Artificial Intelligence for Professional Learning

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1 Introduction

Artificial Intelligence (AI) is changing the workplace – in the areas of productivity, administration, HR and recruitment, R&D, logistics, manufacturing, services and relationships with sellers and suppliers, to name just a few (Fleming, 2020). As AI replaces some job roles and changes others, work practices evolve. This means that professionals have to be able to learn and work with AI systems and other digital technologies (McKinsey, 2017). For example, a recent IBM study emphasised the need to scale professional learning to maintain a skilled workforce able to adapt (LaPrade et al., 2019). Meanwhile, AI systems have also been seen as a way to scale professional learning (Edlich et al., 2019). For example, in some places AI is already being used to recommend content to workers as a way (so it is argued) to 'personalise learning' or to 'shorten the learning journey', depending on the prior knowledge and specific skills set of each worker(e.g., Area9 Lyceum, 2022).

So, the consensus is clear: (i) AI is having a growing but uncertain impact on businesses, at every level, in every sector and worldwide; (ii) such that business leaders and workforces need to better understand what AI is, its potential and challenges, and how it might best be leveraged for profit, while maintaining the highest ethical standards; and (iii) the judicious deployment of AI-assisted educational applications might help organisations deal with changes in job roles and professional practice. However, the context of professional learning differs significantly from formal educational contexts (such as schools and universities). Accordingly, in this chapter, we explore the impact of AI on workplace learning. We begin by critiquing the hyperbole of Artificial Intelligence and then introducing workplace learning, differentiating it from formal education. We then examine the application of AI in formal educational settings, and the application of AI to support workplace learning, before concluding by speculating some future possibilities.

2 Artificial Intelligence

As is well-known, it is notoriously difficult to define Artificial Intelligence (note we capitalize Artificial Intelligence to distinguish it as a field rather than intelligence that is artificial). However, the definition provide by UNICEF is refreshingly helpful:

> AI refers to machine-based systems that can, given a set of human-defined objectives, make predictions, recommendations, or decisions that influence real or virtual environments. AI systems interact with us and act on our environment, either directly or indirectly. Often, they appear to operate

> autonomously, and can adapt their behaviour by learning about the context. (UNICEF, 2021)

As explained elsewhere (Holmes & Porayska-Pomsta, 2023; Holmes & Tuomi, in press), this definition is preferred for several reasons. For example, while it does accommodate data-driven AI techniques such as artificial neural networks and deep learning, it does not depend on data and therefore also includes rule-based or symbolic AI, as well as any new paradigm of AI that might emerge in future years (such as "neuro-symbolic" AI, Susskind et al., 2021). It also highlights that AI systems necessarily depend on human objectives and sometimes *"appear to operate autonomously"* rather than do operate autonomously: *"it is people who are performing the tasks to make the systems appear autonomous"* (Crawford cited in Corbyn, 2021). This is important given the critical role of humans at all stages of the AI development pipeline.

AI often suffers from exaggeration and hyperbole (Berryhill et al., 2019). For example, AI systems failed to live up to their promise in the COVID-19 pandemic ("Our review [of 2,212 studies] finds that none of the models identified are of potential clinical use." Roberts et al., 2021, p. 199). In addition AI systems may be biased, because the data on which they are trained is biased, or the algorithms that drive them are biased (Ledford, 2019). They can also be brittle: a small change to a road sign can prevent an AI image-recognition system recognising it (Heaven, 2019). Meanwhile, the AI large language models (LMs), such as OpenAI's GPT-3 and Google's Lamda which have recently made dramatic headlines (GPT-3, 2020; Tiku, 2022), often generate nonsense (Hutson, 2021; Marcus & Davis, 2020) and can present real-world risks of harm, especially given:

> the tendency of training data ingested from the Internet to encode hegemonic worldviews, the tendency of LMs to amplify biases and other issues in the training data, and the tendency of researchers and other people to mistake LM-driven performance gains for actual natural language understanding. (Bender et al., 2021, p. 616)

In any case, despite its history and the dominant narrative, AI should not be thought of in purely technical terms. Instead, AI is a complex sociotechnical artefact that needs to be understood as something that is constructed through complex social processes (Eynon & Young, 2021). In other words, when we consider AI, we must consider both the human dimension and the technological dimension in symbiosis.

3 Professional learning

In contrast with learning that takes place in formal educational settings such as schools and universities, professional learning includes both formal learning (in real or virtual classrooms) and informal learning (learning that is contextualised within the workplace environment), both of which can be important for the development and maintenance of expertise in the modern workplace (Cacciattolo, 2015; Eraut, 2012; Milligan & Littlejohn, 2014). Formal learning (in schools and universities, and for professional learners) is usually designed around pre-defined learning goals and is driven by participation in a structured curriculum. Informal or 'workplace learning', on the other hand, range from more behavioural in orientation such as 'on the job' training or observing how an expert colleague carries out a task, to the more knowledge-oriented, such as engaging in strategic discussions with colleagues or asking a manager for advice. Accordingly, workplace learning has a different emphasis, structure and environment compared with formal learning. It is more guided by immediate work needs and facilitated through work experiences, and is shaped by both *what* is learned and *where* the learning takes place. For all these reasons, the outcomes of workplace learning are less predictable than those in formal learning (Tynjälä, 2008).

Boud and Garrick propose workplace learning is associated with two outcomes. First, "*the development of individuals through contributing to knowledge, skills and the capacity to further their own learning both as employees and citizens in wider society*" and, second, "*the development of the enterprise through contributing to production, effectiveness and innovation*" (2012, p. 6). Thus, while in formal learning the learning is separated *from* work, workplace learning combines learning *with* work. This integration of work and learning raises issues of self-regulation, the social mediation of learning, and human agency, all of which any related application of AI ought to address.

3.1 Self-regulated learning

Informal professional learning, workplace learning, is dependent on each individual having the internal drive to plan, facilitate and reflect upon their own learning through self-regulation (Enos et al., 2003). It is enhanced when professionals are motivated by and interested in their learning, when they are able to plan their learning goals in ways that help them achieve their work goals (Sitzmann & Ely, 2011), when they are able to adapt the ways by which they approach their learning, and when they self-evaluate their learning in efficacious ways (Littlejohn, in print). Such 'self-regulated' learning is influenced by a combination of psychological (cognitive and affective), behavioural and environmental factors that form its foundation (Bandura, 1991; Pintrich, 2000; Zimmerman, 2002).

Zimmerman's influential model of self-regulated learning provides a framework for analysis of the ways learners set and attain their learning goals (Zimmerman, 2006). The model proposes a number of affective, cognitive and behavioural constructs that influence learning, which Littlejohn and colleagues explored through a series of studies that examined how professionals self-regulate their learning using digital platforms (Fontana et al., 2015; Littlejohn et al., 2015; Margaryan et al., 2013; Milligan et al., 2014). Seven constructs were identified as important (see Table 1): the learner's confidence in their learning capacity; their ability to set and adapt their learning goals; their ability to use a repertoire of learning approaches and to alter these when they are not effective; their readiness to think critically about how they can apply learning to other potential areas of application; their ability to integrate new knowledge; their readiness to seek help; their ability to compare their own performance against others and to experiencing a sense of achievement when learning; and their resilience to challenge.

Table 1. Self-regulated learning constructs that are important for professional learning

SRL CONSTRUCT	DESCRIPTION
self-efficacy	confidence in learning capacity.
goal-setting	ability to use and adapt goals to plan learning.
task strategy	ability to plan learning and adopt a repertoire of learning approaches.
task interest	interest and readiness to determine the wider value of a learning task.
learning strategy	ability to integrate new with existing knowledge .
help seeking	seeking help from other people or resources
self-satisfaction & evaluation	readiness to compare own performance against an external goal & satisfaction from this comparison
learning challenge	resilience to challenge

3.2 The Social Mediation of Learning

Workplace learning has to take into consideration not only the needs of the individual, but also the social dimension of the collective, since workplace learning goals are socially mediated through interactions with others. To address this issue, Littlejohn and colleagues (2012) proposed that in digital environments, analysis of data should support both self-regulation and social mediation of learning through a process they termed 'charting'. Charting is a process designed to support learners to draw on digital tools, resources, people and environments to self-regulate their learning and, in doing so, contribute to collective knowledge online. It is based on four broad processes. When the learner charts a learning goal, they draw on technology to (i) *connect* with people and resources that are related to the goal. As they (ii) use (or *consume*) these resources, they (iii) *create* new resources that they (iv) *contribute* back to the collective. Thus, charting involves the processes of connecting, consuming, creating and contributing resources back to the collective in ways that can be used by others. Charting may also be used to connect learners to others with similar goals, creating networks of people who may support each other, while each learner's goals and motivations are continually reviewed as a form of self-regulated learning.

3.3 Human Agency

Human agency is a set of abilities that are nurtured throughout a human's life, which involve the human capability to influence what they do through their own actions (Bandura, 2006). Personal agency is the ability of a learner to maintain an interest in expanding their knowledge, to be willing to invest effort in learning and to be able to adapt their learning orientation as they engage in learning (Bandura, 1986; Pintrich, 2000; van den Boom et al., 2004; Zimmerman, 2000). Behaviours such as setting goals and adapting approaches to learning are characteristics that each learner can improve through practice. Constructs, such as interest, motivation, self-evaluation and self-satisfaction, can also be influenced by the learner themselves, though this is more challenging for learners to change without support (Winne, 1995; Zimmerman, 2000). The personal agency needed for informal professional learning (workplace learning) is different than the agency needed to engage in formal learning (courses and training) where goals have been predetermined and learning is scaffolded by a teacher (Littlejohn et al., 2016).

Interagency is also important for workplace learning (Collin, 2008; Fuller & Unwin, 2011). Work environments are complex sites representing divergent interests that are accommodated through processes of negotiation and accommodation (Engeström, 2004). Professionals have to engage with resources, both physical and digital, people and knowledge immediately available to them to support their learning (Argyris & Schon, 1974). As they do so, professionals develop the "*capacity to work relationally with others on complex problems*" (Edwards, 2010, p. 8).

4 The Application of Artificial Intelligence in Education

The application of Artificial Intelligence (AI) in formal education is increasingly being fêted as an "*altogether new way of spreading quality education across the world*" (Seldon & Abidoye, 2018, p. 4). According to a leading AI entrepreneur, Kai-Fu Lee (formerly a senior executive at Google, Microsoft, SGI, and Apple):

> We know the flaws of today's education…. AI can play a major part in fixing these flaws…. AI will make learning much more effective, engaging, and fun…. I believe this symbiotic and flexible new education model can… help every student realize his or her potential in the Age of AI. (Lee & Qiufan, 2021, p. 118)

Meanwhile, international organisations are loudly proclaiming that AI will "*give learners greater ownership over what they learn, how they learn, where they learn* *and when they learn"* (OECD, 2021, p. 3); and that AI *"helps teachers realize impressive outcomes"* (IBM, 2018), especially *"given its ability to provide content tailored to students' learning needs"* (World Bank, 2022). In short, so the argument goes, AI will *"transform education"* (OECD, 2020, p. 7). As a consequence of this enthusiasm, and despite there being limited evidence for the veracity of these claims, AI for education was one of the top three AI venture capital investment areas in 2020 (Zhang et al., 2022).

While the application of Artificial Intelligence to support teaching and learning (AIED) has been researched for more than 40 years, almost as long as AI itself, it is only in the last 10 years or so that it has emerged from the research lab to be taken up widely in schools, higher education institutes, and other formal learning contexts. It is also being extensively commercialised, creating a market expected to become worth more than US$20 billion within five years (GMI, 2022), that was only accelerated by the school shutdowns necessitated by the COVID-19 pandemic. Nonetheless, it remains unclear for educators how to take pedagogical advantage of this still emerging educational technology, and how it can actually impact meaningfully on teaching and learning (Holmes et al., 2019; Miao & Holmes, 2021; Zawacki-Richter et al., 2019). Inevitably, over the years, AIED research has diverged, creating and researching AIED tools that may be grouped in three distinct but overlapping categories: learner-supporting AI, teacher-supporting AI, and institution-supporting AI. These categories have been extended to a taxonomy of AIED (Holmes et al., 2019; Holmes & Tuomi, in press).

4.1 Learner-supporting AI

The focus of most AIED research and commercialisation has been on learner-supporting AI, usually for subjects such as mathematics, or other non-interpretative subjects like physics or computer science. The Holmes and Tuomi taxonomy (in press) identifies (in order of availability, from 'commercially available', through 'researched', to 'speculative') the following types of learner-supporting AI: the so-called *Intelligent Tutoring Systems* (e.g. Spark from Domoscio, 2022), *AI-assisted apps* (e.g., Photomath, 2022; translation software from SayHi, 2022; and homework-answering apps, Dan, 2021), *AI-assisted simulations* (e.g., AR, Behmke et al., 2018; VR, McGuire & Alaraj, 2018; and games-based learning, LaPierre, 2021), *AI to support learners with disabilities* (e.g., Alabdulkareem et al., 2022; Anuradha et al., 2010; Barua et al., 2022; Benfatto et al., 2016; and StorySign by Huawei, 2022), *automatic essay writing* (Sharples, 2022), *chatbots* (e.g., Hussain, 2017), *automatic formative assessment* (Foster, 2019; Metz, 2021), *learning network orchestrators* (e.g., Lu et al., 2018), *dialogue-based tutoring systems* (which use a dialogic Socratic-approach to teaching and learning: e.g., Nye et al., 2014), *exploratory learning environments* (Mavrikis et al., 2018), and *AI-assisted lifelong learning assistants* (Holmes et al., 2019).

The most prominent learner-supporting AI are the so-called intelligent tutoring systems (ITS), which are now being offered by large numbers of multi-million-dollar-funded corporations around the world (Holmes et al., 2019; Miao & Holmes, 2021), and tend to focus on subjects such as mathematics, or other non-interpretative subjects like physics or computer science. With ITS, the learner engages with an online system that delivers some standardised content, an activity and possibly a quiz. The learner's individual responses (where they click and what they answer) then determines the next piece of information, activity, and quiz they are given. In this way, each learner follows their own adapted pathway through the material to be learned. In summary, the aim of ITS is to enable learners to learn independently of teachers, which is achieved by attempting to automate teacher functions in the form of an artificial personal tutor.

However, while the AIED research community has long demonstrated the efficacy of ITS (and some other learner-supporting AI tools), in short studies researched in limited contexts (e.g., Beal et al., 2007; Ma et al., 2014; Vanlehn et al., 2005), there is surprisingly little to justify its wide use in well-resourced classrooms, other than the marketing materials and mostly unsubstantiated hopes expressed by many policymakers. Robust, independent evidence remains scarce (Miao & Holmes, 2021), and claims that AI will dramatically improve the way learners learn (e.g., OECD, 2021) remain aspirational or speculative (Holmes et al., 2019; Nemorin, 2021, cited in Miao & Holmes, 2021).

Meanwhile, ITS and similar tools have been criticised (Holmes et al., 2019; Holmes & Porayska-Pomsta, 2023; Holmes & Tuomi, in press) for undermining student agency (students have no choice but to do what the AI requires), disempowering teachers (turning them all too often into mere technology facilitators), and missing out on learning through social engagement; as well as for being focused on pathways leading to the homogenisation of learners rather than on outcomes such as developing self-regulation skills or leading to self-actualisation; and for being solutions- rather than problem-driven. In particular, ITS tend to embody a naïve approach to teaching and learning, involving spoon-feeding pre-specified standardised content, adapted to the individual's achievements, while aiming to avoid failure. In other words, despite suggestions to the contrary, the approach is effectively behaviourist or instructionist, and ignores more than sixty years of pedagogical research and development. Typical ITS overlook, for example, *deep learning* (Entwistle, 2000), *guided discovery learning* (Gagné & Brown, 1963), *productive failure* (Kapur, 2008), *project-based learning* (Kokotsaki et al., 2016), and *active learning* (Matsushita, 2018)(Matsushita, 2018). This *de facto* behaviourist approach, especially the spoon-feeding, prioritises remembering over thinking, and knowing facts over critical engagement, thus undermining robust learning.

4.2 Teacher-supporting AI

Over the same 40-year period, there has been relatively little focus on AI designed specifically to support teachers (aside from the dashboards that are common in educational technologies, Jivet et al., 2017). Recently, however, there has been some research and some, often controversial, commercial products. The Holmes and Tuomi taxonomy (in press) lists (again in order of availability) *plagiarism detection* (e.g., Turnitin, 2022), *smart curation of learning materials* (Perez-Ortiz, 2020), *classroom monitoring* (Lieu, 2018; Moriarty-Mclaughlin, 2020; Poulsen et al., 2017), *automatic summative assessment* (which was tried, then abandoned, by the Australian government, Hendry, 2018), *AI teaching and assessment assistants* (Guilherme, 2019; Holmes et al., 2019; Selwyn, 2019), and *classroom orchestration* (e.g., Song, 2021).

4.3 Institution-supporting AI

Finally, institution-supporting AI is quietly growing behind the scenes, despite there being limited research in this area. The Holmes and Tuomi taxonomy (in press) lists in order of availability AI-assisted *admissions* (e.g., Marcinkowski et al., 2020; Pangburn, 2019; Waters & Miikkulainen, 2014), *course-planning* (e.g., Martinez-Maldonado et al., 2021), *scheduling and timetabling* (e.g., Lantiv, 2022)(e.g., Lantiv, 2022), *school security*, *identifying 'drop-outs' and 'students at risk'* (e.g., Baker et al., 2020; Lykourentzou et al., 2009), and *e-proctoring* (Chin, 2020; Henry & Oliver, 2021; Kelley, 2021). Again, some of these developments – especially *e-proctoring* (c.f., Chin, 2022) – are controversial.

5 The Application of Artificial Intelligence in Workplace Learning

So how might AI contribute to workplace learning? Already, many workplaces are using AI applications, mainly with the aim of improving productivity by automating routine and repetitive tasks or by using business analytics with the aim of improving efficiency and supporting humans to focus on complex and creative tasks. In addition, AI-assisted analytic systems are being deployed to provide insights into the working patterns of employees.

Meanwhile, as we have seen, to date almost all applications of AI focus on providing support for learners in formal learning settings in subjects such as mathematics or other non-interpretative subjects like physics or computer science. For workplace learners who have different needs and who only rarely sit in classrooms, a virtual AI-powered tutor (perhaps instantiated on their mobile phone) might have potential. Nonetheless, currently there are very few learner-supporting tools developed specifically for adult learners outside the classroom.

One AI-assisted tool that has been developed for professional learners is Area9 Lyceum (2022). However, Area9 sits alongside work activities, rather than being embedded within them, and is effectively an ITS of standardised content. A key problem with such applications, ones that sit alongside work rather than embedded within it, is that the learner also needs to learn how to apply the new knowledge and skills learned in the classroom to their work setting, which requires significant extra cognitive effort (Markauskaite & Goodyear, 2017).

Other applications of AI to support professional learning tend to focus on matching employees with training opportunities (e.g., eightfold, 2022) or enabling professionals to access information faster (e.g., Chubb et al., 2021). While this may be helpful in terms of work efficiency, it does not reduce the need for teaching support to provide feedback and to scaffold learning. In addition, virtual assistants and bots are also being used to support training and mentoring in the workplace (e.g., Khandelwal & Upadhyay, 2021), though these systems are not able to replace the complex forms of support that an experienced teacher or mentor can offer. However, possible future co-working relationships between humans and machines open up opportunities to circumvent this problem by supporting professional learning while people work. For example, people working alongside robots on a car assembly line in future may receive feedback from the robots about the ways in which they work. There are other potential feedback opportunities via so-called smart assistants, healthcare management systems, social media monitoring and by tapping into other applications of AI. However, it is important to note that to take advantage of these and other future workplace learning opportunities each professional will have to use personal agency to empower them to engage in learning (Enos et al., 2003; Sitzmann & Ely, 2011).

Littlejohn and colleagues have set out an argument for a reframing of AIED for workplace learning focused on participation, where learning goals are set by the professionals themselves and are defined by work priorities and individual agency, rather than by a curriculum (Littlejohn et al., 2012). The proposed approach was based on a series of empirical studies that interrogated the choices professionals made when they decided what they needed to learn and how they went about their learning. These studies took place in the energy sector (Margaryan et al., 2009) and finance sector (Milligan et al., 2015). Effective learning in the finance sector, which was self-reported based on improved work practices and processes, was associated with the capacity to self-regulate learning.

As we have noted, currently there are few innovative or targeted examples of the application of AI to support workplace learning. Accordingly, we end this chapter by speculating three brief possibilities (the Holmes and Tuomi taxonomy, 2022, might be used to identify others), grounded in existing research but yet to be widely available for workplace learning.

5.1 Responsive Open Learning Environments

As we have seen, AIED systems are often designed to deliver relevant and standardised content to learners, depending on their profile and stage of learning. However, in job roles with a high degree of specialism (e.g., research scientists, finance professionals, or design engineers), the professionals themselves are best placed to decide on and plan their learning needs, rather than drawing from a standardised curriculum (Kroop et al., 2015). These professionals may be working at the boundaries of knowledge beyond standard curricula. In these cases, an AI-assisted system (building on ITS) might support the learner by offering them options from which they can choose (something that no existing ITS currently offers). For example, *Responsive Open Learning Environments*[1] is a prototype digital system in which the professionals themselves define the new practices they need to learn (Kirschenmann et al., 2010) (while ITS almost always work towards pre-specified fixed learning outcomes). They then plan their own learning by browsing and selecting a set of web-based resources and tools to support their learning. The system is based on conventional forms of AI that use demographic data and recommender analytics to provide content that is sequenced and structured for specific job roles. However, the learners can alter these structures in ways that make sense to them. Since the system is based on Machine Learning, the more the system is used, the better it 'learns' specific combinations of content appropriate for specific roles – in other words, these sequences of content and activities continually change as learners use the system. Currently, we are not aware of any such systems being widely available.

5.2 Chatbots

Chatbots – applications that support text or voice conversations with an AI-assisted agent – analyse questions posed by the learner and respond in a conversational way. These systems could be used to allow organisational "know-how" and "know-who" to be shared with and used by employees during their day-to-day work (Casillo et al., 2020). For example, when a new employee begins work, chatbots might help them to orient themselves faster into the organisation by answering routine questions such as "*where can I find information about x*" or "*how do I do y*". In fact, there is already some evidence that chatbots can improve onboarding of new employees (e.g., Casillo et al., 2020). However, case examples and commercial offerings tend to focus on the transfer of simple information (e.g., "*where do I find the organisation's training manual*") rather than transforming practice (e.g., learning how to manage more effectively).

[1] https://premium.golabz.eu/about/projects/role

5.3 *Institution supporting AIED and the workplace*

Changing work processes or practices can be difficult if the organisational environment is not changed at the same time. There are a number of reasons why these changes are demanding: ingrained practices make it difficult for people to incorporate emerging forms of practice into their work; new practices may change the ways employees inter-relate, for example if they work remotely (at a distance); groups of employees may work in silos and organisations have to develop systematic ways to work across these diverse groups (Littlejohn et al., 2019). This means that new processes and practices can only be introduced when work is reconsidered and restructured. To overcome this issue, employees need to be supported to reflect on their workplace and to restructure the environment if needed. This situation is very different from learning in formal education, and again no existing AI-assisted educational tools are designed to or capable of helping professionals learn and transfer their new knowledge to the workplace – although there is potential for an AI-assisted system that supports teams in considering whether and how to restructure work.

6 The future of AI and workplace learning

As we have seen, so far almost all AIED applications have been designed for formal settings, including a few designed for formal professional learning. There are few examples of AI-assisted tools to support specifically and effectively informal professional or workplace learning.

Even in formal settings, while many AI applications gather and analyse data representing learner behaviours that might inform teachers, they cannot replicate the work of accomplished human teachers or trainers who use their experience and questioning to assess the cognitive ability and affective state of each learner and to support and scaffold learning (Holmes et al., 2019). There are various other issues: AI-assisted educational tools failing to leverage social engagement learning opportunities, or leading to homogenisation rather than self-actualisation, or perpetuating poor pedagogic practices. In addition, AI-assisted systems are also not able to model or teach *how to learn* affective characteristics such as confidence and persistence. Similarly, while some AI-assisted systems (such as those using augmented reality) might be helpful for modelling behavioural and some cognitive expertise, it is clear that professional education, whether formal or informal, cannot be replicated by AI-assisted systems – now or in the foreseeable future, despite the marketing claims.

A key issue for informal workplace learning in particular, is that it is (or, at least, it almost always should be) the learner – rather than a teacher or curriculum designer or commercial AI company – who decides what is to be learned, why and how. In these contexts, AI-assisted systems ideally would support learner agency to actively plan, perform, self-regulate and reflect on their learning. However, currently, as this chapter has highlighted, no AI-assisted systems have been designed to support agency. On the contrary, most such systems actively undermine both student agency and self-regulation skills (or, at least, none have been identified that address the self-regulation skills identified in Table 1). Similarly, no such systems support the processes of charting in workplace learning.

However, this chapter does not suggest that AI-assisted applications can never support informal workplace learning, only that few current systems do, and that there needs to be a radical shift in trajectory, to prioritise the human learners, if we are to take advantage of the power of AI. Future imaginaries include:

- ***AI to support authentic assessment of work tasks***. For example, a trainee technician uses augmented reality visualised through safety goggles to learn how to replace a broken starter unit in an engine. The engine starts working and the data is automatically sent to an expert technician who signs off accreditation, indicating that this task has successfully completed by the trainee.
- ***AI to orchestrate network building and collaborative knowledge creation***. A number of engineers in diverse job roles across a large organisation are working on broadly similar tasks. Their work is facilitated by a digital platform that uses AI technologies to support the forming of a network of professionals, to share critical tasks identified by the engineers, and to mutually learn and build knowledge together.
- ***AI adaptive learning to facilitate student charting, agency and self-actualisation***. Individual workers on a gig economy platform might learn new skills such as collaboration, critical thinking, confidence and persistence by means of an AI-assisted system that facilitates charting and prioritises both personal- and inter-agency and self-actualisation. This would be especially beneficial for workers who have little opportunity to be in direct contact with colleagues.

As we have shown, the trajectory of AI developments for professional learning needs to be redirected – towards the design of AI-assisted informal learning applications that support agency, social and mutual learning, self-regulation and human rights, and that embody ethical-by-design AI techniques and innovative pedagogies. Only if we achieve that will we unleash the power of AI to enhance – and not compromise – professional learning.

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