*. London: Routledge.

National Institute of Health (2014). NIH embraces bold, 12-year scientific vision for BRAIN Initiative. Available at: <https://www.nih.gov/news-events/news-releases/nih-embraces-bold-12-year-scientific-vision-brain-initiative>

Popenici, S. A., & Kerr, S. (2017). Exploring the impact of artificial intelligence on teaching and learning in higher education. *Research and Practice in Technology Enhanced Learning*, 12(1), 22.

Porsdam Mann, S., de Lora Deltoro, P., Cochrane, T., & Mitchell, C. (2018). Is the use of modafinil, a pharmacological cognitive enhancer, cheating? *Ethics and Education*, 1-17.

Raley R. 2013. Dataveillance and countervailance. In: Gitelman L (ed.) *Raw Data Is an Oxymoron*. 121–145. Cambridge: MIT Press.

Reardon, S. (2017). Artificial neurons compute faster than the human brain. *Nature* (26 January 2018). Available at: <https://www.nature.com/articles/d41586-018-01290-0>

Roberts-Holmes, G., & Bradbury, A. (2016). Governance, accountability and the datafication of early years education in England. *British Educational Research Journal*, 42(4), 600-613.

Schank, R. (2016). Should we fear AI or just fear the people who write about AI? Available at: <https://educationoutrage.blogspot.hr/2016/05/should-we-fear-ai-or-just-fear-people.html>

Selwyn, N., Henderson, M., & Chao, S. H. (2015). Exploring the role of digital data in contemporary schools and schooling— '200,000 lines in an Excel spreadsheet'. *British Educational Research Journal*, 41(5), 767-781.

Selwyn, N. (2014). Data entry: towards the critical study of digital data and education. *Learning, Media and Technology*, 40(1), 64-82.

Selwyn, N., & Facer, K. (Eds.). (2013). *The politics of education and technology: Conflicts, controversies, and connections*. New York: Palgrave Macmillan.

Sharples, M., de Roock, R., Ferguson, R., Gaved, M., Herodotou, C., Koh, E., Kukulska-Hulme, A., Looi, C-K, McAndrew, P., Rienties, B., Weller, M., Wong, L.H. (2016). *Innovating Pedagogy 2016: Open University Innovation Report 5*. Milton

Keynes: The Open University. Available at:

https://iet.open.ac.uk/file/innovating_pedagogy_2016.pdf

Shin, D. (2018). Empathy and embodied experience in virtual environment: To what extent can virtual reality stimulate empathy and embodied experience? *Computers in Human Behavior*, 78, 64-73.

Valdis, M., Chu, M.W., Schlachta, C.M. & Kiaii, B. (2015) Validation of a Novel Virtual Reality Training Curriculum for Robotic Cardiac Surgery: A Randomized Trial, *Innovations*, 10(6), 383-388.

Watters, A. (2016). The Ideology of the Blockchain (for Education). *Hack Education*, 14 April 2016. Available at:

<http://hackeducation.com/2016/04/14/blockchain-ideology>

Watters, A. (2013). Click Here to Save Education: Evgeny Morozov and Ed-Tech Solutionism. *Hack Education*, 3 March 2013. Available at:

<http://hackeducation.com/2013/03/26/ed-tech-solutionism-morozov>

Williamson, B. (2018). 10 definitions of datafication (in education). *Code Acts in Education*, 17 March 2018. Available at:

<https://codeactsineducation.wordpress.com/2018/03/17/10-definitions-datafication/>

Williamson, B. (2017). Brain data, neurotechnology and education. *Code Acts in Education*, 4 May 2017. Available at:

<https://codeactsineducation.wordpress.com/2017/05/04/brain-data-neurotechnology-and-education/>

Williamson, B. (2016). Artificial intelligence, cognitive systems and biosocial spaces of education. *Code Acts in Education*, 17 May 2016. Available at:

<https://codeactsineducation.wordpress.com/2016/05/17/ai-cognitive-systems-education/>

Wilson, A., Wilson, C., Thompson, T. L., Drew, V., and Doyle, S. (2017) Learning analytics: challenges and limitations, *Teaching in Higher Education*, 22(8), 991-1007.

Zuboff, S. (2015) Big Other: surveillance capitalism and the prospects of an information civilization. *Journal of Information Technology*, March 2015, (30)1, 75–89.

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