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Using Artificial Intelligence and the Internet of Things to Enable Context-Dependent Recommendations in the Smart City and Smart Factory[1]

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Artificial Intelligence and the ongoing digitization of the physical world through the Internet of Things are two trends that will significantly shape the world of learning and training of tomorrow. In this article, we present background information on Artificial Intelligence, with a focus on education, and the Internet of Things, and present two examples from different domains that illustrate how information collected through sensors is used to understand the context of the user (or learner), and, on that basis, to provide context-dependent recommendations and support. The first example covers exercise culture, youth culture and digitization in the Smart City, while the second example is applicable in the domain of Smart Factories.

Keywords: *Adaptivity, Artificial Intelligence, Context, Internet of Things*

Introduction

What will tomorrow's world of learning and training look like? In this paper, we present two technological developments that have the potential to significantly change the way how people learn, for work and in private. On the one hand, recent years have shown an impressive progress in Artificial Intelligence (AI), whether it is the advent of self-driving cars or the performance in games such as Go, where Google's Alpha Go Zero has learned to bet the best human players by playing against itself. Can we replicate such successes in education? The second major technological development is the Internet of Things, where sensors and actors "digitize" the physical world, and in this way, make it accessible to and actable upon from the digital world. The article starts by giving an introduction into Artificial Intelligence in Education and then into the Internet of Things. We then present two use cases that illustrate the potential of these technologies. The first example covers Smart Cities and shows how the environment can be used to

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change behavior. The second example goes into the Smart Factory and describes how to enable and upskill human workers.

Artificial Intelligence in Education

The usage of Artificial Intelligence in Education (AIED) has enabled significant flexibility and adaptivity of learning processes with respect to the individual learner. For instance, Active Math (Melis et al. 2001) is a web-based learning environment for Mathematics that creates on the learners' demand courseware adapted with respect to their knowledge state and learning goals. Similarly, the physic tutor Andes generates problems specifically targeted to the individual learner in order to achieve the best possible learning gain (VanLehn et al. 2005). Despite the wide range of domains and functionalities covered by AIED research, the implemented systems follow the same general design pattern, which is based on three components: a domain model, a learner model, and a pedagogical model. The domain model consists of a semantic representation of the concepts of the area to be taught and their relationships. It also contains the learning objects and metadata that provides additional information about the learning objects and links the learning objects to the concepts occurring in the ontology. The learner model represents the current knowledge state of the learner and is used as a basis for adaptivity and personalization. It updates itself according to the learner's progress. The pedagogical model contains the knowledge how to select, adapt, and sequence learning objects, and how to provide support with respect to the information from the learner model. Together, these three components enable a generation of learning environments that achieves flexibility impossible with standard learning managements systems. AI-based environments can analyze processes, diagnose learning problems and opportunities, and address these by selecting or even generating personalized learning materials (Arnold et al. 2012).

Recently, the application of methods from data analytics and machine learning to education has become highly innovation research fields called Educational Datamining (EDM) and Learning Analytics. They have proved valuable; both from a research perspective as a means to better understand effects of learning environments on learners, as well as by supporting human learning through the automatic detection of and reaction to potentially problematic learning behavior. Models generated through mining data-tracks of learners can detect in real time the learning progress, motivation, meta-cognition of a learner and thus enable appropriate automatic reaction, such as suggesting which content to rehearse or actions to take by the learner, e.g. Baker (2014). For instance, by using datamining methods to determine specific advice given to students, average grades can be improved significantly (Greer et al. 2015). EDM techniques are used to find correlations between learner actions and measurable results such as test scores, retention, etc., but also serve as a basis of cognitive models of mental states such as motivation, perseverance, etc., of the learner.

Even if the potential of EDM has been recognized, existing research is characterized by limitation in scope and time. To a large extent, the used data is focusing on interactions in virtual learning environments such as learning management systems or limited real-life data from smartphone sensors (GPS, Gyroscope) (Sampson and Zervas 2013), despite the evidence that combining several data sources significantly improves the detection of learning-relevant user characteristics (Baker 2014). Thus, most correlations between the digital and "real" world cannot be detected. Also, in university settings, the analyzed data often encompasses one semester or less, meaning long-term effects cannot be modelled nor detected neither. Yet, this might change with the Internet of Things.

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" (Union 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 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 object 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 (Kravcik et al. 2017).

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 (Broll et al. 2009), later extended to include social interaction on objects (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). Examples of sensor usage outside of IoT are the built-in sensors of smartphones to support learning of manual tasks (Ando et al. 2014). There, a smartphone is attached to a saw used by students for practicing the technique of sawing. They can inspect their performance in different graphs so that they can improve without the help of a teacher. Also, sensors attached to equipment and tools in industrial environments can be used to support training in stonemasonry (Sivanathan et al. 2017) and also in assembly (Aehnelt and Wegner 2015). There, an assembly trolley is equipped with force sensors, infra-red sensors and inertial measuring devices, which enable the detection of the current performed work step and the display of instructions and notes on a touch display.

In the following, we present two examples that illustrate how information collected through sensors is used to understand the context of the user (or learner), and, on that basis, to provide context-dependent recommendations and support.

Example 1: Exercise Culture, Youth Culture and Digitization in the Smart City

The first example, the Smart Sport project, a joint R&D project with the Deutscher Olympischer Sportbund (German Olympic Sports Confederation), focuses on the Smart City as an educational space for human movement and training, more specifically the exercise culture, youth culture and digitization in urban areas. It aims at stimulating physical exercise in a non-formal setting, i.e., individual and spontaneously with friends, in contrast to the context of a sports club, where more formal sport and competitions are offered, with the help of the Smart Sport app, which uses Artificial Intelligence and sensor technology.

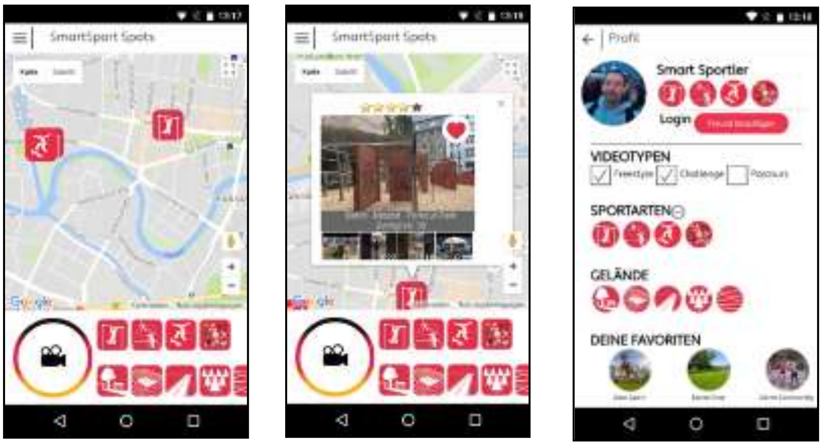
The app supports typical Web 2.0 features and approaches such as community building and sharing of activities within these communities. Young people, the main target audience, can use the app to record, share, and present to others their forms of sport and exercise in public urban spaces. Besides traditional sport, activities include popular sports not yet mainstream, such as parkour, rope skipping or round net (spike ball).

The educational potential focuses on non-formal learning. The app promotes mutual learning in sports through sport videos. Users can upload training materials for others in the form of videos and images, and challenge other players by recording and uploading their performance.

The app uses AI-based technology for adaptivity. It proposes tailored exercise and sports programs in urban and rural areas which take the individual's skills, abilities, interests and goals into account.

Figure 1 contains selected screenshots of the app (version 1.0). The left picture uses a map to display nearby activities that fit the user's profile. The detail view of an activity, i.e. recorded media and ratings, is shown in the middle. The right screenshot shows the profile of the user, namely what media, sports and terrains he prefers.

Figure 1. *Screenshots of the Smart Sport App*



Source: Authors.

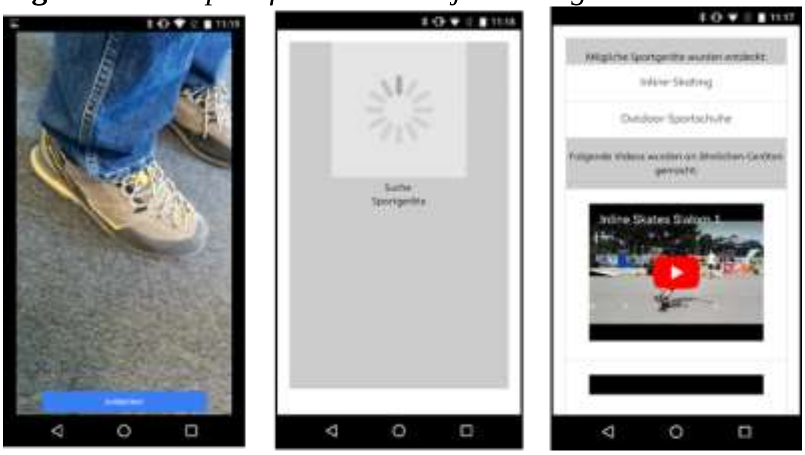
Artificial Intelligence is also used to offer advanced recommendations based on image and video processing and was implemented in version 2.0 of the app. The workflow is shown in Figure 2. Users can take a snapshot of their surroundings or of a specific object, which is analyzed by the app to suggest activities possible depending on the available objects (such as a bank or wall) and terrain type. This functionality is cloud-based: The media recorded by the user is uploaded to an online service for image content analysis (e.g. the Google Cloud Vision), which returns keywords that describe the recorded situation. The Smart Sport server filters the available activities according to the keywords.

Figure 2. *AI-Based Object Recognition Workflow*.

Source: Authors.

Figure 3 presents an example of the object recognition for the use case of equipment recognition. In the leftmost screenshot, the user takes a photo of the equipment he currently carries (in this case a pair of shoes). Then, the AI-based processing starts (middle) and searches for sports gear in the photo ("Suche Sportgeräte"). Finally, the app returns the list of equipment it did recognize and suggest a list of videos that uses the equipment. This example illustrates that image analysis is still an error prone process, as it returned two results, with one (inline skates) being incorrect. The second returned object (outdoor sport shoes) was correct.

Figure 3. *Example of AI-Based Object Recognition*



Source: Authors.

A further adaptive feature of the Smart Sports App is enabled by the IoT technology beacons based on ad-hoc Bluetooth technology. Beacons are small-sized transmitter that trigger actions when nearby. Here, beacons are attached to specific locations and e.g. start an application, show a video or a website, trigger an online service in the users' app when they are nearby. They enable a significantly more precise location-based interaction than the GPS data, and thereby enable an interactive exploration of the environment.

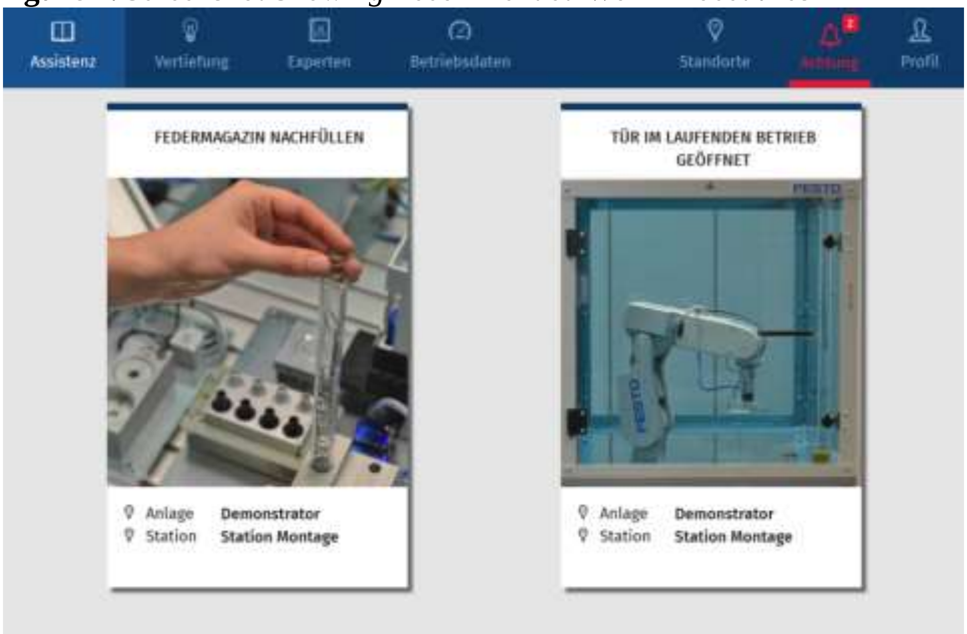
Example 2: Workplace-Integrated Learning in the Smart Factory

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 (Ullrich et al. 2015). 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, i.e. 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 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, Rules for adaptive learning and assistance on the shop floor, 2016). Such assistance during a particular activity may mean step-by-step instructions or superimposition of information in the field of vision through AR. Contextual recommendations include suitable work activities, but also information relevant in the current context, e.g., from manuals (Figure 4).

Figure 4. *Screenshot Showing Recommended Work Procedures*



Source: Authors.

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 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. 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.

Summary

The technology of the Internet of Things to understand the context combined with Artificial Intelligence as a means to encode knowledge about how to use the context, information about the user and about the domain, enables advanced intelligent-adaptive functionalities. Today's research only scratches the surface of what will become possible in the future. The two examples from Smart City and Smart Factory show that already today users can benefit from using context information derived from sensor data. Further research in these areas will profit significantly from the ongoing digitization of further "analogue" environments. This requires improving the state of the art in the following ways:

- Open up longitudinal digital and non-digital data sources: Develop methods to detect, transform, store and make accessible relevant interactions both in the non-digital and in the digital realm spanning over several years, based on mobile device technology and the Internet of Things.
- Big and smart educational data: While today general processing of data in Petabyte range is possible, it is necessary to investigate the specific needs of Big Educational Data. This involves the creation of semantic (smart) data formats to enable re-use of data over and above single studies, the identification of educationally specific data processing functions, and adequate visualizations of analysis results.
- Improve analysis by using deep learning algorithms: In machine learning, the usage of deep learning algorithms has yielded success where other methods failed. In the field of education, deep learning holds a significant potential to detect correlations between learner actions and learning outcomes, for instance the effects and consequences of the learning medium (MOOC, learning nugget) and IT-based tools, or detection of "beneficial" or "harmful" media use.
- For learning purposes it is crucial to provide also clarifications and explanations of machine made decisions and reasoning.

In this article we focused on the technological perspective: the potential that new technologies carry for innovation in education. At least as important as technology is organization and implementation: How is learning and working organized? What new types of learning become possible, e.g., more collaborative, more user-driven? Successful realization of new education has to combine both perspectives.

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