The Potential of the Internet of Things for Supporting Learning and Training in the Digital Age

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Abstract: The rapid progress in the development of information and communication technologies opens new opportunities in education, which go hand in hand with new risks that may be difficult to foresee. Our aim here is to focus mainly on the Internet of Things and related technologies, in order to investigate how they can improve this field. We claim a proper analysis and interpretation of the big educational data can enable more precise personalization and adaptation of learning and training experiences, in order to make them more effective, efficient and attractive. Nevertheless, it will require new approaches to implement novel tools and services for more effective knowledge acquisition, deeper learning and skill training, which can take place in authentic settings and stimulate motivation of learners.

Keywords: Internet of Things, Personalization, Adaptation, Learning, Training, Augmented Reality, Wearables, Learning Nuggets, Nudges, Blockchain

1. Introduction

Development of humans is highly influenced by the tools and media they use (cf., e.g., Maurer et al. in this issue). Neuroplasticity research has shown that our experiences change our brains throughout our life course (Doidge 2007), which means that people can always learn and acquire new knowledge and skills. The Internet together with other information and communication technologies (ICT) have a huge impact on the behaviour of people (Carr 2011), which includes also serious issues, like a loss of concentration abilities or problems with critical thinking and deep learning (cf. Zlatkin-Troitschanskaia et al. 2017). Every medium develops some cognitive skills at the expense of others (Greenfield 2009). Whether a tool helps or harms depends on the individual abilities and the way of its usage. Moreover, the long-term effects can differ diametrically from the short-term ones and may be very difficult to predict (cf., e.g., Knauff in this volume). These are risks that should not be ignored, and we must analyse them and try to understand their consequences, in order to avoid the potential harm that can be caused to humans. This requires monitoring of a long-term technological impact on users and assessment of possible risks (as a part of the PLATO program, cf. Zlatkin-Troitschanskaia et al. 2017).

On the other side, the unique opportunities offered by new ICT (like the Internet of Things, wearables and augmented reality) are extremely tempting for researchers and developers in the field of Technology Enhance Learning (TEL). A proper analysis and interpretation of the big data in education can help us better understand the effectiveness and efficiency of learning experiences, as well as individualize and optimize them. In addition, long-term effects of ICT on learning can be monitored, which should help also in cultivation of so important metacognitive skills, like self-regulation, self-monitoring and self-reflection (cf., e.g., Meyer in this volume). These skills are crucial in dealing with cognitive biases of humans, which are often misused against them. On the other hand, there is a big challenge to exploit these biases for the benefit of the learner. This would be a significant achievement in TEL. In the time when lifelong learning becomes unavoidable, cultivation of learning skills is crucial. But learning requires effort and energy from the learner, therefore stimulation of a natural curiosity, dealing with uncertainty, as well as development of the art of doubting and critical thinking have to be part of this process.

Another important aspect is the authenticity of learning embedded in other processes, like work (cf. Shavelson in this volume). This directly influences motivation and consequently efficiency of the learning and training experience, leading not only to acquisition of new knowledge, but also to cultivation of specific target skills. This is of crucial importance in the time when such paradigmatic change takes place like the transition towards Industry 4.0 (Wahlster 2014).[1]

2. The Internet of Things

The Internet of Things (IoT) is "a global infrastructure for the information society, enabling advanced services by interconnecting (physical and virtual) things based on existing and evolving interoperable information and communication technologies" (ITU 2012). IoT can improve authenticity of learning experiences, raising the motivation of participants, which has a crucial impact on the efficiency of the learning process. Better personalization and

[1] This brings new challenges for professional development, with a direct inclusion of employees in its planning and realization. Lifelong competence development is important for various reasons. Companies need to identify their competence gaps and fill them efficiently. Employees can have their own aspirations regarding their lifelong professional development and plan them accordingly. Moreover, there is also the interest of the whole society to reduce the unemployment rate.

adaptivity of learning can be informed by the information collected through a rich palette of available sensors, like those for environment analysis, for home automation and manufacturing, as well as bio-sensors. It brings a potential for a new quality of personalized learning experiences, based on a better understanding of the users, their current status (including attention, emotions and affects) as well as their context. It also opens new horizons for design and implementation of novel virtual learning environments. Together with wearable technologies (WT) and augmented reality (AR) they can substantially enhance the usage of human senses in order to learn, to acquire new knowledge and train new skills.

From a technical perspective, IoT consists of objects that are identifiable, able to communicate and to interact (Miorandi et al. 2012). Identifiable means that objects have a unique digital identifier – *Electronic Product Code* (EPC), which is typically broadcast using *Radio-Frequency Identification* (RFID) technology, a very basic way of communication. Further communication, i.e. sending and receiving data to other objects, is enabled by various wireless technologies, realizing the step from single things to a network of things. The objects are not passive, but use sensors to collect information about their environment, and actors to trigger actions. On top of the hardware, software layers enable applications. IoT middleware provides a common way to access heterogeneous IoT devices, and simplifies the development of IoT applications. The technical challenges of IoT are not yet solved and its diverse areas are subject of active research. Nevertheless, IoT technology has matured sufficiently to be commercialized and to be used as enabler for research, including educational one.

Early work on IoT for education focuses mostly on using RFID for recognizing an object and presenting a list of information items or activities for that object (e.g., Broll et al. 2009), later extended to include social interaction on objects (e.g., Yu et al. 2011). Research on using the full IoT potential for learning is still in an early stage, with previous work sketching challenges and opportunities and describing architectures (Thomas et al. 2012, Atif et al. 2015), and there is still a significant gap of knowledge when it comes to research that goes beyond the technological perspective.

3. Big educational data

A plethora of sensors together with log files generated by e-learning platforms contribute to the big educational data, which represents a huge amount of information on the performed learning processes. To analyse and understand this data properly is a real challenge for researchers, developers, and users as well. As mentioned above, the gap between the technological and pedagogical perspective is essential (cf. Zlatkin-Troitschanskaia et al. 2017). Nevertheless, certain research fields help to overcome it, providing a base to build on.

Educational Data Mining (EDM) aims at automatically extracting meaning from large repositories of data related to learning activities, using computational methods for discovering data patterns. This may enable for instance identification of effective learning paths for a particular user as well as activities associated with better grades. Romero and Ventura (2010) list the most typical tasks in the educational environment that have been resolved through EDM techniques: analysis and visualization of data, providing feedback for supporting instructors, recommendations for students, predicting student performance, student modelling, detecting undesirable student behaviours, grouping students, social network analysis, developing concept maps, constructing courseware, as well as planning and scheduling.

Learning Analytics (LA) aims to improve the overall effectiveness of the learning experience, providing relevant alerts and predictions. Its use can be divided into five stages (Pardo 2014): collect, analyze, predict, act, and refine. It is crucial to enable various degrees of privacy and data security, to allow different levels of integration, depending on special preferences of individuals and other bodies, like companies (Kravčík et al. 2016a). Visualization of observable data on the learner's behaviour can even provide feedback about their non-observable cognitive and metacognitive learning activities (Nussbaumer et al. 2012). A major aspiration related to LA is to measure learning not only in formal, but also in informal environments.

4. Personalized and adaptive learning

As mentioned earlier, the big educational data is an important source of information that is available for individualized learning. The descriptions of the domain can be adjusted for a particular user in the current context, according to the chosen pedagogical methodology and preferred adaptation strategies. To overcome related technological and conceptual differences, semantic interoperability between heterogeneous information resources and services needs to be achieved (Aroyo et al. 2006). Modern context-aware and ubiquitous ICT allows for *smart learning*, providing the learner with the right support, depending on the current context and personalized to the individual needs, which are determined also from the learner's behaviour. Hence, smart learning requires an appropriate fusion of education and technology (Li et al. 2016).

4.1 User and context modeling

Personalization of a learning experience must take into account the information about the user, especially the learning objective (like target competences) and personal preferences. These inform the selection of an appropriate pedagogical approach, in order to make the learning process effective, efficient, and attractive. The actual contextual constraints lead to adaptations considering the current environment as well as available objects.

Santos et al. (2016) identified several issues in personalization of learning experiences, like effective detection and management of contextual and personal data of the learners, including also their affective status. This should lead to better understanding of the person, processing information from various resources (e.g., wearables with physiological and context sensors) and related big data. It is also important to harmonize different learning objectives, like short- and long-term ones, according to the learner's preferences. As these preferences can change quickly, available sensors can help significantly in the recognition of such alterations. High-dimensional data collected from sensors can be utilized to infer contextual preferences based directly on the individual's behavior (Unger et al. 2017). But the learners, and sometimes also others who are involved (e.g., teachers, tutor, parents), should know what information the machine collected about them. An *Open Learner Model* makes a machines' representation of the learner available as an important means of support for learning (Bull and Kay 2010).

There was a lack of support for user modeling to harness and manage personal data gathered from IoT. The IoTum user modeling framework (Kummerfeld and Kay 2017) aims to fill this gap. It makes it easy for IoT application developers to use as well as to achieve light-weight, flexible, powerful, reactive user modeling that is accountable, transparent and scrutable (Kay and Kummerfeld 2012). Other approaches deal with elicitation of human cognitive styles (Raptis et al. 2017), affective states (Sawyer et al. 2017), as well as modeling psychomotor activities (Santos and Eddy 2017).

4.2 Adaptive learning and training

Each type of education should be based on a sound pedagogical methodology, which takes into account the learners with their aims, abilities, and preferences, but also the subject domain and the contextual settings. A suitable instructional design stimulates the motivation of participants as well as makes the learning experience effective and efficient. Nevertheless, each learning design can be specified only to a certain degree of detail and then it must be adapted to concrete settings, which can dynamically change over time. This run-time adaptation has to reflect the status and behaviour of learners, keeping them ideally in the *flow* status with their full attention and concentration on their tasks, avoiding frustration from too high demands on one side as well as boredom from trivial activities on the other.

Cultivation of *metacognitive skills* is a big challenge, as they have a direct impact on the individual's quality of life and are essential for lifelong learning. In this context, the effectiveness of education can be improved by the application of *Self-Regulated Learning* (SRL) (cf., e.g., Dormann et al. in this issue). For this purpose, the employed technologies should support an individualised approach as well as a right balance between the learner's freedom and guidance, in order to stimulate motivation, while considering also the effectiveness and efficiency of the learning experience. Moreover, useful assistive services have to be *open* and take into account the available technology and learning culture of learners. At the same time, they should be *responsive,* providing the right mix of adaptivity and recommendations of available options, in order to facilitate various degrees of guidance and freedom (Nussbaumer et al. 2014). Effective support for SRL must integrate advice in the form of personalized nudges (alerts that can be easily avoided) and reflection facilities in a suitable way (Kravčík and Klamma 2014). In any educational setting proper *awareness* and *reflection* services provide valuable feedback for participants and can cultivate their metacognitive skills. The challenge is to interpret the data collected in the learning process meaningfully and present them in an understandable form. To support this by useful technology, its designers and developers have to incorporate knowledge from various fields, including education, psychology, neuroscience and informatics (Kravčík et al. 2017).

Training of skills just from texts and pictures is usually difficult, therefore more dynamic and interactive media are required here, which is crucial for workplace learning. In order to demonstrate a particular skill, operation, or action, the challenge is to find relevant information segments in a vast amount of multimedia resources for a particular objective, context and user. Personalization and adaptive techniques applied on annotated video data may be a good direction in facilitating informal learning at the workplace (Kravčík et al. 2016b). Another promising alternative is offered by AR and WT towards smart ambient learning (Koren and Klamma 2016). Real-time automated feedback can be provided by a combination of wearable, voice-analysis, and motion-sensing technologies when people practice nonverbal communication skills for public speaking (Schneider et al. 2016). This outlines new ways of assessment, based on the direct monitoring of the human behaviour in the authentic settings and providing either a real-time feedback or an analysis of the performance over a certain time. Motor skill learning is an area where WT and user modelling can be synergistically combined for providing support (Dias Pereira dos Santos et al. 2017). Moreover, new opportunities for immersive procedural training open up, like capturing and re-enactment of expert performance, enabling immersive, in-situ, and intuitive learning (Guest et al. 2017).

A crucial limitation of the available adaptation and recommendation services is usually a lack of their understandability and scrutability, which is a typical problem when Artificial Intelligence (AI) techniques like Deep Learning are employed (de Bra 2017). For learning purposes such machine made decisions should be explainable by rules or evidence, in order to raise the trust of users. Generally, a loss of control stimulates negative feelings of users, therefore also clear and manageable privacy policies are required (Colbeck 2017).

5 APPsist system

To demonstrate intelligent adaptive learning technology that paves the way towards Industry 4.0, we introduce the APPsist system, which represents the first general applicable service-oriented architecture, with company specific specializations. Its smart services include user-centered support of qualification and training of employee, as well as user-adaptive context-based support, exploiting formalized expert knowledge.

APPsist is an example of how data collected from sensors is used for knowledge acquisition and assistance. The goal was to develop a new generation of mobile, context-sensitive and intelligent-adaptive assistance systems for knowledge and action support in smart production. The researchers and developers focused on the skills and competences of the staff and attempts to compensate for any skills that may be lacking with respect to performing tasks at the workplace – action support. In addition, knowledge-support services facilitate the continuous expansion of staff expertise through the acquisition of knowledge and skills in relation to production, product, and process. Here, the aim was to promote the professional development of the staff so that they can gradually start to perform more demanding tasks and serve as a counterbalance to the demographic change and the shortage of skilled workers. This support includes the setup and operation of a manufacturing unit in the production process, as well as the preventive maintenance, maintenance, and troubleshooting.

The solution offers both assistance and knowledge services for employees. These software components provide specific types of support: assistance services assist in solving a current problem, while knowledge services support the transfer of knowledge, it means the achievement of individual medium- and long-term development goals (Ullrich et al. 2015). Such assistance during a particular activity may mean step-by-step instructions or superimposition of information in the field of vision through AR (Fig. 1). Contextual recommendations include suitable work activities, but also information relevant in the current context, e.g., from manuals.

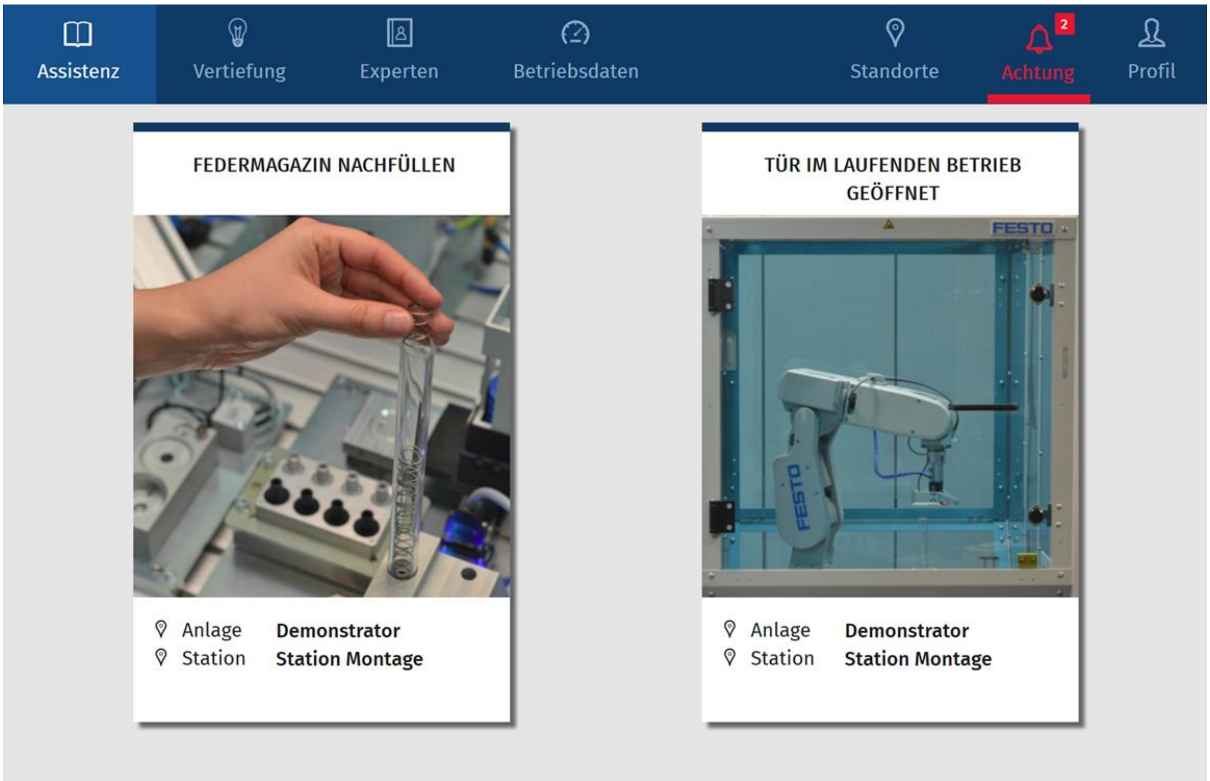

Fig. 1: Screenshot showing recommended work procedures

The current state of the art is represented by service architectures whose functionality results from the interplay of a large number of services. Each of the services thereby implements a specific, independent functionality and makes these available for other services. The APPsist system is based on a service-oriented architecture (Ullrich et al. 2015) that can be applied and connected to an existing machine park. It uses the available sensor data, which serves to monitor and control the production process, to interpret the activities of human operators interacting with the machines and to offer suggestions of what activities to perform. For instance, when APPsist detects a machine state that corresponds to a problem, it checks which maintenance activities can solve the problem and which operators are allowed to perform the maintenance activity. Using a mobile application, it then offers relevant content (instruction manuals, background information) and maintenance procedures to the operators. So APPsist can offer personalized learning and training experiences leading towards acquisition of the target knowledge or skill, recommending appropriate work procedures, but also suitable learning content. This support takes into account the development goals of the workers as well as their performed work activities.

In the context of using IoT for learning and training in manufacturing it is relevant that APPsist puts machine sensor data into relation with activities of the human operators and uses it to interpret whether the operator' actions were correct or incorrect (Ullrich et al. 2016). Thus, actions performed in the "analogue" world become digitally available, and usable for analysis, interpretation and reaction. With the ongoing digitization of spaces through the IoT technology, the amount of data becoming available for digital processing will further increase. Further research is required to investigate how such data can be used for learning and training, but examples such as APPsist show that this is possible.

6. Perspectives and conclusion

Industry 4.0 brings many challenges and demands to improve informal learning, especially directly at the workplace. This should open new opportunities for retraining and upskilling of employees. Generally, learning offers should be based not only on individual preferences of users, but also on the effectiveness and efficiency of the learning and training experience, considering also the current context, including learner's emotional status and attention. New sensors and IoT offer more alternatives for collection and analysis of the big data acquired in formal, informal and workplace learning processes. They can enable a better recognition of learner's objectives, preferences and context, which should lead to a more precise personalization and adaptation of learning experiences. Their effectiveness and efficiency can be improved by WT and AR, which should lead to novel training methods, cultivating required competences. What can be interesting in the workplace and informal learning context is a combination of learning nuggets and nudges, which means enhancing micro-learning offers (nuggets) with suitable recommendations (nudges). While the former typically represent small segments of content, the later can be useful in driving learning processes.

IoT is decentralized, connecting autonomous devices directly to one another. Compared to the traditional top-down models it represents an alternative, which can provide greater privacy and security, but trust is a crucial issue here. The *blockchain* technology (Tapscott and Tapscott 2016) is critical for the IoT, as it allows devices to autonomously execute digital contracts and function as self-maintaining, self-servicing devices. This new paradigm delegates the trust at the object level, allowing animation and personalization of the physical world. Moreover, it provides novel refined facilities for users to control their privacy and protect their data. The blockchain technology has the potential to disrupt various areas and education is one of them. There are several opportunities how to do it (Tapscott and Tapscott 2017) and from our perspective the most crucial one is a new education, replacing the prevalent broadcast model with preparation for lifelong learning (cf. Gardner in this volume). This includes all competences relevant for a knowledge worker, including critical thinking, problem solving, collaboration, and communication.

IoT can strongly contribute to the collection of a huge amount of data on various artefacts, their relationships and people interacting with them. The challenge is to analyse and interpret this data properly, generating meaningful knowledge about the context and about individual users. Based on this, suitable learning and training experiences can be designed and provided to humans. Moreover, IoT enables new opportunities how these experiences can be personalized and adapted to the current context automatically. It means encoding educational instructions as well as personalization and adaptation strategies directly in IoT, which can be seen as a virtual (parallel) machine. This requires new programming approaches in this field. But whatever we do, we need to control and monitor the delegation of certain decision making activities to machines, in order to observe their long-term impact and to minimize related risks.

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