Chapter 15
Technologies for Professional Learning

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Abstract This chapter interrogates the concept of technology as driver for change in professional learning and as a (potential) enabler for new forms of learning. Changes in technology-enhanced professional learning are influenced by the interrelationship of work practices, learning processes and technology systems. Based on an analysis of current research in professional learning with technologies, we identify a number of important trends. First, work practice tends to be agile and constantly changing so professionals are tending to use technologies to support just-in-time learning alongside formal professional training and education. Second, with widespread adoption of digital media in society, there appears to be increasing reliance on recommendations from AI systems for learning alongside guidance from workplace mentors or experts. Third, employers and employees want to find ways to extend assessment of formal educational qualifications through accreditation of the outcomes of informal, work-integrated learning. To shape the ongoing transformation of both work(places) and learning, the chapter highlights the ways diverse disciplines need to align reflectively, critically, and constructively to bring together theories and methods from learning sciences, computer science and human-computer interaction to identify problems and engineer solutions. Finally, we propose three constructs that are critical for technology-enhanced professional learning, but often are not taken into consideration: the goals and motivations of learners, the work environment and structure, and the tools and resources available for work and learning.

Keywords Professional technology-enhanced learning · Socio-technical design · Future work · Future of learning

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15.1 Technology as Enabler of Changed Learning Practice

Global, organisational and technological changes are transforming the world of work, which elevates the need for lifelong professional learning. Organisations continually are seeking ways to solve increasingly complex problems.by developing solutions that require the integration and application of different areas of specialist knowledge. Professionals have to find ways to work on problems with others who have different areas of specialist knowledge, deepening their own knowledge. A consequence of this increased specialism and complexity of work problems is a marked change in the ways people work together: workers collaborate around shared problems, working together in ways that build knowledge, solve problems and create products. Changes in ways of working lead to new forms of organisation, as workers collaborate around shared problems, working in teams, groups and networks that are often geographically distributed. As work practices constantly evolve, there is a need for professionals to learn new skills and knowledge on an ongoing basis (Hager, 2004; Hadwin et al., 2011; Illeris, 2011). This cycle of ever-more complex work problems, increasing specialisation of roles and new organisational structures has led to an unprecedented demand worldwide for professional learning (Littlejohn & Margaryan, 2014).

Professional learning is expected to increase by 50% globally by 2040 (AlphaBeta, 2019). This demand is unlikely to be met through established forms of professional development, such as training and workshops that traditionally have enabled large numbers of people to reach a specific level of competency. In the past learning a standard curriculum has been helpful to enable large numbers of workers to learn skills and knowledge that apply to standard work practices. However, large-scale training of a standard curriculum is not helpful for workers who need to learn specialist knowledge and individual work practices (Littlejohn & Margaryan, 2014). Each professional has to learn specific skills and knowledge to apply to niche problems and work tasks. There is a general recognition that simply scaling up conventional forms of professional development – such as training or degree programmes that require a long-term, full-time commitment by students, – will not provide the volume or variety of professional learning needed. Many of the theories, assumptions and models that underpin professional learning have been developed with large-scale formal training in mind, therefore new approaches are needed to meet this growing demand for professional learning.

Adapting work and upskilling the workforce requires reconstructing the views of and processes within institutions and companies, taking into consideration the required diversity and decentralisation of training in ways that better support lifelong learning. Recent reports have called for forms of lifelong learning that support professionals upskilling more regularly (AlphaBeta, 2019). This has led to the development of a range of shorter and more focused learning opportunities, such as just-in-time learning, where people learn the new knowledge or skills they need for an immediate work task. There is recognition that different forms of expertise require diverse approaches to professional learning, depending on the domain of application (Boud et al., 2000). Some occupations, such as healthcare, require workers to continually update their skills and knowledge through certification, which could involve longterm commitment to a course where credit is awarded, or short-term skills learning with granular credits, sometimes termed micro-credentialling or badging. In other occupations, such as computer coders, there is a culture of demonstrating expertise by producing outputs such as algorithms, rather than by accumulating qualifications or certificates.

Aside from the size and granularity or certification of learning, there are other features around which professional learning could be reimagined. Professionals learn an increasing range of skills and knowledge on-the-job, through everyday work tasks (Colley & Jarvis, 2007). This movement places emphasis and value on informal learning. The term 'informal learning' is considered contentious because it may imply that informal learning – learning through everyday work tasks – is somehow inferior to formal learning (Billett, 2004). Yet there have been few largescale attempts to rethink professional learning by integrating learning with work (Littlejohn et al., 2016a). An insight review by the Australian Government, the Australian Qualifications Review (AQR, 2018), questioned whether and how informal learning might be recognised as new forms of professional practice evolve. The same year the UK Government commissioned a foresight report to examine how professional learning might be expanded in ways that extend beyond formal training (Fuller & Unwin, 2016). The report emphasises the importance of learning for work both through formal training and informal, on-the-job learning. The degree of formality of learning, whether formal (pre-planned and structured) or informal (one-the-job) is an important dimension along which to consider how professional learning might be enabled.

Another feature around which professional learning can be reconceived is the application of technology. Technology tools often are the enablers of new and emerging forms of work practice, some of which would not be possible without technological support. For example, platforms such as Amazon and AirBnB connect traders with customers, Fiverr connects freelance workers with people who want to hire them and enterprise platforms support professionals distributed across global organisations to connect, form groups, collaborate, disperse then reform around well-defined problems. Technology tools may use algorithms or Artificial Intelligence (AI) to automatically build expertise profiles and use these to recommend experts for a given subject or problem (cp. Reichling & Wulf, 2009; Lindstaedt et al., 2010).

Although technologies are (in part) drivers for new ways of working and learning, they have not yet been fully exploited as enablers of changed learning practice (Littlejohn & Margaryan, 2014). This may be because the tools to support learning often are developed with formal training in mind and are designed for use outside the workplace. Technologies for formal learning include enterprise systems such as Learning Management Systems as well as Massive Open Online Course platforms, such as Coursera (www.coursera.org) that support distributed, Online Learning.

Digital systems can gather multi-modal data about professionals, including demographic data, contextual data, and data that indicates the affective state of the learner, through face tracking, temperature or even skin conductivity (Malmberg et al., 2018; Järvelä & Hadwin, 2013). Artificial Intelligence-based systems are being developed to interpret these multi-modal data and make decisions on behalf of the learner (see for example Järvelä et al., 2018). However, the interpretation of these sorts of data have been questioned by learning scientists, concerned that the assumptions that underpin the algorithms that analyse data and make decisions for the learner are dangerous, because they have societal stereotypes and biases coded within them (Williamson, 2016).

Thus, embedding professional learning technologies in organisations is controversial. It requires a 'whole system' approach that takes into consideration digitalisation and innovation management. Yet, research and development of technology tools for professional learning seldom focuses on the whole work system and tends to view learning as taking place in a bounded digital environment, missing opportunities to exploit a range of socio-material resources at work. Most workplaces are sites for learning that are imbued with a range of useful tools and resources for the learner, including people, materials and technologies (Boud & Garrick, 1999). Therefore, it is important to take the whole system into consideration. At the same time, workplace structures and processes may constrain how learning take place and how insights can be acted on. This means that, although the organisation of work sets the conditions of learning, it is the reciprocal interaction between the individual and the workplace that determines learning (Tynjälä, 2008).

Work-based field studies on professional learning technologies are rare. There is insufficient understanding of how professionals use technologies in practice in real-world settings to work and learn. Particularly specialist workers, for whom learning is likely to be most effective when closely aligned with work practice and who mainly learn through work. Thus, there has been less attention paid to the research and development of technologies that support informal, work-integrated learning such as learning through reflecting on work tasks, Augmented Reality to overlay digital information within workplace settings, or the use of Artificial Intelligence systems to guide decisions and build connections through work tasks. Research and development of technology-enhanced professional learning requires critical insight into the ways professionals work and learn within their work environment (Littlejohn & Margaryan, 2014) and, at the same time, needs research, development and design of technologies that align learning with emerging ways of learning for work.

This chapter examines critical approaches within the learning sciences that examine work practice and professional learning alongside design methodologies used to research technology systems. The chapter argues the importance of bringing together these methods and perspectives in order to research and develop tools that mediate the relationship between professional work and learning in specific work contexts. In Sect. 15.2 we consider the diverse areas of knowledge, including work, learning and domain knowledge, that are necessary to research technologies for professional learning. Section 15.3 offers an overview of trends in technology-enhanced professional learning, illustrated through examples and case studies, before, in Sect. 15.4, examining current directions of research in the fields of learning science and computer science.

15.2 Where We Are Going: Directions in Technology-Enhanced Professional Learning

15.2.1 The Inter-relationship of Work, Learning and Technology

In the previous section we described how professional learning is moving towards lifelong learning, as people continually adapt their skills and knowledge. Some of the changes in the ways professionals learn are facilitated by technology. This section explores trends associated with professional learning, examining how technologies are influencing these.

15.2.1.1 From Longterm Commitment to Training to Just-in-Time Learning

Gaining a qualification, such as a diploma, degree or professional qualification, is no longer sufficient for a lifelong career. Professionals routinely participate in lifelong learning, refreshing their knowledge and skills through different approaches to learning. Many professional organisations now require people to engage in continual learning to retain their professional affiliation, with a growing number encouraging professionals to engage in online versions of face-to-face professional training.

Massive Open Online Courses (MOOCs) have become popular over the past decade as a way for professionals to learn skills over a few days or weeks. MOOCs are online courses staged in real-time with the geographically distributed participants (Littlejohn & Hood, 2018a). The term ‘massive’ refers to the large number of learners who participate in a MOOC, typically thousands or tens of thousands. ‘Open’ refers to the fact that often anyone, anywhere – no matter his or her background, prior experience or current context – may enrol in a MOOC. When they were first offered, around 2008, MOOCs were heralded as ‘the next big thing’ in higher education, though, more recently, they have been criticised for the poor quality experience many offer (Margaryan et al., 2015).

A number of commercial MOOC platform providers have been established over the past decade, including Coursera,[1] Udacity,[2] EdX[3] and FutureLearn[4] to partner with universities or other organisations to offer courses. MOOC platform providers have been seeking ways to generate profit and view the business-to-business market as a potential growth area. Coursera in particular has been partnering with

[1] www.coursera.org

[2] www.udacity.com

[3] www.edx.org

[4] www.futurelearn.com

universities and other organisations to provide courses for professions. Coursera uses data analytics to connect MOOC learners with companies who are advertising vacancies, charging the company a fee. These and other analytics-based forms of revenue generation are becoming embedded within online higher education, with data viewed as a valuable source of income. The ethical implications are difficult to predict and control. Algorithms may bias opportunities and selections and learners may be unaware of how their data is being used (Berendt et al., 2017).

Professionals need to have ways to learn how to solve a specific and immediate work task. Online platforms with professional communities can help professionals find experts who can help them or can help them find out how someone else has solved a similar problem. For example, coding specialists connect using online platforms, such as Stack Overflow, to share code, understand how specific coding problems might be solved by learning from peers about solutions to problems. Stack Overflow was not developed as a learning platform, but it supports professional learning by bringing together people with similar problems.

Intelligent systems are being developed to support specific work tasks, replacing professionals or augmenting their expertise so they are freed up to focus on more complex tasks. For example, pattern recognition software is being used to diagnose specific cancers, freeing up cancer specialists to work with patients. These systems using 'Artificial Intelligence', are increasingly being used to guide professionals in their work and learning.

15.2.1.2 From Guidance by an Expert Teacher to AI Recommendations

Artificial Intelligence (AI) is a range of analytic methods based on machine learning, where large amounts of data are gathered and fed into algorithms that use statistical models to identify patterns and inferences. These systems require large amounts of data (so-called "Big Data') including personal data about learners. The more the algorithm is fed data, the greater the system 'learns' and applies this new knowledge to make predictions or decisions. In this way decisions about what the learner should do next shifts from the teacher to a system. Most systems are designed as a support system to help teachers decide how to support students, rather than as a direct replacement for the teacher. For example, AI systems that provide early prediction of 'at-risk' students can be used by teachers to identify which students to direct support towards. Predictive models are used to analyse data on individual learner profiles and data related to learner interaction within online environments to forecast whether a student is 'at risk of dropping out' of a course (Siemens & Long, 2011; Wolff et al., 2013). These data are then presented to learners or teachers using a variety of dashboards to support decisions about the next steps (Papamitsiou & Economides, 2014).

One example of a predictive system is 'OU Analyse', a system developed by The Open University, UK to provide early prediction of 'at-risk' students. The system uses data about each student's demographics, including their age, gender, place of residence and prior qualifications and combines these data with observed activity within the university's Virtual Learning Environment (Moodle). Each individual's data is analysed in relation to data from prior cohorts of students to predict the likelihood of passing the next Tutor Marked Assessment. These predictions are visualised for course tutors as a course overview dashboard where they can view the progress of individual students (see Kuzilek et al., 2015 and https://analyse.kmi.open.ac.uk). Progress is illustrated using a 'traffic light' system, to show whether a student is likely to pass their next tutor-marked assessment, based on their previous actions, grades and those of previous students. The system then uses the data to make a decision whether remedial action is needed and recommends to the tutor or student what the learner should do next.

At the informal learning side, Fessl et al. (2017) for instance have developed an adaptive reflection guidance concept and technology that reminds and supports professionals to reflect about relevant aspects of their work practice. The reflection guidance implemented by the authors prompts for action, which motivate users to do something, typically to use the app in which reflection guidance is embedded. The system prompts for reflection, which directly relates to content or data that is available within the app in which reflection guidance is implemented. By prompting the professional to reflect, the intention is to trigger reflection about specific content or data as representations of work practice. This reflection, of curse, is on a representation of work practice, rather than on realworld practice. Nevertheless, it offers a step forward in terms of integrating and assimilating knowledge into practice. As informal learning becomes a more recognised form of legitimate professional learning, organisations are seeking ways to authenticate informal forms of assessment. The next section outlines some examples.

15.2.1.3 From Assessment and Accreditation by an Organisation to Informal Accreditation

In partnership with the MOOC platform providers, universities have been developing ways to allow professionals to gain qualifications faster through small-sized, credit bearing, 'micro credential courses' such as Microdegrees or Nanodegrees (Littlejohn & Hood, 2018a). The university supplies the course materials, assessment and accreditation and the platform provider supplies technology and marketing services. One example is the Masters in Computer Science offered by Georgia Tech which students can complete in 10 months. Four thousand students enrolled in this Masters in 2017, each paying 10 monthly payments of $200 (USD) to study the course and gain the qualification.

Assessment has a number of social norms associated with it and is, therefore, been an area of professional learning that is difficult to change. One example of change is offering 'Badges" (micro certificates) that signify small amounts of learning or completion of a short course through 'Badged Open Courses': online learning events that offers some form of recognition for completing the course (Law, 2015). Recognition is recorded as a 'digital badge' from a recognised university, college or organisation demonstrating that the learner reached a specific competency or completed a course. This certificate can be added to an online portfolio or CV. The value placed in a 'Badge' depends on the context of the learner. For example, an eye surgeon might not place high value on a digital badge from a BOC on Advanced Computing from MIT. However, a young professional in Bangalore may view the Badge as a way to make their CV stand out to startup companies in the city. A survey of learners studying in the UK Open University's 'OpenLearn' platform identified that 80% wanted their online learning achievements recognised and valued Badges released under a Creative Commons licence.

A variation on Badging is 'competency-based accreditation', where professionals participate in a learning event and demonstrate their competency to an acknowledged expert who assesses and records the learner's competency level. Competency based accreditation is being used by online international communities or networks of people with a shared interest. For example, #PHONAR (https://phonar.org/) is an open, online photography course where learners and experts to help them gain expertise and develop online portfolios. Students learn through developing a portfolio of photographic images. Learning is realised through developing and maintaining connections with other students and photography experts and with the resources produced to support learning (for example course content materials) and as a by-product of learning (such as photographs, comments and other artefacts). The course requires learners to be proactive, taking responsibility for building and nurturing connections with relevant people and resources that can help them learn. The decentralised nature of the internet provides the environment to support an open and participatory culture of knowledge building through collaboration, participation and engagement. Although the course has a set of overarching objectives, each learner (implicitly or explicitly) sets and achieves personalised goals. The topics in the forum discussions tend to be emergent and responsive to the immediate needs of the learners. This approach is different from conventional courses, where the curriculum and objectives are predefined.

One difficulty with assessing online learning is in ensuring that the accreditation is from a trusted source. Attempts are being made to adapt the 'blockchain' technology system used to legitimise digital money (Bitcoin) to substantiate qualification credits (Sharples & Domingue, 2016). Blockchain is a set of linked data items stored on distributed, participating computers where the next item can only be added through ca system of consensus. Each computer performs a significant amount of data mining work to corroborate an item before it can be added to a blockchain. Blockchains are being used to provider learners with persistent records of achievement provided by universities and other recognised organisations.

Effective ways to assess learning are of fundamental interest to the learning sciences, but often difficult to address in workplace environments. Learning science researchers are trying to find ways to recognise learning when skills and knowledge are acquired through the performance of every-day work. One example, is in 'learning from incidents', when there is an accident or near-miss in a hazardous work environment (Littlejohn et al., 2017). However, understanding whether people are learning is not as simple as observing a reduction in the number of incidents experienced by a company. A study by Murphy et al. (2018) identified a range of indicators that can be measured by organisations to signify whether people are learning from incidents. Examples of indicators range from communications, that can be analysed through online, semantic analysis, to leadership actions that can be detected through online surveillance to product development that demonstrates effective learning from incidents. A study of sexual and reproductive health education in low-to-middle income countries will use data from news agencies to identify whether health workers in refugee camps are learning new forms of practice. Future research is likely to focus on identifying a range of different indicators that signal effective, informal learning.

15.2.1.4 From Formal to Informal Learning

Informal learning increasingly is supported through use of the technologies people use for work. Eraut and Hirsh (2010) has drawn attention to the importance of learning through work, emphasising that learning can be both 'intentional' and 'unintentional'. Intentional learning takes many forms ranging from formal learning – workshops, training and classroom teaching to 'non-formal' learning, such as asking a colleague for advice. Examples of unintentional learning include watching a colleague doing a routine job in a new way and adopting a new form of practice. Unintentional learning is not always recognised as learning. For example, a professional working in a new organisation with a different work culture may develop new forms of practice, without appreciating or acknowledging that learning has taken place.

The knowledge gained through formal training needs to be contextualised within work practice and this contextualisation often happens informally. This contextualisation process may be difficult or impossible due to a misalignment of what is taught in formal trainings, and what is practical or culturally acceptable in workplace contexts. For example, hospital laboratory professionals may learn new laboratory detection processes (Littlejohn et al., 2019). However, this learning cannot be applied to the workplace if the right form of equipment is not available (Charitonos et al., 2018).

Informal learning is especially relevant where professionals are working at the boundaries of knowledge and cannot rely on courses to expand their knowledge (Littlejohn et al., 2016a). Self-regulated learning takes into consideration various affective, behavioural and cognitive factors that influence learning (Zimmerman & Kitsantas, 2005), alongside the social and situative features of the workplace. In these informal learning settings, the workplace context and culture influences and shapes learning, by constituting the environment in which professionals expand and develop their practice (Fuller & Unwin, 2016). Therefore, these sorts of learning practices cannot be understood without also understanding work practice. The relationships between work practice, learning and technology use is explored in the next section.

15.2.2 Synthesis: How Do Technologies Support Work and Learning?

The previous section exemplified a number of ways technologies are already being used to support professional work and learning, both in formal training contexts and while learning on-the-job. Technologies support a range of diverse activities, from providing access to information resources, enabling communication, supporting co-work and knowledge building, to drawing on data to recommend actions and make decisions.

The typology below illustrates a range of technologies and their uses, based on work by Pammer-Schindler (2019):

- Learning Management Systems or Virtual Learning Environments support the *documentation of learning activities and assessment outcomes* in ways that mirror conventional teaching and learning in universities and colleges.
- Platforms such as Social Media Environments (eg YouTube, Slideshare) or Massive Open Online Course (Coursera, EdX) support the *distribution and consumption of digital learning materials.* Mirroring conventional forms of distance learning, these platforms are designed to support the delivery of course materials, though the social technologies could be used to enable learners and teachers to interact in ways that are difficult in classrooms. For example, learners can directly enquire about problems they encounter and can link their own materials and make these available for others.
- C*ommunication technologies and social software* (*eg* Slack, WhatsApp) support discussions amongst learners and between learners and teachers (cp. Stahl et al., 2014). These technology systems allow people to communicate and collaborate at a distance, either in real-time or asynchronously, thereby supporting learning in ways that are not possible without the technology.
- *Virtual simulations and augmented reality systems* support experim*entation* in ways that can be safer (for example learning how to perform a hazardous procedure), cheaper, or not possible in reality (such as observing molecular structures) (cp. de Jong & Van Joolingen, 1998). One specific form of simulation is gaming technology which can be used to support learning in a ‘playful’ environment (for an overview of serious games or learning games – cp. van Eck, 2006).
- *Data analytics* are used to derive insights about learning drawing data from all kinds of sources using educational data mining techniques and learning analytics (cp. Baker & Siemens, 2014). The outputs can be used by various stakeholders including learners (to support their learning), teachers (to support teaching activity), and relevant institutions (to support institutional decision making and resource planning).
- *Artificial Intelligence based systems* proactively make decisions about the learner, such as predicting learner outcomes, recommending next steps and guiding learning activities in ways that complement human teachers (for an overview of recommender systems – cp. Manouselis et al., 2010; intelligent tutoring – see

Baker, 2016 for a critical discussion that includes an overview of intelligent tutoring literature).

From these examples, there are relatively few studies of technology-supported, informal learning in workplace contexts, triggering at least two major problems. First, formal learning contexts take prominence, missing opportunities to investigate how informal learning can be supported by technology systems. Second, TEL research in workplace contexts often is orientated towards investigation of the technology- systems. Rather than focusing on work practices and how these can be supported by technologies. This may be because technologies themselves are still maturing, and hence have not had significant take-up by organisations. These two problems have to be considered to advance beyond the state-of-the-art in technology-enhanced professional learning.

15.2.3 How to Go Beyond What Is: What Researchers Need to Know to Advance the State-of-the-Art

The previous section identified two problems that have to be addressed to advance beyond the state-of-the-art in technology-enhanced professional learning. Overcoming these issues requires knowledge from the learning sciences, specifically focusing on how professionals learn in different contexts, computing science, concentrating on the knowledge needed to design technology solutions as well as knowledge from the domain of work. Thus, the research and development of technical systems has to integrate knowledge from at least three domains: learning sciences, computer science and relevant knowledge from the domain of application (for example knowledge about the Manufacturing Sector, Health Sector, Energy Sector and so on). This section examines these diverse perspectives.

15.2.3.1 Learning Sciences: A Critical Perspective

The learning sciences encompass a range of distinct traditions, from educational psychology which may involve quantitative testing of laboratory-based simulations, to socio-cultural traditions, using qualitative anthropological or ethnographic methodologies to examine learning in 'realworld' settings. Many of these studies adopt a critical approach, aiming to uncover the underlying phenomenon and causality, rather than focusing on a solution. This critical approach makes it difficult to envision how technology developments, such as the introduction of Artificial Intelligence, might change learning processes. This critical approach also lacks a design-orientation, which is necessary however in order to develop technologies that are suitable for (professional) learning whilst at the same time being transformative.

15.2.3.2 Computer Science and Human-Computer Interaction: A Design-Oriented Perspective

Computer science is carried out within distinct communities with different epistemologies. Focussing solely on communities that also or solely focus on computer technologies for learning, a few stand out, such as artificial intelligence and data mining for education (AIEd, EdM, LAK), natural language processing for educational purposes (Sig Edu of ACL), or human-computer interaction from the perspective of learning as a particular domain of application (CHI). These different epistemologies range from contextual design to technical (algorithmic) approaches. The distinctiveness of these approaches are evidenced in the different sorts of research questions asked by each of the communities, such that for instance analytics-focussed communities tend to require that research is about analytics, and subordinately to that allowing the research of algorithms or learning-centered research questions. Overall, technology-based research tends to be design-focused. This approach runs the risk of designing technologies around known approaches to learning, missing opportunities to develop new conceptualisations of learning (cp. Fischer, 2007).

15.2.3.3 Domain Knowledge

Domain-specific knowledge of how to teach a particular subject exists around fundamental fields of knowledge, such as mathematics, computer science, language learning (with, again, specific knowledge for specific languages), etc. Such domain-specific didactical knowledge has had a chance to evolve for major subjects taught in primary and secondary education; where in many countries there are specific degree programs for teachers in particular subjects. Specific didactical knowledge is not to the same degree existent for fields taught in higher education and is significantly non-existent for specific fields of professional expertise. This is probably mostly due to the fact, that significantly fewer people learn about the specifics of how to measure car engines at the time of car engine development than people who need to learn mathematical foundations. However, there is such a thing as domain-specific didactical knowledge (see, for example, Kirschner et al., 2006).

15.2.3.4 Synthesis of Perspectives

Computer science and learning science each assume distinct viewpoints, with learning sciences leading towards a critical perspective and computer science taking a design perspective. Ideally these distinct views would be integrated in ways that underpin the research, design and implementation of technology-enhanced professional learning. We acknowledge that there have been attempts to integrate these perspectives without having a single, dominant perspective. For example, conferences such as the EC-TEL (European Conference on Technology-Enhanced

Learning) explicitly calls for researchers to take into consideration both perspectives, though papers often assume either a "learning" or a "technology" focus. Therefore, a key challenge in the research and development of technologies for professional learning is in considering both a critical and design perspective in order to analyse and critique existing and emerging workplace learning practice; and to design technological support for learning practice enabled through technology support. Thus, in order to design targeted and specific support for professional learning that is contextualised within domain knowledge and specific work practice, domain-specific didactical knowledge for professional learning needs to be developed in parallel with technology support for professional learning. The following section proposes a way forward to achieve this goal.

15.3 Professional Learning Systems: A Structure to Critically Inform Technology Design

Technology systems can gather and interpret multi-modal data using Artificial Intelligence to make decisions for the learner. However, there are concerns that the assumptions that underpin the algorithms that analyse data and make decisions have societal stereotypes and biases coded within them (Williamson, 2016; Berendt et al., 2017). Therefore, the design of technologies for professional learning must be informed by a range of critical data that inform technology-based support. Computer scientists normally use a design-oriented perspective, which complements the research methods described in the other chapters of this book. However, this design perspective is not sufficient in itself if the assumptions underpinning the design are based on social norms and conventions.

A proposal to move beyond the current status quo is to take a systemic, critical perspective that aims to de-construct the learning context in ways that critically inform the design of the technology. This critical perspective has to precede the design in order to provide a systemic baseline on which to design the technology.

This approach is illustrated through a usecase set in a global manufacturing organisation developed by one of the authors. Usecases are used by computer scientists to inform the design of technology systems by describing the context of use. The purpose of this usecase was to redesign training materials to support outcome-oriented learning..

The empirical work (focus group discussions, and interviews) leading up to the final usecase description pinpointed that the workplace had a diverse and heterogeneous set of approaches to training at different educational and organisational levels. These approaches varied in terms of the participants, from apprentices to academics; from early career professionals to senior managers; level of competency or skills, from theoretical to practical; from transversal issues, such as soft skills to core domain knowledge and skills; length of training and commitment to study, from two days to multiple weeks. In parallel, there were multiple types of representations of training, and sometimes multiple representations for a single type of training: every training was described within the training management system, such as a system for booking the training room, registration, payment, and so on. For some types of training, learning materials were centrally available, while for others, only trainers could source the materials and make these available to participants. Some forms of training were designed around self-learning, with interactive electronic assessments, while others included assessments and exams with exam questions. Initially, only a training ID and a title denoted that these different representations referred to the same training.

The research team carrying out the study suggested including a description of the learning goals. There are several benefits to this approach: the learning goals are included in every description of the different forms of training within the organisation's training management system, as well as in the other enterprise systems, such as content or learning management systems. Therefore, the learning goals can be used as index to learning materials. In interactive electronic quizzes, learning goals can be used to give professional learners an overview of their learning progress. If each individual's progress is available in the system, future design could use data to provide an overview of the whole organisation. These contextual data provide critical information about the professional learner and the tools and resources available to him or her within the workplace, yet these data are not normally taken into consideration in usecases. These data can better inform the design of learning analytics systems, interactive systems for self-study, and automated learning guidance. However, this example provides only a first step towards aligning critical and design perspectives. Aligning these approaches is not straightforward, as discussed in the next section.

To overcome the challenge of aligning both a critical perspective on work and learning and a design-oriented perspective on designing effective technology supports, the research and design space had to be structured to provide a focus for critique, and to both constrain and direct design.

In this chapter we propose as useful overarching themes for combining the critical and design perspective when designing technologies for workplace learning:

1. **Goals and Motivation**: What is the primary goal of learning, and what is the main motivation of the learners? What is the value of what is being learned for work?
2. **Work Structure**: How is work and learning structured? What are relevant roles, divisions of labour, organisational culture?
3. **Tools**: What are the mediating objects (knowledge or practical resources) used for work/learning? How is the object of learning represented – in curated learning materials, in materials that can be re-purposed for learning, or in the form of data?

These questions can be used to guide design-oriented fieldwork that aims to elicit design context and to identify design opportunities..

This framework provides a starting point to consider various designs perspectives that can be built to support users within a usecase. The usecase methodology can be used to consider workplace resources and tools that can be adapted to support both formal and informal learning. This framework supports the design process to scaffold the development of technological tools for specific work contexts. Table 15.1 illustrates examples of technology tools used to support professional learning, focusing on the three themes. The goal of this table is to lay out the design space and give example options.

15.3.1 Goals and Motivation

A concern expressed by learning scientists is that, by not taking into account the learner's context, technical designs may oversimplify how we understand learning. Research suggests that there is considerable variety in learners' motivations for professional learning (Littlejohn et al., 2016b). The goals of the professional learner usually align (tacitly or explicitly) with work tasks (Littlejohn et al., 2012). The learner's work role, discipline and geographic location affects their interest in topics (Liyanagunawardena et al., 2013), Confidence, prior experience and motivation (Milligan et al., 2013), and a learner's occupation (Hood et al., 2015) have been found to mediate engagement. Some professionals primarily are motivated by solving immediate work tasks, expanding knowledge, or broaden their skillset in order to work more effectively (Milligan & Littlejohn, 2017). Others may be motivated to gain a qualification, depending on their context of work. For example, health workers often require certification to carry out tasks, while computer scientists are more motivated to solve tasks and demonstrate their competency through their outputs (Littlejohn & Hood, 2018b).

Research by one of the authors on how professionals self-regulated their learning suggests that learners displaying higher levels of self-regulation were more likely to conceptualise MOOCs as non-formal learning opportunities and to independently structure their learning and engagement to best serve their self-defined and self-identified needs (Littlejohn et al., 2016b). These needs might be to learn how to carry out a task more effectively. Alternatively, the need may be to gain certification to allow them to carry out work tasks (for example health professionals require certification for most work tasks).

Diverse motivations influence the socio-technical learning design: Where certification is the goal, technologies that connect learners to educational institutions may be useful. These systems include computer-mediated distance learning or MOOCs. New systems are being developed to allow certification or forms of formal recognition of learning outside education courses or MOOCs. This brings with it challenges in the transition. For example, in a case led by one of the a blended learning course for the unemployed is under discussion, provided by an unemployment agency. The usecase has an associated online system that supports self-study, by combining multimedia content with interactive learning exercises. In this usecase, the time spent on learning should be documented, as there is concern that in the online system will encourage learners to spend less time learning. Underlying this concern is the

Table 15.1 Overview of examples

	Formal learning	TEL examples	Informal learning	TEL examples
1 What are the main goals, motivators for learning?	Gain accreditation. Develop skills/competencies relevant for current or future work.	Online classroom. MOOCs and online courses. Competency development systems used by organisations, such as Volkswagen. Augmented reality headsets (see Sect. 15.2).	Solve problems and gain competencies (eg through onboarding, or lifelong professional learning). Modular access to content/knowledge resources. Participation in a community of practice.	Global knowledge networks, which are wikis used by companies (eg Shell) to support professionals in sharing their knowledge. Referencing text snippets to allow flexible access to content resources. Collaborative mood tracking as a trigger for peer support.
2 How is work and learning structured? What are relevant roles, divisions of labour, organisational culture?	Learning is usually guided by course structure and objectives. Time and space may be allotted by the organisation; or learning happens in the learner's private space of life	Blended learning course (partly online and partly face-to-face). Online apprenticeships. Predictive Analytics. MOOC (Coursera). BOC (Open Learn). Simulations.	Finding time and space for learning is a challenge Is a teacher (maybe an informal one) available – someone to ask, someone who supports learning?	Augmented reality, where an automotive technician wears a headset which overlays information about an engine she is repairing. Mediating communication and contextualisation in communities-of-practice/interest. Automated learning guidance. 'Charting' systems that prompt learners to define learning goals then connect them with other relevant people and resources.

3 What are the mediating objects (knowledge or practical resources) used for work/learning? How is the object of learning represented – in curated learning materials, in materials that can be re-purposed for learning, or in the form of data?	Learning guided by content resources Resources created by an external provider or in-house.	MOOCs/online courses. Learning materials are available. – content creation and updating is a challenge in specialised learning domains.	Learning guided by resources often sourced by the learner and created by peers or other learners. – materials created for other purposes than learning are re-purposed. Learning goals may be explicitly available, or, where not, other conceptual artefacts possibly structure the learning domain. Data can represent relevant aspects of work practice as basis for data-driven learning.	Semantic analysis of the discussions within a team to analyse team cohesion. Use of Wikis (eg Wikipedia) as a site for learning, as distributed editors work together to create wiki entries. Augmented search applications, where AI systems 'learn' from the searching/ sourcing behaviours of people. Re-purposing materials that are by-products of work for learning. Intelligent Digital Workspace – dynamic and living organisational memory enhanced with learning guidance Analytics of work practice that support learning.

concept that learners should spend significant time on learning. In reality, it is the quality of engagement, rather than the quantity of time on task, that will bring about competency development. Outcome assessment is complex and difficult to actuate, so professional's competency assessment often involves a lightweight assessment of learning outcomes. These concepts, from conventional training, are often directly transferred and applied to online settings, where time on task learning is tracked and documented as 'learning time'. Tracking is technologically challenging but possible when all learning takes place within a single system. However, if learning is across multiple sites and systems, tracking time is technologically challenging.

If the professional's goal is to solve a work problem, they may engage in 'just-in-time' learning focused around a specific work task and exploring a narrow concept, rather than a broad field of knowledge. In this case professionals will likely benefit from modular access to granular knowledge resources they can learn from. Modular access to resources is an important form of support for workplace learning and is sometimes termed "flexible delivery" (Smith, 2003). This terminology may seem unconventional to learning scientists, who understand that 'learning' cannot be 'delivered', but who are likely to agree that flexible access to knowledge resources is important for professional learning. The "flexible delivery" approach provides a baseline for a research design prototype for professional learning. A flexible technological system can reference and link fine-grained content, and aggregate granular content resources into constellations of relevant materials that can be used by the professional learner. The prototype system uses semantic technologies to gather data used to realise aggregations of knowledge resources. This enables the professional to have fine-grained access to knowledge that is relevant to the his or her work task (Lindstaedt et al., 2010).

If the professional is problem solving within a team or community, technology systems can be used to support communication within a community-of-practice to support collaborative problem-solving. For instance, while evaluating a collaborative mood tracking application in business-to-business call centres, Rivera-Pelayo et al. (2017) observed that reflection-in-action could be mediated by a technology tool. Online reflection was brief, but it triggered a lot of of face-to-face dialogue, where problems were tackled and solved. These forms of supported conversations, leading to formation of a community-of-practice might increase the learner's motivation to learn, through the creation of a respectful social environment or by explicitly rewarding the learner with recognition for his or her expertise.

15.3.2 Work Structure

For professionals, finding the time and space for learning is a challenge. In some work settings the time for work is unstructured. This means that finding time for learning within work hours in principle can be done, but is not easily organised so may not take place. Traditional forms of training are organised during working hours. For computer-mediated formal training, particularly informal learning,

learning may take place outside working hours. Pammer-Schindler et al. (2018) describe a case where, despite the work-relevance of trainings, no explicit learning resources (i.e. time) are allocated for computer-mediated training. Even in cases where the working day can be used for learning, workload may be high, which inhibits people from learning during work. Another challenge is finding a space to learn. Both in Pammer-Schindler et al. (2018) and Fessl et al. (2014), the authors describe cases where clients (e.g. patients in a doctors surgery) may expect immediate attention of a professional (e.g. a receptionist) who is learning at work, and may raise questions about professionalism when the professional is found to be doing something other than work. Where these sorts of issues are not addressed by the system designers, they remain a problem for the learner to solve him or herself.

Similarly, finding time and space for learning is challenging in online professional learning. In some settings, such as an online classroom, there is a clearly defined teacher and learners who aim to achieve the same learning goals. However, in MOOC settings students teach their peers and the teacher-student role is not well defined. It is a characteristic of the work and learning structure, whether and in which roles teachers and co-learners all participate in the same organisation. This interchangeability of roles impacts the types of contextualisation that can happen around formal training.

Informal learning scenarios are equally complex, since it is difficult to predict how a professional might learn informally or who they might learn from. In vocational apprentice training, supervisors are typically assigned to apprentices. This assignation has is quasi formal and the supervisor may be responsible for the professional development of those whom he or she manages. In one case from a large-scale global organisation, a manager was responsible for identifying the training needs of those he managed and was also accountable for assessing the impact of the training. However, a key problem was that the training impact assessment was not mandatory. This meant that the training organisers and learners did not have useful information about the quality and suitability of the training in terms of impact on practice. This is a problem because support for learning can be made available by capitalising on quality management processes. For example, if an employee is uncertain about a procedure, or how to deal with a potential problem, a triage system (a chain of reporting and discussion) developed for quality assurance can be adapted to support learning. The use of these supports can be mediated and contextualised through online discussions within Communities of practice (cp. Santos et al., 2016) or online learning networks

One of the authors has explored how professionals learn on-the-job within online networks in the petrochemical industry (Littlejohn et al., 2012; Margaryan et al., 2009). These studies identified four key learning actions as firstly consuming knowledge and resources created by others. This can be supported by search tools, social media, recommender systems and AI systems that recommend pathways and resources. Second, creating new knowledge, by authoring and extending resources to elaborate and record current practice. Creating actions are supported by enterprise systems such as Sharepoint as well as open knowledge creation tools such as Google Docs, blogs, wikis, media players as well as video or audio capture. Third, connecting with people and resources (information sources), including linking with peers who share interests or goals to develop ideas, share experience, provide peer-support, or work collaboratively to achieve shared goals. Connections are made through conventional tools, such as email and videoconferencing (eg Skype). However, a range of systems including WhatsApp, Slack, Twitter and other systems are increasingly being used for work. Fourth, contributing new knowledge resources either formally (as reports, publications, and other standalone artefacts) or informally (as reflections, ideas, ratings and other context-dependent content). In this way, one individual's learning becomes available to others. As professionals self-regulate their learning, they 'chart' their learning pathways, therefore we term this metacognitive process of planning and instantiating learning 'charting'.

Another way to guide the learner is via an automated learning guidance. Lindstaedt et al. (2010) developed an adaptive system based on semantic models of work tasks, concepts that shall be learned, and user's current competencies in order to adapt learning support to the user's level of competence in relation to the concept that shall be learned. Fessl et al. (2017) have developed a reflection guidance concept that is based on Schön's (1983) distinction between reflection-in-action, and reflection-before/after-action, i.e. reflection that is intertwined with operative work, and reflection that is temporally separated from work. The reflection guidance concept is largely domain-independent, but concrete instantiations hide didactical knowledge about the domain of application, such as what kind of data are useful representations of the learning domain; and which types of data patterns are salient and potentially useful for reflection.

15.3.3 Tools

Automated learning guidance systems, using Artificial Intelligence, are being used to support novices to gain expertise (cp. Kirschner et al., 2006). The rationale behind these systems often is to point the novices towards available and relevant learning materials. However, this approach has a number of questionable assumptions, including the supposition that expert knowledge can be codified and transferred to novices. State-of-the-art systems are using 'analytics of work practice' to support professional learning. These systems guidance from the system (for example, pointing the professional to relevant information and resources) with human guidance from an expert, mentor or coach. In this system the learner him/herself sometimes acts as an expert. This system brings together at least three fields of knowledge needed to design future technologies for professional learning: the knowledge about technology systems, knowledge about learning and domain knowledge about the workplace. These three knowledge domains have to be combined to create advanced adaptive and intelligent technology systems.

Data analytics can be an enabler for learning guidance. However, there are concerns that the algorithms that inform analytics systems are based on traditional models of education and professional development. New analytics systems are being developed to gather domain data as basis for evidence-based practice guidance for professional learning. This closes the gap in knowledge around how professionals learn, how they use technologies to learn, and about the impact of socio-technical interventions. These sorts of data can be used to overlay augmented reality within authentic work situations, in ways that integrate professional work and learning. The tools and resources in the workplace – information systems, specialist technologies and non-technical resources such as guidelines; templates error categories, or taxonomies – will structure work and learning. A key question is whether and how existing systems and resources should be incorporated in a novel systems design.

A project led by one of the authors developed a system to support automotive engineers. These production workers were part of a car assembly line in Austria and had specific responsibility for rectifying cars that failed to meet the required quality standard, for example had surface scratches in the paintwork. These arbitrary errors in assembly-line produced cars are complex. Within the organisation there was a taxonomy of error categories and errors were logged, but there was no systematic way to compare or analyse instances of how errors had been repaired. Having data on similar errors not only can improve the efficiency and effectiveness of the assembly line, but allows opportunity for the organisation, teams and individual workers to learn. The challenge of designing a system for workers to document and analyse errors within a pressurised work environment is a challenge for human-computer interaction specialists. A key information retrieval challenge is to determine which errors are similar and which solutions to errors are transferrable and this decision making requires the knowledge and skills of the production workers. In this case professional learning was supported through structured reflection of prior error handling cases, based on the concept of adaptive and computer-mediated reflection support (cp. Fessl et al., 2017). By aligning the benefits of a digital system – to record and document representations of errors – with the strengths of the workforce – the knowledge around how specific errors can be resolved – an intelligent digital workspace can provide support for work and learning. Rather than producing 'learning materials', the system supports the production workers in knowledge sharing. The system connects to existing workplace tools and artefacts, such as the taxonomy of errors, the company's quality management system, and a system that documents the assembly-line production.

In these sorts of examples, where learning is integrated within work practice, existing work systems can be used to log relevant activity data about work practice, which generates data that can support workers reflection about their work practice. In this way the analytics of work practice supports (data-driven) learning, rather than performance monitoring. It is critical that the data used to represent work practice is relevant for learning. Pammer et al. (2015) have investigated how activity log data from the computers used by of IT and strategy consultants can be used to help them reflecting on their workflow and time management in the case of IT and strategy consultants, with study participants having generated useful insights about own time management. Prilla (2015) examined ways to support physicians to learn how to have difficult conversations with patients and their relatives. There are no data within medical information systems that can be used to support physicians' learning. Therefore, additional data that can be used as basis for reflection needed to be gathered. This raises critical issues around data sensitivity, with respect both to professionals and their patients. Computer scientists are facing growing challenge and scrutiny over the design of these sorts of systems. Therefore, these issues of data protection and other issues that influence decision making in technological systems need to be considered and informed by critical analyses that provide a baseline for designing technology systems.

15.4 Conclusion: The Future of Professional and Digital Learning

Technologies have the potential to help shape and transform professional work and learning.

However, learning scientists have real concerns that technology systems developers have an overly simplistic view of the ways professionals learn. At the same time computer scientists are worried that criticism of technology system development, without a solution, does not help identify a positive way forward. Technology systems have to be designed in ways that do not incorporate societal stereotypes and biases, are supportive of learning, usable and acceptable for professionals.

Overcoming these challenges is an interdisciplinary problem that requires knowledge from at least three areas: the learning sciences, computer science (most notably human-computer interaction and artificial intelligence) and the domain of application (i.e. healthcare knowledge, finance knowledge etc depending on the workforce). In this chapter we have proposed a way forward that brings together methods and approaches from both a critical and design-oriented perspective.

In this chapter we suggest a structure to support critical design of technology systems for professional learning, illustrated by examples that represent the state-of-the-art for computing science. These examples illustrate how the design space has to transform to take into consideration a wide range of contextual and critical data to support the development of more innovative and transformative solutions.

However, deeper approaches to combining critical approaches with design approaches are needed to alleviate concerns around the use of data for efficiency gains or income revenue valanced against data protection, unintended biases being coded into systems, unfounded assumptions underlying data analysis and contextual information about the workplace and context of professional learning not being taken into consideration. These concerns are very relevant for the modern age and call for an integrated approach to research, bringing together different critical and design perspectives, alongside a stronger inter-relationship between the learning sciences and computer science.

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