Chapter 14: Professional Learning Analytics

Allison Littlejohn[1]

[1] UCL Knowledge Lab, Institute of Education, University College London, London, United Kingdom

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ABSTRACT

Professional learning is an important component of productivity in contemporary work environments characterised by continual change. Learning for work takes various forms, from formal training to informal learning through work activities. In many work settings professionals collaborate via networked environments leaving various forms of digital traces and 'clickstream' data. These data can be exploited through learning analytics to make both formal and informal learning processes traceable and visible to support professionals with their learning. This chapter examines the state-of-the-art in professional learning analytics by considering the different ways professionals learn. As learning analytics techniques advance, the modelling techniques that underpin these methods become increasingly complex and the assumptions that underpin the analytics become ever-more embedded within the system. This chapter questions these assumptions and calls for a new, refreshed vision of professional learning analytics for the future which is based on how professionals learn. There is a need to broaden our thinking about the purpose of learning analytics build systems that effectively to address affective and motivational learning issues as well as technical and practical expertise; intelligently align individual learning activities with organisational learning goals and to be wary of attempts to embed professional expertise in code written by software developers, rather than by the professionals themselves. There are also ethical concerns about the degree of surveillance on learners as they work and learn with anxieties about whether people understand the (potentially serious) consequences [19]. Finally, learning analytics generally are developed for formal learning contexts, in schools, colleges and universities, missing opportunities to provide the support professionals need as they learn through everyday work.

Keywords: Professional learning, work, training

Contemporary work is characterised by the accelerated integration of technology within the professions [38, Chapter 1]. This change often is symbolised as 'jobs being replaced by technology systems', with reports suggesting millions of jobs will be lost over the next decade. For example, a BBC report [51] estimates that up to 20 million factory jobs could be lost by 2030 as tasks are automated.

1 THE INTEGRATION OF TECHNOLOGY WITH WORK

There is evidence that some jobs already are already disappearing. Telesales and service staff are being replaced by 'chatbots', computer-based communication systems designed to interact with humans via the internet [60]. Hotel reception staff are being superseded by automated check-in systems [46]. Paralegal tasks are being carried out by document checking systems that search for and recommend documents specific to each legal case and similar systems are gathering together news items around specific topics, replacing some journalist positions [6]. However, some of the most profound changes in employment are not where humans are replaced by machines, but where digital systems are automating routine tasks, rather than replacing humans.

Computational systems tend to be good at specific tasks that are difficult for humans, such as identifying patterns in large datasets and completing computational analysis extremely quickly. For over a decade, cancers have been spotted using computational systems that compare large datasets and identify patterns that lead to diagnosis [59]. Automating routine work means that Oncologists have more time to focus on more complex tasks, leaving doctors to focus on recommending treatment plans. The finance sector has been reshaped by 'Fintech' systems that identify trading patterns and carry out transactions in micro seconds, much faster than any human [18]. This semi-automation of trading frees Traders to consider and research future investment areas. Thus, the integration of technology with work continually changes what professionals do, dynamically changing work practice and creating a need for professionals continually to learn new ways of working [38, Chapter 1].

For some years now employers have been aware that the digitisation of work offers opportunities to capitalise on the data generated as a by-product of learning in digital systems. Data mining and analytics techniques can be used to support and enhance work and learning. Learning analytics systems were first developed for use in university education to provide learners, teachers and managers with information [53]. Many of these early learning analytics systems were based on predictive models that analyse individual learner profiles to forecast whether a learner is 'at risk of dropping out' [66]. These data usually are presented to learners or teachers using a variety of dashboards to inform students of their likely progress, with recommendations for remedial action; teachers were given information about likely learner outcomes; university managers were provided data to plan for future income, costs and impact [45, 53].

These systems are also being applied to Professional Learning, particularly when professionals sign up for formal qualifications at universities or through online learning organisations. There have been fewer attempts to situate professional learning analytics within workplaces, whether inside organisations or in virtual spaces where sole workers gather together, such as crowd-work platforms. Some of the systems that have been developed have been based around organisational administration and competency mapping. For example, some organisations use systems that map data about current and future job roles with data on the current competencies of employees to help companies train and recruit people with the skill-sets needed [8]. However, these systems are based on a competency supply chain model, rather than supporting professionals as they work and learn.

Applying data analytics techniques to complex learning contexts is complicated; it is difficult to know what data to gather, analyse and what conclusions can be drawn from learning analytics [19]. This chapter examines the evolution of professional learning analytics. The chapter begins by tracing the progression of learning analytics systems, followed by an analysis of different forms of professional learning. The chapter then maps learning analytics systems and techniques within a typology of professional learning, considering whether and how different analytics techniques that support the various ways professionals learn. The chapter concludes by putting forward a vision for professional learning analytics, drawing attention to areas that require attention from all those involved in the future development of learning analytics.

2 LEARNING ANALYTICS

Learning analytics is a methodological research area aimed at "the measurement, collection, analysis and reporting of data about learners and their contexts, for the purposes of understanding and optimising learning and the environments in which it occurs" [58, 55]. Learning analytics aims to be multi-disciplinary, using ideas from learning science, computer science, information science, educational data mining, knowledge management and, more recently, Artificial Intelligence [22, 40]. Learning analytics uses computational systems to leverage the massive amounts of data generated as a by-product of digital learning and work activity to support learners in achieving their goals [3, 4]. Examples include systems that track learner progress and predict outcomes, recommending remedial action; facial recognition or skin conductivity systems that gather data that are used to interpret learners' emotions and how these relate to learning; location indicators that track the position of a learner and infer moments of interaction with others (see [68]).

AI scientists have been building on approaches in machine learning, computer modelling and statistics used in the business sector to support education [40]. Some Learning platforms use Artificial Intelligence (AI), a range of analytic methods used to harvest, structure and analyse computationally large data sets to reveal patterns, trends, and associations [45]. One branch of AI is based on 'machine learning' where large amounts of data are gathered and fed into an 'engine', which uses statistical algorithms to identify patterns and to make decisions based on the trends identified. The system is considered 'intelligent' because, as data is fed into the engine, it 'learns' to make more informed decisions about individual cases.

AI techniques are based on the use of 'Big Data' which are "information assets characterized by such a high volume, velocity and variety of data to require specific technology and analytical methods for its transformation into value" [41, p. 103]. The volume of data available is increasing as people work using digital systems. As they work, people leave various forms of digital traces and large amounts of data, generally known as 'Big Data' [39]. Analysis of these data potentially provides a means of improving operational effectiveness by enhancing and supporting the various ways professionals work, learn and adapt. The velocity with which these data are generated is escalating rapidly as more data becomes available via different computational systems people use for work. These systems draw upon and use a diverse variety of data. Data sets gathered and used for analysis involve multiple data types including behavioural data (how often a learner accesses a site), discourse data (what learners say or type), learner disposition data (key characteristics associated with each learner, such as how they prefer to learn) and biometrics data (including [58]).

Techniques used in learning analytics include discourse analysis, where learners discussions and actions provide opportunity for helpful interventions [22]; semantic analysis, tracing the relationship between learners and learning [67], learner disposition analytics, identifying affective characteristics associated with learning [55] and content analytics, including recommender systems that filter and deliver content based on tags and ratings supplied by learners. These techniques are useful in encapsulating the complex factors that influence how professionals learn.

The application of LA and AI to support professional learning largely has been focused on conventional approaches to online education, where students access learning materials and submit assessment or assignment materials to demonstrate they have achieved a set of pre-defined competencies. Examples of learning analytics include combining learner profiles with online behavioural data (the number of times a student accesses a Virtual Learning Environment) to predict the likelihood of a student dropping out of a course or being admitted to a program, to offer timely support or to provide feedback and guidance [31, 68].

These examples of learning analytics are designed to support formal education, where learning is structured and the outcomes of learning are pre-defined. However, there is ample evidence that professional learning takes different forms in different contexts and often achieved through engaging in everyday work tasks, rather than through formal, accredited learning [17].

3 PROFESSIONAL LEARNING

Keeping skills and knowledge up-to-date is crucial for all professionals, whether experienced workers or novices, and is also important for organisations to remain competitive. This means that professional learning tends to be driven by the demands of work tasks and is interwoven with work processes [16]. Professional learning is much broader than formal education, since formal learning alone does not provide all the knowledge needed for work [62]. Professional learning includes "the activities people engage in to stimulate their thinking and professional knowledge, to improve work performance and to ensure that practice is informed and up-to-date" [38].

However, when professionals are asked about how they learn, they tend to think of formal training, where learning is focused on assessment, learner outcomes and explicit pedagogical models [17]. Examples include workshop training, professional courses (such as certificated programs or postgraduate degrees) which are intentionally structured and some are assessed around pre-defines outcomes. Intentional learning may be pre-planned and structured as formal learning for example degree programs, classroom training, practical workshops, coaching or mentoring [62]. Other forms of intentional learning tend to be less well defined and structured, such as coaching, mentoring or questioning a more expert colleague. Although these types of learning are intentional, they are loosely structured and more difficult for professionals to recognize as 'learning'.

There is evidence that professionals do much of their learning through engaging in everyday work tasks, which is termed 'non-formal learning' [14, 17, 20]. Learning through work tends not to be planned, assessed or accredited. This makes it difficult for professionals to recognise it as a form of learning, without being prompted to reflect on particular types of experience or specific changes in their capabilities [17]. For example, professionals may learn new ways of working when they move to a new location or team [37]. People may be unaware of they are learning, because their practice evolves over time [37]. Nevertheless, learning through work is a critical component of ongoing improvement and innovation and the adoption of new practices in the workplace [37]. These different forms of professional learning are illustrated in Figure 1:

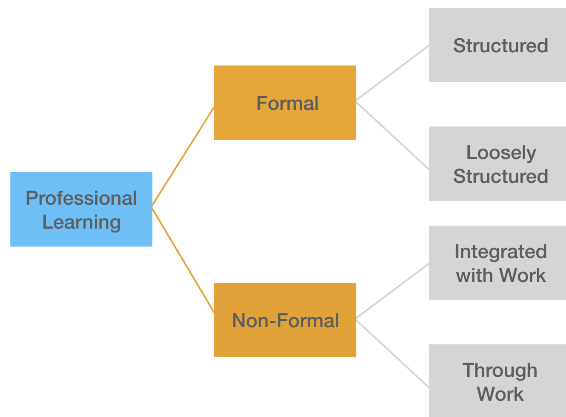

Figure 1: Typology of professional learning, informed by [16, 14]

These different forms of learning facilitate development of diverse types of knowledge [63, 37]. Structured education and training tend to focus on learning theoretical and practical knowledge, while more loosely structured coaching and mentoring allow opportunities to learn other types of knowledge, such as socio-cultural and self-regulative knowledge. All these knowledge types are critical for the adoption of new practices for work. Change in practice requires the construction of conceptual and practical knowledge as well as the development of socio-cultural and self-regulative knowledge [15]. Construction of multiple types of knowledge is most readily achieved through a combination of intentional learning opportunities with on-the-job learning [24]. As such, workplace learning operates as a reciprocal process [5] shaped by the affordances of a specific workplace, together with an individual's ability and motivation to engage with what is afforded [5, 20].

There is a tight relationship between the workplace context and learning when people learn at work. There is a growing body of evidence that professional learning is more effective when integrated with work tasks (see for example [10, 62, 20, 14]. However, it is difficult to distinguish unintended, on-the-job learning from everyday work tasks, so it is difficult to recognise when professionals learn through work [2, 13].

Professional learning is influenced by the learner's internal motivation, personal agency and work tasks [37]. These three critical components need to be taken into consideration when designing computational systems to support work and learning. To ensure personal agency, professionals have to be able adapt and self-regulate their learning. To trigger motivation, learning should be integrated with, rather than separate from, work practices. These important factors have not always been taken into consideration when designing analytics systems. The next section explores these gaps by examining how learning analytics techniques and systems have been applied within professional learning contexts.

4 PROFESSIONAL LEARNING ANALYTICS

Professional learning analytics provides an opportunity to make both formal and non-formal learning processes traceable and more explicit in order to support individuals and teams to work and learn [39, 35]. This vision of professional learning analytics is based on a system of mutual support through which each professional both connects with, draw from and contributes back to the collective knowledge [43]. In theory these actions create a common capital via the selective accumulation of shared by-products of individual work activities, initially motivated by personal utility [23, p.15]. These actions would be supported by a set of algorithms, data mining mechanisms and analytics that create a "common capital through re-usable knowledge via the selective accumulation of shared by-products of individual activities motivated, initially, by personal utility" [23, p.15].

4.1 Analytics for Formal learning

Early attempts to apply learning analytics to professional learning contexts involved the transfer of techniques from formal education, such as university education, to professional learning contexts. In formal education, students tend to follow a learning pathway with predefined objectives and regular assessments. This sequenced developmental path is similar to forms of training and formal learning for professionals. Key applications of learning analytics in formal education include learner profiling and prediction of outcomes [68].

One of the most common applications of learning analytics is learner profiling and prediction of outcomes using predictive analytics techniques. One example is 'OU Analyse', a system developed by The Open University, UK to provide early prediction of 'at-risk' students. The system is predicated on the idea that each student follows a linear learning pathway and that every few weeks they engage in a 'Tutor Marked Assessment'. Learners are profiled by gathering demographic data about each student's age, gender, place of residence and prior qualifications. These data are combined with data related to 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 [34]). 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. Predictive analytics systems are helpful in suggesting remedial action to students at risk of not passing an assessment. However, there are significant concerns for learners in predicting future learning outcomes based on past activity. The system can (inadvertently) create unseen problems for learners and teachers. The system can create 'sound clouds' that normalise specific behaviours of learners and misinterpret others, so learners have to follow 'normal behaviours' to be accepted by the system [37]. By relaying on a computational system, rather than their own professional judgement, to assess learner progress, teachers can become 'deskilled' [19]. Predictive analytics systems require large amounts of data (so-called "Big Data') including personal data about learners. Large-scale collection and analysis of personal data are of concern to human-rights advocates, who have called and continue to call for stronger data protection legislation and implementation (see for example [64, 65, 48]). Yet there are few analyses of the likely impact of AI in education on workers freedoms and fundamental rights.

Pre-defined, structured courses often are not helpful for people who work in highly specialised roles. Early analytics systems to provide personalised *adaptive system* support were based on intelligent tutoring systems that provide immediate, customised content or feedback to learners, usually without intervention from a human teacher or expert. More recent adaptive systems for Professional Learning bring learning and work together by embedding professional learning with work practice so people learn as they work. Many organisations recognise that training is not effective if professionals learn a new process then do not use their new knowledge and embed it within their practice. Recognising the importance of enabling people to learn new expertise at the point of need, organisations have been seeking ways to capture and disseminate expertise. These work-integrated systems include *augmented reality systems* that are used to support professionals to learn about their work environment by providing just-in-time information for professionals as they carry out their work. Augmented reality involves overlaying layers of digitally-generated information on top of the work environment, using location sensors to detect where the worker is located. These layers of information are made visible using Wearable Technology, such as augmented reality spectacles or observing real-world objects via a smartphone screen. For example Wearable Technology headsets can be used to capture data and information as an experienced professional works, and then disseminate this information to less experienced colleagues at the point of need to help them learn. The headset video records how an aerospace technician dismantles a valve in an aircraft engine and carries out a repair. The video has audio commentary and metadata added. When a novice technician carries out the same task, the video information is transmitted via an augmented visual interface, allowing the novice to learn in detail how to triage and repair the valve.

One example of an augmented reality system is *Wearable Experience for Knowledge Intensive Training* (WEKIT), which was designed and built as part of an EU funded project which commenced in 2015 [11]. WEKIT aims to make informal learning processes traceable and recognisable so that novices can develop expertise in an agile way. The system is based on a three-stage process: mapping skill development pathways, capturing and codifying expertise, making the expertise available to novices at the point of need. In the first stage a community of professionals and stakeholders (the WEKIT.club) map out recognised skill development pathways for industry. In the second stage a group of software developers use the pathway templates to develop technology tools to support novices in learning new procedural knowledge - for example how to turn on (or off) a specialist valve. Finally, the expertise is transmitted to the novice via the augmented visual interface. Head-mounted digital displays allow the novice to see the valve overlaid with instructions on how to safely switch it on. Through wearable and visual devices, the system directs each professional's attention to where it is most needed, based on an analysis of user needs.

These three key steps in the transfer of expertise in the WEKIT methodology all have risks associated with them. First, expertise development pathways are difficult to model. Experts are involved in building the pathways and algorithms to support expertise development in an attempt to capture and codify the expertise accurately. However, it is difficult for an expert to understand the optimal learning pathway that will enable each novice's expertise development, since this depends on the novice's prior experience. Second, not all expertise can be codified. Augmented visual interfaces and collaborative digital interfaces can help with some aspects of expertise development. However, professionals draw on explicit and tacit knowledge as they carry out tasks. Tacit expertise, such as the 'gut feeling' that a piece of equipment is operating optimally, takes time to be developed. Thirdly, the novice has to be actively involved in learning new expertise, with the scaffolding being reduced as they become more expert. Otherwise there is a risk they will simply follow instruction, rather than learn. In the future smart systems might not only draw the learner's attention to a specific task, but could record how the novice carries out the task and compare this with how the expert carries out the repair. This would require additional analytics that compares visual recorded data with the expert video data and interacts with the novice, offering dialogue of how to improve his or her work.

While these examples structure professional learning around *competency frameworks*, other professional learning analytics systems provide *personalization through adaptive systems*. These systems are based on the idea of each professional developing a personalised learning pathway, with learning goals aligned with their work tasks. Early examples of personalised professional learning were based on the idea that people with specific job roles or expertise would benefit from bespoke learning pathways that brought them into contact with specific content. When a high degree of specialism is needed, professionals themselves are best placed to decide on their learning needs and the unique combination of expertise they require [32]. One example is the ROLE system (Responsive Open Learning Environments role-project.eu) [28] where individuals define specific concepts and practices they need to learn, then browse and select a set of web-based resources and tools that support their learning. The analytics method uses a recommender system to combine the web-based content resources in different ways to support specific job roles. The web-based resources are sets of learning materials that the professionals sequence and tailor for their own use. The more the system is used, the better it 'learns' specific combinations of content appropriate for specific job roles. These resources can be reproduced and adapted to support other people with similar roles. The system uses demographic data to provides appropriate content that is sequenced and structured in a bespoke way.

Some analytics systems are based on the assumption that people might learn more effectively by using strategies that have been effective for other people in similar roles [39]. One of these systems is LearnB, which has been trialled in the automotive industry [57]. The tool is designed around a self-regulated learning framework which gathers data on factors that have been shown to influence learning at work [56]. These factors include the specific learning and development goals that workers plan and the range of activities they engage in to learn. Learn B collects and analyse these data to identify and connect people with similar learning goals [57, 25]. Common goals are identified and analysed using semantic analysis techniques. These data are fed into social technology systems that recommend topics people might benefit from learning and different learning strategies they might adopt, based on the learning patterns of others. The system uses the organization's Performance Review systems to guide professionals in documenting their learning experiences. The system then makes these experiences available for others who might benefit from learning in a similar way in the future. In theory, by documenting learning experiences, it is possible to analyse and compare experiences and performance and map these against organisational benchmarks. It might be useful, for example, to know that a new skill can be learned in a few hours [56](. On the other hand it may be reassuring for professionals to know that it takes an average of six months experience to become competent in a new procedure (Ibid). The system evaluation provided evidence that professionals benefited from updates about their social context – knowing, for example, what resources other people used and how long they took to learn specific concepts and practices [56]. Supporting self-regulation and other forms of metacognition encourages professionals to take an active approach to their learning. However, in the LearnB trial professionals were operating within a traditional organisational culture with a 'top down' competence system. The problem with this system is that the organization pre-determines the competencies needed for each job role and recommends the ways people demonstrate how they learn these capabilities [9].

These sequenced and (relatively) linear developmental pathways in formal learning are different from the non-formal learning most professionals engage in, which require good self-regulation ability [17, 37].

4.2 Analytics for Informal Learning

There are a growing number of applications of AI and learning analytics systems in non-formal settings. Some of these applications have come from groupwork or projects in higher education, while others have been pioneered in industry settings. These approaches include use of intelligent agents, natural language processing, learning through sensory modality. These sit alongside semantic analytics systems that connect professionals with the people and knowledge they need to learn new tasks.

The development of *intelligent conversational agents* opens up opportunity for dynamic support for professionals as they carry out their work. The initial application of conversational agents in work contexts was to help workers with administrative tasks, such as using computer applications, scheduling meetings or managing to-do lists [21]. A number analytics systems use intelligent conversational agents to stimulate and monitor the effects of professionals practices for individuals and within teams. In some cases, these have been embedded into established forms of practice already used in industry. For example, intelligent agents have been used to stimulate reflective practice, which plays an important role in learning at work [7]. Performance is said to improve through appreciation of the causal mechanisms behind actions and outcomes which increases certainty in the ability to complete a task [69]. This meta-level understanding can be stimulated through reflection, yet, despite its importance, reflection can be overlooked as a purposeful practice. Particularly in stressful work situations when (ironically) reflection is most needed. An EU funded project, 'MIRROR – Reflective learning at work', provided a platform for experimentation to identify whether and how a range of computer applications (Apps) might stimulate and monitor the effect of reflection on work. Apps can encourage reflection on a range of factors, such as mood (are you stressed or worried?), team-work (is the team working well?) or progress (are you working effectively?) [50]. In some cases quantitative data is gathered, for example 'mood' can be traced by asking people to indicate how they feel during work tasks by selecting relevant emoji. Work progress can be monitored through qualitative data gathering using online diaries. These data can be analysed and reflection stimulated through group-work with human agents (for example colleagues or mentors) or with intelligent agents (for example chatbots).

Mirror [49] is an analytics-based system that supports professionals in learning from their own and others experiences. Reflection is a significant component of self-regulated learning which may improve learning and performance through motivational and affective factors [37]. The Mirror system is based on a set of applications ('Mirror' apps) designed to facilitate informal learning during work [33]. These apps were used in Health settings to support analysis of individual and team actions. These reflections allowed both individuals and teams to learn which practices had the most impact within their organisation. For example, the 'Talk Reflection App', was developed to support physicians treating patients suffering from acute strokes and other neurological emergencies in learning how to interact better with patients and their relatives [47]. The App tool prompts individual doctors to reflect on specific work situations by answering questions, such as how they felt. Each individual can share answers with colleagues (human agents), who document their own experiences, and can learn through reading the responses of others or talking with them. Evaluation studies of the MIRROR Apps found a clear link between individual and team learning and organisational learning (linked to Human Resource procedures, rewards and promotions) [29]. However, for computational systems to be effective in changing work practice, the technology tools have to be adopted into everyday work to effect change. This can only be achieved if end users (workers) are involved in the design and implementation of a system from the outset. Some systems use multi-modal conversational agents that use chat and voice modalities to support reflection. For example, Roberta is a system that supports individual and team reflection as teams work together via an online teamwork platform, Slack [30]. The conversational agent, Roberta, prompts individuals or teams to log and reflect on their daily progress and outcomes. This triggers reflection, prompting workers to identify at a meta-level what actions they might take to improve how they work. When chat (text based interaction) and voice modes were trialled, chat was considered easier to review, but slightly less personal compared with voice [30]. These Apps are being used by individual workers to reflect on and improve their practice. Evaluation studies provide evidence that these Apps work well only when professionals appreciate the value of reflection and adopt this into their everyday work practice [30].

Attempts to embed computational systems within everyday work practice have focused on replicating existing practices online. For example, Sankaranarayanan et al. [52] developed a computational system to simulate 'Mob Programming' practices in an online environment. Mob Programming is an approach used in software development where a team simultaneously work on the same output, at the same time, in the same environment. The benefits of this approach range from facilitated knowledge sharing and learning to the use of distributed knowledge [27]. During Mob Programming team members swap roles to facilitate learning, disseminate knowledge and to make sure no single person dominates the output. In the computational system, a human team facilitator is substituted for an Intelligent Conversational Agent. The Agent gathers data from an online chat system and monitors code edits and highlights examples that participants can emulate. The Agent also analyses these data and indicates when people should swap roles to keep the activity progressing. Data analysis can identify whether work is carried out evenly across the team and can monitor whether the chat is related to project activity. From this analysis, the Agent can draw conclusions about different factors such as team dynamics and learning potential. The Agent can reassign the tasks and monitor the effects. This type of system potentially provides a powerful way to embed professional learning within day-to-day work tasks.

However, there are ethical questions around the continual monitoring of professionals.

By exploiting organisational and professional networks, professionals can, in theory, achieve agile learning in ways that support immediate work problems [9]. This type of self governing, bottom-up approach to professional learning requires an understanding of how and where professionals interact and exchange ideas about their work. Analytics techniques have been used in attempts to visualise informal organisational and professional networks. de Laat and Schreurs [35] developed and piloted Network Awareness Tool (NAT) - a tool that uses Social Network Analysis techniques - within a school to identify online teacher networks. The tool visualised multiple, isolated networks of teachers within the organisation. This sort of tool could be used to support teachers in reflecting on how networks could be exploited or restructured. However, to achieve effective networking it is important to understand how people interact in both online and physical networks. Endedijk traced and visualised networks of care workers in a physical HealthCare setting using wearable tracking devices [12]. These devices gathered geospatial data (e.g. the location, proximity and direction) of each care worker and analysed these data to identify how professional networks were dynamically formed. The study provided evidence of limited connections within and across the professional network. These data can be used by the organisation, team managers and the professionals themselves to reflect on ways they can improve their networking in ways that exploits the human capital within each team [12]. The idea of supporting professional learning through informal networks is powerful, particularly when it allows consideration of information flow through informal networks. However, information flow in itself does not indicate learning, so these techniques have to be supplemented by other methods to test the underlying assumptions.

Another technique being used to assess team cohesion and teamwork is *Natural Language Processing* (NLP). NLP techniques are being incorporated into learning analytics systems as a promising way to support non-formal learning. These systems process and analyse dialogue to trace learning and development by comparing how different groups, for examples novices and experts, express concepts and ideas or by tracing discourse development over time. The development of linguistic cues is an important signifier of social identity and expertise development within communities of practice [36]. Analysis of social media narratives over time could identify whether, while using web based learning resources, whether novices were moving towards using expert language. Yan, Naik and Rose [67] carried out novel research where they analyse natural language. The researchers examined the use of natural language within Reddit – a social media platform used to aggregate stories within online communities. They used a natural language processing analysis technique, Content word filtering and Speaker preferences Model (CSM) to detect how the use of language develops within online communities. By extracting ‘functional story schemas’, they identified schematic structures that characterise specific sub-narratives within the community. These schemas serve as lenses that reveal ‘community norms’ within Reddit sub-communities. The NLP analytics techniques can detect and make visible when teams work coherently, or where there are structural problems. These techniques can be used to compare the ways experts and novices work, allowing support to be tailored. However, there are assumptions around behaviours built into the system. These assumptions become foundational ‘norms’ that are difficult to change; the more the system ‘learns’ the more these conventions become assimilated. Future techniques have to find ways for systems to become more intelligent through being able to ‘learn’ and ‘unlearn’, rather than setting up ‘sound clouds and ‘stereotypes’.

For decades robots and humans have worked together collaboratively through direct physical interaction, for example in automotive assembly lines [1]. As robots co-work with professionals, there is opportunity to exploit learning through sensory modality. Humans learn by interacting with their environment through touch, which helps to build an understanding of objects and events. For example, robots can teach people how to move their arm during rehabilitation after an accident [44]. By providing smooth, strong virtual surfaces and other haptic effects the robot can turn a shared workspace into a learning space. Haptic technologies have been used effectively in professional learning settings, particularly in medicine and dentistry, where ‘touch’ is important for sensory learning [61]. The computational systems that drive the robots harvest data through various sensors: touch, geo-location, visual and so on. These data can be combined and analysed to provide feedback to the learner. For example, a dentist can learn a new technique by sensing the ‘feel’ of drill while working on a virtual patient before carrying out the procedure on a human [61].

These forms of informal learning need to be evaluated using innovative forms of assessment and accreditation.

4.3 Assessment and accreditation

Professionals could have competency in their everyday work recognised and accredited using automated forms of assessment. For example, when operations staff in a manufacturing plant learn how to operate equipment and carry out a range of tasks to a specific level of competence under supervision before they full fill their probationary period and are allowed to work unsupervised. Supervisors verify when they reach the competency level by observing, questioning and then verifying the learner has reached a level of competence and computational systems are being used to gather and store information on learner progress using blockchain technology [42]. Blockchain technologies have been proposed as a way to ensure the authenticity of the data, allowing an audit trail of activity that is useful for documenting learning progress [26]. A blockchain is a distributed record of online activities, or digital events, which has a consensus method to agree whether a new ‘block’ is legitimate [54]. This system allows formation of a permanent, distributed record of intellectual effort and reputational reward. A central claim is that blockchain 'democratises' education by opening up records of achievement beyond traditional forms of certification in ways that allow employers to view a wide range of achievements. Computational systems are not simply records of achievement.

5 CONCLUDING REMARKS: FUTURE PROFESSIONAL LEARNING ANALYTICS

Although in its infancy, professional learning analytics is set to form a foundation for future learning and work. Learning analytics are already supporting professionals in improving their performance. Analysis of these approaches point to the need to develop systems that support professionals as they learn through everyday work, rather than only focusing on analytics systems for professional courses or work-based training.

Several approaches use machine-based analytics to augment human intelligence. However, the connection between the system and the human is a point of risk for a number of reasons. First, professionals have to be able to identify and act upon their learning needs, therefore the ability to self-regulate learning is critical to the success of many analytics techniques. Second, without a parallel shift in the culture and the mindsets of people within the organisation, learning systems based on analytics will have limited impact. This is particularly relevant in work settings where task outcomes are difficult to predict. Learning in these situations is most effective when integrated with work tasks. Professional learning analytics can be more powerful when incorporated into work-integrated systems: platforms that support experts and novices in co-working, smart systems or augmented reality environments, such as those described earlier. Future implementation of approaches to learning analytics should consider these human elements.

Finally, there are a range of ethical considerations that need to be embedded not only within the use of analytics systems, but to inform their development. By contributing their data to a system, professionals can benefit from analytics systems that help them to connect with information, knowledge and people that can help them learn or carry out a new task [37]. However, there needs to be better transparency around how these data are combined with other datasets and used. If professional learning analytics is considered as a race, we are still in the starting blocks.

REFERENCES

[1] Prasad Akella, Michael Peshkin, Ed Colgate, Witaya Wannasuphoprasit, Nidamaluri Nagesh, Jim Wells, Steve Holland, Tom Pearson, and Brian Peacock. "Cobots for the automobile assembly line". In: *Proceedings 1999 IEEE International Conference on Robotics and Automation (Cat. No.99CH36288C)*. IEEE. DOI: 10.1109/robot.1999.770061. URL: https://doi.org/10.1109%2Frobot.1999.770061.

[2] Chris Argyris. "Double-loop learning, teaching, and research". In: *Academy of management learning & education* 1.2 (2002), pp. 206–218.

[3] Ryan S. Baker. "Stupid Tutoring Systems, Intelligent Humans". In: *International Journal of Artificial Intelligence in Education* 26.2 (Feb. 2016), pp. 600–614. DOI: 10.1007/s40593-016-0105-0. URL: https://doi.org/10.1007%2Fs40593-016-0105-0.

[4] Bettina Berendt, Riina Vuorikari, Allison Littlejohn, and Anoush Margaryan. "Learning analytics and their application in technology-enhanced professional learning". In: *Technology-enhanced Professional Learning: Processes, practices and tools* (2014), pp. 144–157.

[5] Stephen Billett. "Workplace participatory practices". In: *Journal of Workplace Learning* 16.6 (Sept. 2004), pp. 312–324. DOI: 10.1108/13665620410550295. URL: https://doi.org/10.1108%2F13665620410550295.

[6] Guido Boella, Luigi Di Caro, Llio Humphreys, Livio Robaldo, Piercarlo Rossi, and Leendert van der Torre. "Eunomos, a legal document and knowledge management system for the Web to provide relevant, reliable and up-to-date information on the law". In: *Artificial Intelligence and Law* 24.3 (June 2016), pp. 245–283. DOI: 10.1007/s10506-016-9184-3. URL: https://doi.org/10.1007%2Fs10506-016-9184-3.

[7] David Boud, Rosemary Keogh, and David Walker. "Promoting Reflection in Learning: A Model". en. In: *Reflection: Turning Experience into Learning*. London: Kogan Page, 1985, pp. 18–40. ISBN: 978-1-135-84546-9.

[8] Chen-Fu Chien and Li-Fei Chen. "Data mining to improve personnel selection and enhance human capital: A case study in high-technology industry". In: *Expert Systems with Applications* 34.1 (Jan. 2008), pp. 280–290. DOI: 10.1016/j.eswa.2006.09.003. URL: https://doi.org/10.1016%2Fj.eswa.2006.09.003.

[9] Julie Clow. "Work Practices to Support Continuals Organisational Learning". en. In: *Technology-Enhanced Professional Learning: Processes, Practices, and Tools*. Ed. by Allison Littlejohn and Anoush Margaryan. Devon: Routledge, Oct. 2013, pp. 17–27. ISBN: 978-1-135-01113-0.

[10] Kaija Collin. "Development engineers' work and learning as shared practice". In: *International Journal of Lifelong Education* 27.4 (July 2008), pp. 379–397. DOI: 10.1080/02601370802213856. URL: https://doi.org/10.1080%2F02601370802213856.

[11] WEKIT Consortium. *Wearable Experience for Knowledge Intensive Training (WEKIT)*. en-US. http://wekit.eu/.

[12] Maaike Endedijk. "Presentation at the Technology-Enhanced Professional Learning (TePL) Special Interest Group". In: *Technology-Enhanced Professional Learning (TePL) Special Interest Group*. Glasgow: Glasgow Caledonian University, May 2016.

[13] Yrjö Engeström et al. "Activity theory and individual and social transformation". In: *Perspectives on activity theory* 19.38 (1999), pp. 19–30.

[14] Michael Eraut. "Informal learning in the workplace". In: *Studies in Continuing Education* 26.2 (July 2004), pp. 247–273. DOI: 10.1080/158037042000225245. URL: https://doi.org/10.1080%2F158037042000225245.

[15] Michael Eraut. "Learning from other people in the workplace". In: *Oxford Review of Education* 33.4 (July 2007), pp. 403–422. DOI: 10.1080/03054980701425706. URL: https://doi.org/10.1080%2F03054980701425706.

[16] Michael Eraut. "Non-formal learning and tacit knowledge in professional work". In: *British Journal of Educational Psychology* 70.1 (Mar. 2000), pp. 113–136. DOI: 10.1348/000709900158001. URL: https://doi.org/10.1348%2F000709900158001.

[17] Michael Eraut and Wendy Hirsh. "The significance of workplace learning for individuals, groups and organisations". In: *ESRC Centre on Skills, Knowledge and Organisational Performance (SKOPE)* (2010).

[18] Bin Fang and Peng Zhang. "Big Data in Finance". In: *Big Data Concepts, Theories, and Applications*. Springer International Publishing, 2016, pp. 391–412. DOI: 10.1007/978-3-319-27763-9_11. URL: https://doi.org/10.1007%2F978-3-319-27763-9_11.

[19] Tara Fenwick and Richard Edwards. "Network alliances: precarious governance through data, standards and code". In: (2014).

[20] Alison Fuller. *Workplace Learning in Context*. Routledge, Jan. 2004. DOI: 10.4324/9780203571644. URL: https://doi.org/10.4324%2F9780203571644.

[21] Yolanda Gil and Varun Ratnakar. "Towards intelligent assistance for to-do lists". In: *Proceedings of the 13th international conference on Intelligent user interfaces - IUI '08*. ACM Press, 2008. DOI: 10.1145/1378773.1378822. URL: https://doi.org/10.1145%2F1378773.1378822.

[22] Nabeel Gillani and Rebecca Eynon. "Communication patterns in massively open online courses". In: *The Internet and Higher Education* 23 (Oct. 2014), pp. 18–26. DOI: 10.1016/j.iheduc.2014.05.004. URL: https://doi.org/10.1016%2Fj.iheduc.2014.05.004.

[23] Antonietta Grasso and Gregorio Convertino. "Collective intelligence in organizations: Tools and studies". In: *Computer Supported Cooperative Work (CSCW)* 21.4-5 (2012), pp. 357–369.

[24] Christian Harteis and Stephen Billett. "The workplace as learning environment: Introduction". In: *International Journal of Educational Research* 47.4 (Jan. 2008), pp. 209–212. DOI: 10.1016/j.ijer.2008.07.002. URL: https://doi.org/10.1016%2Fj.ijer.2008.07.002.

[25] Teresa Holocher-Ertl, Claudia Magdalena Fabian, Melody Siadaty, Jelena Jovanović, Kai Pata, and Dragan Gasevic. "Self-regulated Learners and Collaboration: How Innovative Tools Can Address the Motivation to Learn at the Workplace?" In: *Towards Ubiquitous Learning*. Springer Berlin Heidelberg, 2011, pp. 506–511. DOI: 10.1007/978-3-642-23985-4_47. URL: https://doi.org/10.1007%2F978-3-642-23985-4_47.

[26] Anya Kamenetz. *Big data comes to college*. 2014.

[27] Herez Moise Kattan, Frederico Oliveira, Alfredo Goldman, and Joseph William Yoder. "Mob Programming: The State of the Art and Three Case Studies of Open Source Software". In: *Agile Methods*. Springer International Publishing, 2018, pp. 146–160. DOI: 10.1007/978-3-319-73673-0_12. URL: https://doi.org/10.1007%2F978-3-319-73673-0_12.

[28] Uwe Kirschenmann, Maren Scheffel, Martin Friedrich, Katja Niemann, and Martin Wolpers. "Demands of Modern PLEs and the ROLE Approach". In: *Sustaining TEL: From Innovation to Learning and Practice*. Springer Berlin Heidelberg, 2010, pp. 167–182. DOI: 10.1007/978-3-642-16020-2_12. URL: https://doi.org/10.1007%2F978-3-642-16020-2_12.

[29] Kristin Knipfer, Barbara Kump, Daniel Wessel, and Ulrike Cress. "Reflection as a catalyst for organisational learning". In: *Studies in Continuing Education* 35.1 (Mar. 2013), pp. 30–48. DOI: 10.1080/0158037x.2012.683780. URL: https://doi.org/10.1080%2F0158037x.2012.683780.

[30] Rafal Kocielnik, Daniel Avrahami, Jennifer Marlow, Di Lu, and Gary Hsieh. "Designing for Workplace Reflection". In: *Proceedings of the 2018 Designing Interactive Systems Conference*. ACM, June 2018. DOI: 10.1145/3196709.3196784. URL: https://doi.org/10.1145%2F3196709.3196784.

[31] K. V. Phani Krishna, M. Mani Kumar, and P. S. G. Aruna Sri. "Student Information System and Performance Retrieval Through Dashboard". In: *International Journal of Engineering & Technology* 7.2.7 (Mar. 2018), p. 682. DOI: 10.14419/ijet.v7i2.7.10922. URL: https://doi.org/10.14419%2Fijet.v7i2.7.10922.

[32] Sylvana Kroop, Alexander Mikroyannidis, and Martin Wolpers. *Responsive open learning environments: outcomes of research from the ROLE project*. Springer Nature, 2015.

[33] Barbara Kump, Kristin Knipfer, Viktoria Pammer, Andreas Schmidt, Ronald Maier, Christine Kunzmann, Ulrike Cress, and Stefanie Lindstaedt. "The Role of Reflection in Maturing Organizational Know-how". englisch. In: *Proceedings of the 1st European Workshop on Awareness and Reflection in Learning Networks* (2011), pp. 30–45.

[34] Jakub Kuzilek, Martin Hlosta, Drahomira Herrmannova, Zdenek Zdrahal, Jonas Vaclavek, and Annika Wolff. "OU Analyse: Analysing at-Risk Students at The Open University". en. In: *Learning Analytics Review* LAK15-1 (Mar. 2015), pp. 1–16. ISSN: 2057-7494.

[35] Maarten de Laat and Bieke Schreurs. "Visualizing Informal Professional Development Networks". In: *American Behavioral Scientist* 57.10 (Mar. 2013), pp. 1421–1438. DOI: 10.1177/0002764213479364. URL: https://doi.org/10.1177%2F0002764213479364.

[36] Eric Lesser and Laurence Prusak. "Communities of Practice, Social Capital and Organizational Knowledge". In: *Knowledge and Communities*. Elsevier, 2000, pp. 123–131. DOI: 10.1016/b978-0-7506-7293-1.50011-1. URL: https://doi.org/10.1016%2Fb978-0-7506-7293-1.50011-1.

[37] Allison Littlejohn and Nina Hood. "How educators build knowledge and expand their practice: The case of open education resources". In: *British Journal of Educational Technology* 48.2 (Mar. 2016), pp. 499–510. DOI: 10.1111/bjet.12438. URL: https://doi.org/10.1111%2Fbjet.12438.

[38] Allison Littlejohn and Anoush Margaryan. *Technology-Enhanced Professional Learning: Processes, Practices, and Tools*. Routledge, Oct. 2013. DOI: 10.4324/9780203745052. URL: https://doi.org/10.4324%2F9780203745052.

[39] Allison Littlejohn, Colin Milligan, and Anoush Margaryan. "Charting collective knowledge: supporting self-regulated learning in the workplace". In: *Journal of Workplace Learning* 24.3 (Mar. 2012), pp. 226–238. DOI: 10.1108/13665621211209285. URL: https://doi.org/10.1108%2F13665621211209285.

[40] Rose Luckin, Wayne Holmes, Mark Griffiths, and Laurie B. Forcier. "Intelligence unleashed: An argument for AI in education". In: (2016).

[41] Andrea De Mauro, Marco Greco, and Michele Grimaldi. "What is big data? A consensual definition and a review of key research topics". In: AIP, 2015. DOI: 10.1063/1.4907823. URL: https://doi.org/10.1063%2F1.4907823.

[42] Alexander Mikroyannidis, John Domingue, Michelle Bachler, and Kevin Quick. "Smart Blockchain Badges for Data Science Education". In: *2018 IEEE Frontiers in Education Conference (FIE)*. IEEE, Oct. 2018. DOI: 10.1109/fie.2018.8659012. URL: https://doi.org/10.1109%2Ffie.2018.8659012.

[43] Colin Milligan, Allison Littlejohn, and Anoush Margaryan. "Workplace Learning in Informal Networks". en. In: *Reusing Open Resources: Learning in Open Networks for Work, Life and Education*. Ed. by Allison Littlejohn and Chris Pegler. Routledge, July 2014, p. 93. ISBN: 978-1-135-04004-8.

[44] Ferdinando A. Mussa-Ivaldi and James L. Patton. "Robots can teach people how to move their arm". In: *Proceedings 2000 ICRA. Millennium Conference. IEEE International Conference on Robotics and Automation. Symposia Proceedings (Cat. No.00CH37065)*. IEEE. DOI: 10.1109/robot.2000.844074. URL: https://doi.org/10.1109%2Frobot.2000.844074.

[45] Nicolae Nistor, Michael Derntl, and Ralf Klamma. "Learning Analytics: Trends and Issues of the Empirical Research of the Years 2011–2014". In: *Design for Teaching and Learning in a Networked World*. Springer International Publishing, 2015, pp. 453–459. DOI: 10.1007/978-3-319-24258-3_39. URL: https://doi.org/10.1007%2F978-3-319-24258-3_39.

[46] Hirotaka Osawa, Arisa Ema, Hiromitsu Hattori, Naonori Akiya, Nobotsugu Kanzaki, Akinori Kubo, Tora Koyama, and Ryutaro Ichise. "Analysis of robot hotel: Reconstruction of works with robots". In: *2017 26th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*. IEEE, Aug. 2017. DOI: 10.1109/roman.2017.8172305. URL: https://doi.org/10.1109%2Froman.2017.8172305.

[47] Michael Prilla, Thomas Herrmann, and Martin Degeling. "Collaborative Reflection for Learning at the Healthcare Workplace". In: *Computer-Supported Collaborative Learning at the Workplace*. Springer US, 2013, pp. 139–165. DOI: 10.1007/978-1-4614-1740-8_7. URL: https://doi.org/10.1007%2F978-1-4614-1740-8_7.

[48] Paul Prinsloo and Sharon Slade. "An elephant in the learning analytics room". In: *Proceedings of the Seventh International Learning Analytics & Knowledge Conference*. ACM, Mar. 2017. DOI: 10.1145/3027385.3027406. URL: https://doi.org/10.1145%2F3027385.3027406.

[49] MIRROR Project. *MIRROR - Reflective Learning at Work*. https://cordis.europa.eu/project/id/257617. June 2010.

[50] Bettina Renner, Gudrun Wesiak, Viktoria Pammer-Schindler, Michael Prilla, Lars Müller, Dalia Morosini, Simone Mora, Nils Faltin, and Ulrike Cress. "Computer-supported reflective learning: how apps can foster reflection at work". In: *Behaviour & Information Technology* 39.2 (Mar. 2019), pp. 167–187. DOI: 10.1080/0144929x.2019.1595726. URL: https://doi.org/10.1080%2F0144929x.2019.1595726.

[51] "Robots 'to Replace up to 20 Million Factory Jobs' by 2030". en-GB. In: *BBC News* (June 2019).

[52] Sreecharan Sankaranarayanan, Xu Wang, Cameron Dashti, Marshall An, Clarence Ngoh, Michael Hilton, Majd Sakr, and Carolyn Rosé. "An Intelligent-Agent Facilitated Scaffold for Fostering Reflection in a Team-Based Project Course". In: *Lecture Notes in Computer Science*. Springer International Publishing, 2019, pp. 252–256. DOI: 10.1007/978-3-030-23207-8_47. URL: https://doi.org/10.1007%2F978-3-030-23207-8_47.

[53] Xanthe Shacklock. *Report: From Bricks to Clicks: The Potential of Data and Analytics in Higher Education*. en. Tech. rep. London, UK: Higher Education Commission, Jan. 2016.

[54] Mike Sharples and John Domingue. "The blockchain and kudos: A distributed system for educational record, reputation and reward". In: *European conference on technology enhanced learning*. Springer. 2016, pp. 490–496.

[55] Simon Buckingham Shum and Ruth Deakin Crick. "Learning dispositions and transferable competencies". In: *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge - LAK '12*. ACM Press, 2012. DOI: 10.1145/2330601.2330629. URL: https://doi.org/10.1145%2F2330601.2330629.

[56] Melody Siadaty, Dragan Gasevic, Jelena Jovanovic, Kai Pata, Nikola Milikic, Teresa Holocher-Ertl, Zoran Jeremie, Liaqat Ali, Aleksandar Giljanovic, and Marek Hatala. "Self-Regulated Workplace Learning: A Pedagogical Framework and Semantic Web-Based Environment". English. In: *Educational Technology & Society* 15.4 (Oct. 2012), pp. 75–89. ISSN: 14364522.

[57] Melody Siadaty, Jelena Jovanović, Dragan Gašević, Zoran Jeremić, and Teresa Holocher-Ertl. "Leveraging Semantic Technologies for Harmonization of Individual and Organizational Learning". In: *Sustaining TEL: From Innovation to Learning and Practice*. Springer Berlin Heidelberg, 2010, pp. 340–356. DOI: 10.1007/978-3-642-16020-2_23. URL: https://doi.org/10.1007%2F978-3-642-16020-2_23.

[58] George Siemens and Phil Long. "Penetrating the Fog: Analytics in Learning and Education". en. In: *EDUCAUSE Review* 46.5 (2011), p. 30. ISSN: 1527-6619.

[59] Dimitris K. Tasoulis, Panagiota Spyridonos, and Nicos G. Pavlidis. "Urinary Bladder Tumor Grade Diagnosis Using On-line Trained Neural Networks". In: *Lecture Notes in Computer Science*. Springer Berlin Heidelberg, 2003, pp. 199–206. DOI: 10.1007/978-3-540-45224-9_29. URL: https://doi.org/10.1007%2F978-3-540-45224-9_29.

[60] Julieo Thompson. "The Evolution of Technology in Call Centers". In: *CCE Theses and Dissertations* (Jan. 2019).

[61] Brian Tse, William Harwin, Alastair Barrow, Barry Quinn, Jonathan San Diego, and Margaret Cox. "Design and Development of a Haptic Dental Training System - hapTEL". In: *Haptics: Generating and Perceiving Tangible Sensations*. Springer Berlin Heidelberg, 2010, pp. 101–108. DOI: 10.1007/978-3-642-14075-4_15. URL: https://doi.org/10.1007%2F978-3-642-14075-4_15.

[62] Päivi Tynjälä. "Perspectives into learning at the workplace". In: *Educational Research Review* 3.2 (Jan. 2008), pp. 130–154. DOI: 10.1016/j.edurev.2007.12.001. URL: https://doi.org/10.1016%2Fj.edurev.2007.12.001.

[63] Päivi Tynjälä and David Gijbels. "Changing World: Changing Pedagogy". In: *Transitions and Transformations in Learning and Education*. Springer Netherlands, 2012, pp. 205–222. DOI: 10.1007/978-94-007-2312-2_13. URL: https://doi.org/10.1007%2F978-94-007-2312-2_13.

[64] Audrey Watters. *The Stories We Were Told about Education Technology*. Dec. 2018. URL: http://hackeducation.com/2019/12/23/top-ed-tech-stories.

[65] Ben Williamson. "Cognitive Computing and Data Analytics in the Classroom". en. In: *British Sociological Association*. Glasgow Caledonian University, Apr. 15, p. 6.

[66] Annika Wolff, Zdenek Zdrahal, Andriy Nikolov, and Michal Pantucek. "Improving retention". In: *Proceedings of the Third International Conference on Learning Analytics and Knowledge - LAK '13*. ACM Press, 2013. DOI: 10.1145/2460296.2460324. URL: https://doi.org/10.1145%2F2460296.2460324.

[67] Xinru Yan, Aakanksha Naik, Yohan Jo, and Carolyn Rose. "Using Functional Schemas to Understand Social Media Narratives". In: *Proceedings of the Second Workshop on Storytelling*. Association for Computational Linguistics, 2019. DOI: 10.18653/v1/w19-3403. URL: https://doi.org/10.18653%2Fv1%2Fw19-3403.

[68] Olaf Zawacki-Richter, Victoria I. Marin, Melissa Bond, and Franziska Gouverneur. "Systematic review of research on artificial intelligence applications in higher education – where are the educators?" In: *International Journal of Educational Technology in Higher Education* 16.1 (Oct. 2019). DOI: 10.1186/s41239-019-0171-0. URL: https://doi.org/10.1186%2Fs41239-019-0171-0.

[69] Maurizio Zollo and Sidney G. Winter. "Deliberate Learning and the Evolution of Dynamic Capabilities". In: *Organization Science* 13.3 (June 2002), pp. 339–351. DOI: 10.1287/orsc.13.3.339.2780. URL: https://doi.org/10.1287%2Forsc.13.3.339.2780.