Mobile Learning in Context

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Abstract

The widespread use of mobile technologies has led to an increasing interest in mobile learning. Context is a central topic of research in that area. In fact, a major benefit of mobile devices is that they enable learning across contexts. In this paper, we explore how context can deliver significant benefits in mobile learning and provide an extensive review of the current literature and research on mobile learning in context. Furthermore, we identify various challenges and research opportunities in this area and propose a conceptual framework for context-aware mobile learning.

Keywords

Mobile learning; context; extrinsic; intrinsic; mobile devices; frameworks; challenges

1 Introduction

As mobile devices are becoming ubiquitous, there is an increasing interest in the educational applications of mobile technologies, a research area referred to as mobile learning. Mobile learning refers to the use of mobile or wireless devices for the purpose of learning while on the move (Park, 2011). In general, mobile learning has often been viewed as learning mediated through mobile devices (Brown, 2005; Peters, 2007). Typical examples of mobile devices include smartphones, tablets, netbooks, laptops, and personal media players. Mobile devices enable learning to take place at any time, in any location, and at a learner's pace. Klopfer and Squire (2008) describe five properties of mobile handheld devices that produce unique educational affordances: portability, social interactivity, context sensitivity, connectivity, and individuality. Furthermore, it has been widely recognized that context is the most distinctive feature in mobile learning (Specht, 2009; Wang, 2004, Yau et al., 2010). Context-aware mobile learning applications leverage the context information of the learner to provide personalized and motivating learning experiences.

Several researchers have proposed theoretical work around mobile learning and proposed models on how to leverage emerging mobile technologies in teaching and learning (Koole, 2009; Park, 2011; Sharples et al., 2007; Uden, 2007). However, comparatively little research has been done to focus on the context attribute in mobile learning and only few frameworks for context-aware mobile learning exist. In this paper, we review studies, projects, and frameworks dealing with mobile learning in context from the rapidly growing body of research on mobile learning. The main aim of this review is to provide a better understanding of the different components of context-aware mobile learning environments.

The remainder of this paper is structured as follows. Section 2 gives an introduction to the term mobile learning and tries to distinguish it from ubiquitous learning. The context is added in section 3 where we give some definitions of the term and describe the benefits and different types of context. In section 4, we review and classify existing literature on mobile learning in context based on what type of context is used and how context is captured. Section 5 discusses existing frameworks for mobile learning in context. We then identify in section 6 future challenges in this area of research and introduce a framework for context-aware mobile learning that addresses these challenges. Finally, section 7 gives a summary of the main results of the paper.

2 Mobile and Ubiquitous Learning

Before going deeper into the topic of context-aware mobile learning, we provide in this section an explanation of the term mobile learning and discuss how it can be distinguished from ubiquitous learning (u-learning) and electronic learning (e-learning).

2.1 Mobile Learning

There are various definitions but there is no single one which is generally accepted. Dewey (1996) gave a very early mentioning of mobile learning as:

“A society which is mobile, which is full of channels for the distribution of a change occurring anywhere, must see to it that its members are educated to personal initiative and adaptability.”

A more recent definition is given by Ally (2005). He defines mobile learning as

“The delivery of electronic learning materials on mobile computing devices to allow access from anywhere and at any time.”

In general, mobile learning has often been viewed as learning mediated through mobile technology. According to Park (2011), mobile learning refers to “the use of mobile or wireless devices for the purpose of learning while on the move”. **Fehler! Verweisquelle konnte nicht gefunden werden.** state that mobile learning is "any activity that allows individuals to be more productive when consuming, interacting with or creating information mediated through a compact digital portable device that the individual carries on a regular basis, has reliable connectivity and fits in a pocket or purse".

Mobile learning can thus be viewed as a subset of e-learning that includes the usage of mobile devices to enable learning anywhere and at any time. Due to the progress in the field of broadband communication, it is nowadays possible to use network connections nearly everywhere. It is possible to be online all the time. Additionally, while the computational power and the storing capabilities increase, the size of today’s mobile devices decreases or stays consistent. According to **Fehler! Verweisquelle konnte nicht gefunden werden.**, the market for mobile devices is growing more and more and smart phones are the most sold ones. On the other hand, the PC market e.g. in Western Europe is shrinking (**Fehler! Verweisquelle konnte nicht gefunden werden.**. This mobile revolution indeed changed the everyday life. All these factors give users a new way of learning. This also enables educational institutions and teachers to harness mobile learning solutions to offer more effective learning experiences.

Mobile learning is thus an interaction or activity of an individual which uses a mobile device, capable of having a reliable connection to communicate with a mobile learning platform, with the main goal to handle or resp. to consume information in an interactive or creative way. Furthermore, mobile learning has some properties depending on the user, the user's environment and the used technology. It is a very time-constrained task, delivering context-oriented content. As the smart phone is mostly used in between two tasks, the time interval where the learner can capture information is very short and the content should not overload his cognitive load. Learning is normally done on-the-fly, this means it is very fast and mostly during spare time e.g. where the user is heading somewhere or has to wait for something to happen. Thus, the provided information has to be personalized to the needs of the user. This is where current context information can be used to select the appropriate information or learning material (see section 3). Moreover, mobile learning includes multimodal interaction using several technologies handled on the mobile device, like speech recognition, sound, touch gestures and so on. Lastly mobile learning can also support a collaborative way where the user contacts others who can also help him (e.g. friends, fellow students or even experts) (**Fehler! Verweisquelle konnte nicht gefunden werden.**; **Fehler! Verweisquelle konnte nicht gefunden werden.**; **Fehler! Verweisquelle konnte nicht gefunden werden.**. But to accomplish mobile learning in a satisfiable way, the properties of the mobile device have to be considered very precisely.

Today's mobile devices are only partially used for telephony, but also for computing, messaging and mostly of course for processing of a huge amount of multimedia load. The fact that mobile phones are mostly always carried everywhere and every day, makes those devices a perfect learning medium which can be used in various situations (**Fehler! Verweisquelle konnte nicht gefunden werden.**; **Fehler! Verweisquelle konnte nicht gefunden werden.**. But one also has to keep in mind that these devices have some deficits, which can be overcome easily if the architecture of the mobile learning platform is developed thoroughly. A mobile device has only a specific amount of battery power which discharges very quickly when it is used together with network communication. The limited bandwidth that is provided by the telcos is also one gap which has to be considered very well, as huge amounts of data cannot be transferred so easily and also in time. Data has to be transferred in real time as the usage intervals of the mobile learning platform are frequent but very short, thus the user cannot be kept waiting for a long period of time. Furthermore, a mobile device is not as powerful as a personal computer. Difficult computing operations have to be done on external servers or by other technology which provides enough computation power to solve hard computational tasks. The mobile device should only process the presentation of the computation results. The presentation of learning content is another important point which comes in mind. The possibility to display graphical elements on the screen depends on its resolution and the mobile device's screen size. Last but not least, modern mobile devices still have a lack of resources. As an example, the main memory or the storage can also be used by other applications running on the smart phone.

So, as one can see mobile learning has to consider several challenges concerning the user and the used technology. Mobile learning has to handle the specificity of the mobile devices with respect to their constraints. Furthermore, the presentation layer has to be adapted to it. Backward compatibility to existing systems has to be guaranteed.

2.2 Ubiquitous Learning

Ubiquitous learning (u-learning) in contrast to mobile learning is not necessarily bound to mobile devices. Although it may rely on mobile devices, one can also use stationary personal computers, photocopiers, televisions, and so on. In general, u-learning is enabled by an environment that can be accessed in various contexts and situations. As van't Hooft et al. (2007) note, u-learning involves learning in an environment where "all students have access to a variety of digital devices and services, including computers connected to the Internet and mobile computing devices, whenever and wherever they need them".

According to **Fehler! Verweisquelle konnte nicht gefunden werden.** and **Fehler! Verweisquelle konnte nicht gefunden werden.**, u-learning should have the following characteristics:

- *Permanency*: Learners never lose their work unless it is deleted on purpose. In addition, all the learning processes are recorded continuously every day.
- *Accessibility*: Learners have access to their documents, data, or videos from anywhere. That information is provided based on their requests. Therefore, the learning involved is self-directed.
- *Immediacy*: Wherever learners are, they can get any information immediately. Thus, learners can solve problems quickly. Otherwise, the learner can record the questions and look for the answer later.
- *Interactivity*: Learners can interact with experts, teachers, or peers in the form of synchronizes or asynchronous communication. Hence, the experts are more reachable and the knowledge becomes more available.
- *Situating of instructional activities*: The learning could be embedded in our daily life. The problems encountered as well as the knowledge required are all presented in their natural and authentic forms. This helps learners notice the features of problem situations that make particular actions relevant.
- *Adaptability*: Learners can get the right information at the right place with the right way.

U-learning is thus a special type of e-learning that is individualized, expands access, enables collaborative work, and can give instant feedback to the learners. Compared to only working on stationary desktop computers, u-learning enables learning environment to be accessed anywhere.

One big difference between learning somewhere on a stationary desktop computer and learning with mobile devices is the context, the user is in. Mobile devices feature some functionality to capture some background information that can be helpful to personalize the learning experience. The context concept is discussed in some detail in the next sections.

3 Mobile Learning in Context

In a mobile learning experience, each learner has to be treated in a different way according to the current situation in which he is learning, e.g. according to his pre-knowledge or the specifications of the device, he is using. Those different conditions are called the context in which the learner is situated.

3.1 Definitions

The term "context-aware" was brought and defined by Schilit et al. (1994) to describe the location, identities of nearby people, objects and changes to the objects. Currently such terminology is used in various research disciplines; linguists provide two meanings for it. Context can be defined as the text in which a word or a passage appears and which helps to ascertain its meaning. A second definition claims that context is the surroundings, circumstances, environment, background, settings that specify the meaning of some event (**Fehler! Verweisquelle konnte nicht gefunden werden.**.

A very popular definition is given by Dey (2001) who define context as "… any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between the user and the application, including the user and the applications themselves." According to the authors, there are three types of information that need to be gathered to describe any specific context - places, people and things (Dey, Abowd, and

Salber**Fehler! Verweisquelle konnte nicht gefunden werden.**. To describe these three entities, four categories are introduced:

- *Identity*: characterizes the entity with an explicit identifier, which has to be unique in the name domain of the application.
- *Location*: includes positioning data and orientation as well as information about regional relations to other entities (e.g. neighbouring entities). This comprises geographical data as well as spatial relations.
- *Status*: contains properties, which can be perceived by a user. For example, for a location this can be the current temperature, the ambient illumination or the noise level. For persons this refers to physical factors like vital signs, tiredness or the current occupation.
- *Time*: is both date and time.

Identity is the major factor in communication situations; Location is ranked as the second most important context measure that users rely on. Location is a complex piece of information because participants refer to it at several levels of detail, such as in a specific building or office, or "in the bus". Although time seems to be a simple piece of context information, the finding was that actual time did not matter very much to the users; relative time, defined as the communicator's time limit before a new activity, on the other hand, is important (**Fehler! Verweisquelle konnte nicht gefunden werden.**.

3.2 Benefits

Harnessing context in a mobile learning experience has a wide range of benefits including personalization, adaptation, intelligent feedback, and recommendation. Adding context information to an application may lead to presenting more personalized data to the learner. If there is no context information available, every learner has to be treated the same way.. Context may contain information about the current situation, in which the learner is in, her pace, knowledge, interest, peers, motivation, etc. This knowledge enables applications to present only those parts of the learning activity that are of interest in that special situation. Context-aware mobile learning systems can adapt to every situation, give intelligent feedback to the preceding learning process, and produce recommendations for new learning items or activities.

3.3 Types

Context can be any kind of information to determine, specify, or clarify the meaning of an event (**Fehler! Verweisquelle konnte nicht gefunden werden.**. The main goal of mobile learning is to let the learner achieve the most efficiency of using a mobile learning solution. Context can be broadly categorized into two types: extrinsic context and intrinsic context.

3.3.1 Extrinsic Context

The extrinsic context deals with a user's current environment. It contains the user's current position (longitude/latitude, bus, office, at home, …), the time of the day and the interval in which the user learns (time), and the object the user currently deals with and how this information can support his learning (analogue-digital). Another example of extrinsic context is the relation to fellow learners.

The location offers a lot of information that are useful to support the learning progress. That is probably why it is often used synonymously with context (**Fehler! Verweisquelle konnte nicht gefunden werden.**. If an application knows where the user currently is, it could advise the user to visit a library which is close to him and which offers books about the topic the user is studying right now. It also can draw his attention to an exhibition that could be interesting for him. Another possibility of location-awareness that is often mentioned is to inform the learner when people of his learning group are close by, so that he can meet with them and chat about current topics to get a deeper understanding (**Fehler! Verweisquelle konnte nicht gefunden werden.**; **Fehler! Verweisquelle konnte nicht gefunden werden.**; **Fehler! Verweisquelle konnte nicht gefunden werden.**; **Fehler! Verweisquelle konnte nicht gefunden werden.**. Moreover, the place determines the frequency of distraction. E.g. the user is much more distracted while waiting at a bus station than while sitting in a train. So this information even helps to define the concentration level of the user.

Time also plays an important role. If the user has to change locations, it is often impossible to continue using the mobile platform because all the attention is needed for processing the environment. So the time interval between changing locations is important as the information presented to the learner should not exceed the time limits because then he is not able to use the information efficiently anymore (**Fehler! Verweisquelle konnte nicht gefunden werden.**. For collecting information about the user it is also of interest at which time of the day, how long the interval is in which the application is used by the user what is next on his timetable (**Fehler! Verweisquelle konnte nicht gefunden werden.**; **Fehler! Verweisquelle konnte nicht gefunden werden.**. This way his individual pace and his habits can be used to improve personal learning.

Relations to other people also affect the extrinsic context. Information about fellow students or colleagues may define or specify recommendations, presented to a learner. Fellow students often work on comparable projects, if an application knows the context information of those fellow students, it can recommend learning material that was used by those other students.

The last mentioned aspect here to capture user's extrinsic context is called analogue-digital. It deals with the possibility to combine digital information and analogue/real world objects. That means to an object the user sees in reality the application provides him with multimedia data. The application on the device has to detect the object, which can be everything like a building or a painting, and download related data from a server (**Fehler! Verweisquelle konnte nicht gefunden werden.**; **Fehler! Verweisquelle konnte nicht gefunden werden.**. For example, Bob is visiting London for the first time. Every time he sees an interesting building like the Westminster Abbey or Big Ben, he focuses with the camera of his mobile device on the building and gets information about how the building looked like and what purpose it had. In a museum he gets informed about the exhibits when focusing on them with his mobile device. Thereby the data can be text, audio or video. The limitation analogue-digital delivers very important context information since the user is highly motivated in that situation and the probability that he really learns is higher. At the moment, the connection between analogue and digital objects is mostly realized in the area of augmented reality.

3.3.2 Intrinsic Context

The second category, user's intrinsic context, deals with the inside of the user. This contains the user's knowledge level, his concentration level, and also his motivation level.

Learners have different knowledge levels. It depends on their concentration when getting in touch to a topic, their previous knowledge, their knowledge about related topics, and their given skills. In the development stage of a learning application it is important to adjust the system to these differences. The less the user knows about a given topic the more basics have to be provided to the user to let him understand the information step by step. Having more knowledge about an information leads to providing more deep and more precise details about the information for the user. The system must inquire the user's knowledge to provide him with suitable learning material and to be able to decide what the user should learn next. **Fehler! Verweisquelle konnte nicht gefunden werden.** presented an approach which shows alternatives to take the knowledge level into account. When a user joins the system for the first time, he is asked general questions to measure his knowledge. Depending on the evaluation, the system offers the user personal learning materials. Every time a user finishes a topic he has to participate in a small test where he has to answer several topic specific questions. Depending on the results, he has to repeat the topic or is unlocked for the next level. Following this idea and adding the knowledge level to the context supports learning since learners get suitable materials so that they learn without being discouraged because of too difficult questions.

Another aspect in this category is the concentration level. It has a great impact on the success of learning. If the concentration is low, the user will hardly learn and needs a lot of repetitions. If the systems knew about the user's current concentration level, it could react, for example, by providing material via different channels to obtain the user's attention. But measuring the concentration is very difficult because it is hard to capture and it changes during the usage of the system. Just asking the user, if his concentration level is low, medium or high does not add further information to the context because the user could simply lie, he might not be aware of his real level, or the level changes during learning (Nguyen et al., 2010). So other techniques are required. One could use other context information like the location or the time to measure the concentration. For example, if you are standing at the main train station with a crowd of people around you, you will probably be not highly concentrated since there are many distractions. So the location contributes to the concentration, but also the time of the day, which could be a sign for your tiredness, and the time available for learning. In different studies (**Fehler! Verweisquelle konnte nicht gefunden werden.**; **Fehler! Verweisquelle konnte nicht gefunden werden.**; **Fehler! Verweisquelle konnte nicht gefunden werden.** they suggest using sensors to capture eye gaze shifts and algorithms to evaluate and interpret the findings. But they also say that it is difficult to accomplish the right interpretation so far.

It is even more difficult to measure the current motivation level of a user. Although it is important context information the motivation level is rarely part of the context of approaches nowadays. The main reason is that it is hard to capture. There are methods of detecting facial expressions with algorithms (**Fehler! Verweisquelle konnte nicht gefunden werden.** but interpreting them does not work sufficiently yet. One possibility of understanding low motivation could be to use the information the system gains out of knowledge testing. If the user cannot answer the questions at the end of a topic correctly, he was probably not motivated. In this case the system should be able to provide information about this topic in other ways like using audio sources, videos, or learning games to motivate the learner and thus gaining his attention.

4 Mobile Learning in Context: State of the Art

As stated before, context is a vital component of mobile learning. Without context information, the same learning experience would be presented to every learner. To capture this information, there are various kinds of sensors, which are offering to read all kinds of information about the situation, the learner is currently in. Sensors can be classified into three main categories: environmental sensors, bio-sensors, and activity sensors. In the next sections, we review and classify existing literature on mobile learning in context based on how context is captured.

4.1 Environmental Sensors

Environmental sensors can be used to capture ambient context information. This can be seen as the location and/or the situation in which the learner is currently in. They offer data like the position (longitude/latitude or more personal: the office, room 123) or amount of noise.

The devices of the current smart phone generation comprise of various kinds of sensors. The most commonly known ones are the location sensors. First, there is the Global Positioning System (GPS), a satellite-based navigation system. GPS works in nearly any weather conditions, anywhere in the world, 24 hours a day. GPS satellites circle the earth twice a day in a very precise orbit and transmit signal information to earth. A GPS receiver utilizes this information to calculate the device's exact location. Essentially, the GPS receiver compares the time a signal was transmitted by a satellite with the time it was received. The time difference tells the GPS receiver the exact distance to the satellite. With the help of two to three other satellites, the receiver can determine the device's position and display it on the unit's electronic map (**Fehler! Verweisquelle konnte nicht gefunden werden.**. As an example, Thüs (2010) proposed an application that uses the current positions and the skills of the system's participants to give learners the possibility to search for nearby people who might help solving a certain problem.

The location of a person is one of the central context information in mobile learning settings that can be used in nearly every environment. GPS provides this data outdoors. Indoor localization technologies have been a focus of research for several years. Today, there are several products available such as SensFloor[1] and UbiSense[2] that realize indoor localization but are still rather expensive and difficult to install. Therefore, current research focuses on technologies that require only minimal changes in the environment. There are different approaches that employ an existing infrastructure, e.g. by using the existing power line infrastructure (Patel et al. 2010) or an existing HVAC (Heating, Ventilating, and Air Conditioning) system (**Fehler! Verweisquelle konnte nicht gefunden werden.**. Another possibility is to use an existing Wi-Fi infrastructure (**Fehler! Verweisquelle konnte nicht gefunden werden.**, but these approaches are still research projects. Machine learning algorithms are used to recognize patterns in these infrastructure based approaches. They also have to be trained for specific scenarios.

As it is commonly known, mobile devices have the capability to take pictures and to record video files. Such information can be useful to automatically detect certain objects in the proximity of the device or to enable augmented reality (**Fehler! Verweisquelle konnte nicht gefunden werden.**; **Fehler! Verweisquelle konnte nicht gefunden werden.**. The image sensor of the camera is responsible for transforming light into electrical signals. When building a camera, there are two possible technologies for the camera's image sensor: CCD (Charge Coupled Device) and CMOS (Complementary Metal Oxide Semiconductor). CCD sensors have been used in cameras for more than 20 years and present many advantageous qualities; among them, better light sensitivity than CMOS sensors. This higher light sensitivity translates into better images in low light conditions. Recent advances in CMOS sensors bring them closer to their CCD counterparts in terms of image quality. CMOS sensors provide a lower total cost for the cameras since they contain all the logics needed to build cameras around them. They make it possible to produce smaller-sized cameras.

[1] http://www.future-shape.de
[2] http://www.ubisense.net

The video sensor is a piece of hardware that uses software application to interpret images. The aim of video sensors is to evaluate a scene recorded by a video camera. Objects on these images and their characteristics, such as moving speed and size, are compared to pre-configured set of templates. When the object matches template, it get marked digitally for further analysis by an operator.

To get to know the user's orientation, there is a built-in digital compass that works just like a magnetic needle compass. The accuracy of digital compass headings can be affected by magnetic or other environmental interference, including interference caused by proximity to the magnets. One of the interesting things you can do with a digital compass is introducing augmented reality-type applications. Mobile augmented reality can use a phone's camera and compass to let a device capture an image of a location. Information from the compass would allow names of locations to pop up on top of the image (**Fehler! Verweisquelle konnte nicht gefunden werden.**; **Fehler! Verweisquelle konnte nicht gefunden werden.**; **Fehler! Verweisquelle konnte nicht gefunden werden.**.

Closely related to the compass is the accelerometer. Though it may sound complicated, it is actually a pretty simple concept. Basically, it is a motion sensor that detects acceleration forces and uses those forces to control the phone. An accelerometer measures proper acceleration, which is the acceleration it experiences relative to and is the acceleration felt by people and objects. Modern smart phones use accelerometers mostly to rotate the display's orientation automatically as you change from a portrait to a landscape position. But it is also possible to gain more information about the learner by employing these accelerometer data-sets to recognize activities like walking or running (**Fehler! Verweisquelle konnte nicht gefunden werden.**.

To get know some information about the surrounding, light/dark sensors, proximity sensors, or audio sensors can be used. Light sensors are very simple and inexpensive, allowing their inclusion in multitudes of consumer products from night lights to cell phones. Ambient light sensors are included in many smart phones to sense the environment lighting conditions, allowing for adjustment of the screen's backlight to comfortable levels for the viewer. A Proximity sensor can detect objects without physical contact. A proximity sensor often emits an electromagnetic field or beam and look for changes in the field. The object being sensed is often referred to as the proximity sensor's target. Different proximity sensor targets demand different sensors. Proximity sensor was used in iPhone to switch display off during calls. The audio sensor is one of the most common sensors in everyday life. This sensor is equipped with microphones in order to detect a sound event. Two types of analysis are necessary: sound event detection is made and secondly a sound classification. To detect different sound events, Lu et al. proposed the framework SoundSense that is able to differentiate between different sounds and to recognize new events (**Fehler! Verweisquelle konnte nicht gefunden werden.**. Another project, called SurroundSense, employs a set of these sensors to describe the surrounding and therefore to classify the location (**Fehler! Verweisquelle konnte nicht gefunden werden.**.

Since today's sensors are mobile and wearable, they can accompany an employee in different locations and situations. As it is common for mobile devices, power consumption and usability are the main limitations of these sensors. Some existing sensor technologies include the common sensors that are built-in into today's smart phones and also sensors mounted on the foot or the wrist. The smart phone has become a ubiquitous device that offers an increasing number of sensors and a mobile data connection. Other capabilities of smart phones like Bluetooth and Wi-Fi can be turned into sensor technologies by scanning for beacons and fingerprints (Göndör, 2010).

Examples of mobile or wearable sensor products and projects include:

- The SenseCam is worn like a necklace and is able to automatically take pictures of the frontal situation. Daily activities can thus be captured as images and support reflection (**Fehler! Verweisquelle konnte nicht gefunden werden.**.
- A sociometric badge was developed in the reality mining project (**Fehler! Verweisquelle konnte nicht gefunden werden.**. It registers when two participants are in proximity to each other. Encounters between persons are monitored by infrared and audio sensors. As a result, the network of real social interactivity can be captured.
- In the research project FootSlam (**Fehler! Verweisquelle konnte nicht gefunden werden.**, foot mounted inertial sensors are employed in order to realize indoor localization in unknown environments. The application calculates the speed and the direction of walking and thus the layout of the current building is deduced.

4.2 Bio Sensors

Wearable bio sensors allow a non-invasive measurement of the learner's physiological features. There are sensors for the heart rate, skin conductance and temperature, respiration, etc. Those signals are not directly connected to learning experiences but they allow the extraction of context information which are relevant to the learning experiences, such as stress and attention level, emotional arousal, and thus provide an affective dimension of learning. By using (bio-) signal processing and classification methods (usually referred to as psychophysiology), the information can be extracted. An advantage of wearable physiological sensors is their suitability for non-computerized learning environments.

An increasing number of sensors are becoming available for mobile measurement of ECG (Electrocardiogram) and EDA (electrodermal activity) data. The company Movisens[3] uses dry electrodes in a sensor belt similar to the watch-like Polar heart rate monitors[4]. The product Actiheart[5] is a small ECG monitor that uses medical electrodes.

Affectiva Q[6] is a product for EDA measurement at the wrist. Since until now, all experts have argued that stress related sweating cannot be measured at the wrist. But this product is seen as a major breakthrough in research, there are first publications documenting their method (**Fehler! Verweisquelle konnte nicht gefunden werden.**. However, there is still not a broad acceptance of these results. The validation of this sensor is complicated by the used licensing scheme.

4.3 Activity Sensors

Activity sensors are desktop-based, Web-based or mobile-based applications that support the learner e.g. in capturing tasks or work progress. This can be an arbitrary application that logs data about in which order a user solves a set of subtasks or which units are currently of importance to a learner. But such an application can also be an SNS (social networking service) in which the user tells her

[3] http://www.movisens.com/
[4] http://www.polar.fi/en
[5] http://www.camntech.com/products/actiheart/actiheart-overview
[6] http://www.affectiva.com/q-sensor/

peers what is of interest for her or, the other way round, the peers support the learner by recommending information.

As an example, DYONIPOS (**Fehler! Verweisquelle konnte nicht gefunden werden.** allows capturing learner activities and presumes tasks from them. Therefore, the system can support frequent tasks. Another project, CAMera (**Fehler! Verweisquelle konnte nicht gefunden werden.**, allows monitoring and reflection of the learner's behaviour and therefore supports reflection of the learning process. To achieve this, contextualized attention metadata (CAM) of different applications are stored.

Logging of learner's activities, behaviour, pace, achievements, etc. is the basis of different approaches in the emerging fields of educational data mining (Romero et al., 2010) and learning analytics (Long and Siemens, 2011). For instance, every form of feedback to the learner's progress requires knowledge about the current and previous steps, the learner accomplished (**Fehler! Verweisquelle konnte nicht gefunden werden.**.

5 Frameworks for Mobile Learning in Context

In the literature, only few frameworks for context-aware mobile learning exist. In this section, we briefly introduce and discuss two of them, namely AICHE (Specht, 2009) and Korpipaa et al.'s (2003) framework for managing context information in mobile devices.

5.1 AICHE

AICHE (Ambient Information CHannEls) is an abstract model proposed by Specht **Fehler! Verweisquelle konnte nicht gefunden werden.** that aids developers in classifying or designing context-aware eLearning applications. Virtually any entity in this model is an information channel bound to a physical artefact or a sensor. Channels are abstract entities carrying content or information. They cannot be seen as something simple as a cable carrying an electrical signal, but rather as a context-aware medium. For example, if the information is a text, it could be displayed on a screen or, for blind users, on a Braille display. In this example, context information is the eyesight of the user and is being used to determine the appropriate output device. Artefacts are (augmented) physical objects to interact with information channels. Simple examples are the keyboard and the mouse as input devices and screens as output. A more interesting approach to deliver information or content is augmented reality. As an example, only the information that is relevant to what is currently being recorded by the camera or displayed in a video could be displayed on a smartphone screen. Finally, sensors are another type of input devices that typically measure something constantly. In the context of AICHE and context acquisition the difference between sensors and input devices is that the former is being used for implicit and the latter for explicit context acquisition.

The AICHE architecture is divided into four layers:

- *Sensor layer*: In the sensor layer, incoming information is being handled. This means, for a type of information, different types of sensors which are able to acquire this information can be specified and also whether to push or to pull this information to deliver it to the system.
- *Aggregation layer*: In the aggregation layer, incoming information from the sensor layer is being collected and packaged into a sensible form. This means, instead of handling raw sensor data in other layers, it is first being abstracted into a more manageable form. In the aggregation layer, the sensor information undergoes two different processes, so called AICHE processes, which are aggregation and enrichment. The aggregation is the process of

collecting and converting relevant sensor data. In the enrichment process, channels, users and artefacts are being enriched with the collected data. As an example with a location sensor: First the value is being converted into an address, e.g. a room number, then this new information is being attached to the user. Now the subsequent layers can adapt to the room in which the user is currently in. The aggregated data represent the context.

- *Control layer*: In the control layer, instructional logic is specified. In this layer the enriched entities from the previous layer undergo two further AICHE processes: synchronization and framing. In the synchronization process, relations between formerly independent entities are being established according to the specified logic. As an example, whenever a user enters a room with a public interactive billboard, this billboard synchronizes with his context information to open a channel in which relevant data for that user is displayed. In the framing process, the channels in the newly formed relation are being supplied by channels with related content or meta-information. To continue the example, another channel could be supplied to display all the users currently present in the room that have access to the interactive billboard. The synchronization and framing processes are being determined by the incoming context.
- Indicator layer: Finally in the indicator layer, the visualizations and the feedback for the user are described. This layer holds most of the devices that are being used to present the information. As mentioned before, there are different possibilities to present data according to the requirements of the learners.

The AICHE framework only concentrates on extrinsic context information (e.g. location, time, activity). In AICHE, intrinsic context information is not addressed. As discussed in section 3.3.2, intrinsic context, such as the motivational level of the learner, his previous knowledge or the level of concentration, is crucial for an effective context-aware mobile learning experience.

5.2 Korpipaa et al.'s framework for managing context information

Korpipaa et al. (2003) proposed a framework which obtains different context information from various sources, and interprets and forwards them to other applications.

The raw data measured by sensors are sent to the framework. There they are converted into human-interpretable context information by using self-defined context ontology. This transformation is realized by methods which match a numeric value to a textual one of the ontology. Applications gain context information by direct requests or subscriptions to context change notification services. Therefor the application only needs to know the context ontology and the methods for communication. A feature of this framework is the possibility to provide higher-level context by combining lower-level context information. In the evaluation this feature achieved satisfying results.

The weak spot of this approach is clearly the concentration on sensor-based sources. The entire context model is based on extrinsic context data which does not cover a user's complete context. Beyond that, the communication within the framework is not realized in an efficient way. This slows down the context updates which are crucial for applications, running on mobile devices.

6 Challenges of Mobile Learning in Context

The main challenge is to effectively capture and combine the different intrinsic and extrinsic context information within context-aware mobile learning environments. Technically, it is possible to get context information about a learner by using different bio, environmental, and activity sensors, as discussed in section 4. In general, current context-aware mobile learning solutions only focus on a single type of context information, e.g. the position. The location context information can be used to determine which data is presented to the learner, which is relevant to the current location. In this case, however, all learners at the same location would receive the same data. To overcome this lack, we need to consider the whole package of the learner's context information (i.e. location, time, environment, relations, motivation etc.).

The challenge, thus, is to capture all the available intrinsic and extrinsic context information and to combine everything into a standardized context model.

To address these challenges, we propose a framework for context-aware mobile learning, which consists of two main components: context capturing and context modelling, as depicted in Figure 1. Capturing context depends on the bio, environmental, and activity sensors available. These include the mobile devices and technologies as well as the apps and services that are used by the learners. An example would be an EDA sensor that is used by an application to determine if the learner is currently under stress and therefore has a high or low level of attention (which would be the output). The context data that is captured by various sensors can then be sent to the context modelling component, by following the framework specifications.

The context modelling component is responsible for processing the received sensor data. First, all the context information is collected, analysed, and adapted. After that, it can be classified into different extrinsic or intrinsic context information. This helps to combine single sensor data into a complete sensor data set reflecting a complete picture of the learner's context information. After the classification and the combination of the received sensor data, a standardized context model can be generated.

The framework should offer an API (application programming interface) that enables third-party applications to get access to the generated context model. These applications can then leverage the received information for e.g. personalization, recommendation, adaptation, and learning analytics tasks.

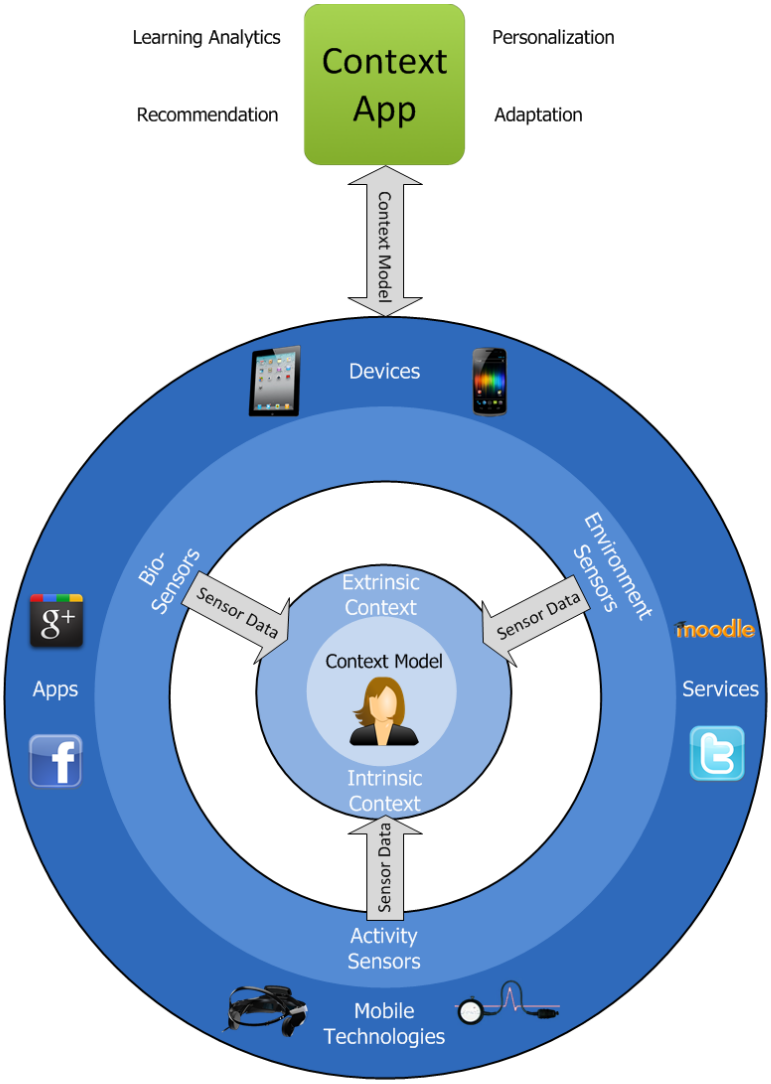

Figure 1 Mobile Learning in Context Framework

7 Conclusion

Mobile learning has attracted a great deal of attention in recent years as teachers, learners, and researchers are increasingly seeing the potential that mobile technologies have to improve the learning experience. Recognizing that context is the most distinctive feature in mobile learning, we focused in this paper on context-aware mobile learning environments. We discussed the benefits and the different types of context (i.e. intrinsic and extrinsic context). We then reviewed the current literature and research on mobile learning in context based on what type of context is used and how context is captured. The review showed that environmental sensors (e.g. GPS, image and video sensors, compass, accelerometer) are the most widely used sensors for capturing context, as compared to bio and activity sensors. Furthermore, we identified future challenges in this area of research and introduced a framework for context-aware mobile learning that addresses these challenges.

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