Adaptive E-Learning Technologies for Sustained Learning Motivation in Engineering Science
Acquisition of Motivation through Self-Reports and Wearable Technology

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Abstract: Surveys show besides the number of students also the drop-out rates are increasing, especially in early phases of studying natural or engineering sciences. The research project "SensoMot - Sensor Measures of Motivation for Adaptive Learning" tries to counter this development by means of improving the quality of teaching in the department of micro technology with the help of an adaptive e-learning system. For that purpose, the mediated learning content should be better adapted to the individual prior knowledge, competencies and motivational profiles of the learners. Furthermore, the continuous sensory data acquisition of physiological parameters of the learner shall be accomplished by current wearable technology. The paper presents first results in the form of conceptual determinations concerning self-reports and physiological measures, instructional design and adaptation techniques and further includes the early involvement of the subsequent users in the development process through an iterative, formative evaluation of prototypical solutions.

1 INTRODUCTION

Motivated learning is the prerequisite for a deep processing of learning content and a long retention performance (Schneider *et al.*, 2017), as well as the basis for joy of learning and persistent interest (Schiefele, 2009). Conversely, disturbances of motivation can lead to superficial learning processes or even to learning blocks. The SensoMot project investigates the detection of critical motivational incidents by two different approaches: first, through self-reporting methods and second, through sensory data acquisition with wearables, in the sense of fitness trackers or smartwatches. These motivational incidents will be used to adapt learning content at runtime and thus enhances motivation. Such increased learning motivation could lead to better learning outcomes in technology-based learning and teaching scenarios (Hartnett, 2016; Schneider *et al.*, 2017). The intention of the paper is to mark a first step towards the examination whether learning motivation can be positively affected by means of adaptive e-learning. Therefore, first insights regarding the potential of sensor measures combined with self-report data for adaptive e-learning will be provided. Accordingly, the theoretical framework is outlined first and the potentials of wearable technology in contexts of educational science are pictured second. Chapter four introduces the study setting for formative evaluation of the prototypical solutions. Chapter five concludes with a summary.

2 THEORETICAL FRAMEWORK

This research focuses on observing motivation in self-regulated e-learning sessions. Therefore, the following chapter will bridge the domains of learning motivation and adaptive educational systems relying on established frameworks and concepts.

2.1 Motivation in Self-Regulated Learning Contexts

According to Rheinberg motivation is defined as the "activating orientation of the current day-to-day living towards a positively assessed target state" (Rheinberg and Vollmeyer, 2012). Consequently, motivation should be able to explain the direction, persistence and intensity of behavior.

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The research focus is on motivation in learning contexts, especially on self-regulated learning in e-learning. Intentional learning activities under one´s own guidance, without direct tutor-instructions or -control are called “self-regulated learning” (Rheinberg *et al.*, 2000). Therefore, the cognitive-motivational process-model of self-regulated learning was used as a framework for describing the effects of the interrelation between person and situation factors on the learning outcomes. As indicated in figure 1 the framework starts with the antecedents of the current learning motivation that result indirectly in learning outcomes for a specific learning task and learning episode via mediating variables during learning (see Rheinberg *et al.*, 2000).

Besides demographic variables and prerequisite domain-knowledge, several motivational person factors are included like self-efficacy beliefs (Bandura, 1977), domain-specific interests (Krapp et al., 1992) and two forms of incentives in the form of intrinsic and extrinsic motivational orientation (Rheinberg and Vollmeyer, 2012).

Situational factors address the instructional design of e-learning environments that should foster the current learning motivation. An established model for the derivation of design recommendations is Keller´s ARCS-model (Keller, 2010). The four major components attention (A), relevance (R), confidence (C) and satisfaction (S) provide the conceptual framework for the use of motivationally fostering actions (Keller, 2007; Niegemann *et al.*, 2008). The mediating variables focus on the learner´s emotional functional state due to conceptual similarities between motivation and emotion. Considering Rheinberg´s definition of motivation it is obvious that positive activation, as part of a circumplex model of affect (Schallberger, 2005), is also a core component of motivation (Rheinberg, 2010).

The operationalized framework depicts learning motivation as a process variable. Direct effects of learning motivation on learning outcomes are not automatically to be expected, but mediated through variables like functional state. Especially complex tasks demand a preferably direct acquisition of motivation and its indicators, because learning outcomes in this case are dependent on many factors. Such "live" acquisition of motivational data can be achieved through self-reports in the form of experience sampling approaches or via physiological parameters (Engeser, 2005).

2.2 Acquisition of Critical Motivational Incidents

Motivation is a broad construct that influences the behaviour of a person for long periods of time. Psychology relies on two methods for surveying constructs such as that. The most widespread method is self-reporting in the form of questionnaires.

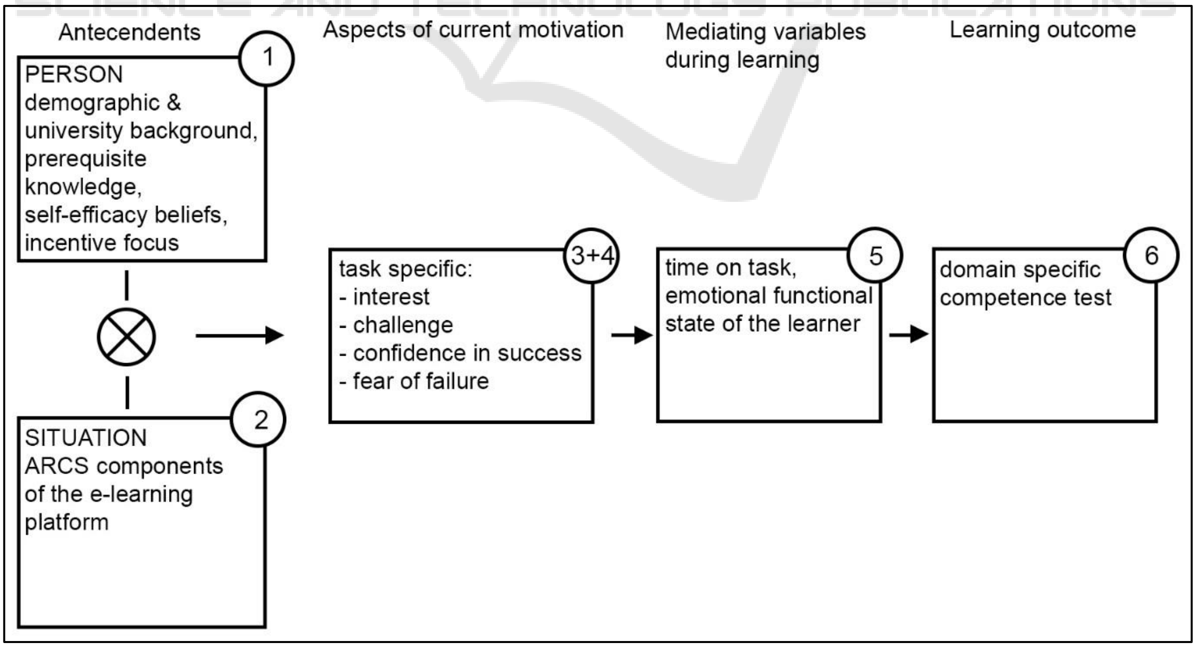

Figure 1: Operationalized framework for learning motivation and its effects on self-regulated learning (in accordance to Rheinberg *et al.*, 2000).

As a result of advances in technology and neurosciences the acquisition of physiological data and its interpretation for psychological phenomenon is getting more popular.

As mentioned before the SensoMot project is utilizing both methods to identify motivational incidents in learning processes. This paper focusses on the self-reporting methods, but a brief overview of the acquisition of physiological data shall be given.

2.2.1 Sensory Data Acquisition of Physiological Parameters

The measurement of physiological data used to involve medical equipment and an experimental setting in a laboratory. Due to the enhances in mobile technology, unobtrusive sensors in the form of wearables, such as smartwatches and fitness trackers, became available (Park *et al.*, 2014).

One group within the SensoMot project is currently investigating their potential to replace expensive equipment and allow the study of physiological data in non-laboratory settings. The aim of their research is to first, identify appropriate physiological indicators for motivation and second, to determine suitable devices for their measurement.

Available physiological indicators range from electroencephalography (EEG), electrocardiography (ECG), pulse, blood pressure, electrodermal activity, electromyography (EMG) to sugar and oxygen levels in the blood. A comprehensive overview of these indicators, their measurement as well as the advantages and disadvantages, can be found in (Sullivan, 2017; Hou *et al.*, 2015; Trepte and Reinecke, 2013). This kind of data in conjunction with the tracking of useage data would allow the localisation of critical motivational incidents in time as well as in space. Due to the continous survey of the physiological data, it would be possible to identify a specific point in time when a change in motivation happened. Combined with logs of the current position in a learning segment, it would be possible to determine which content is responsible for this change. First studies with wearables in the project did not produce stable and reliable results.

Furthermore, current studies hint at an insufficient quality of the physiological data acquired by wearables (see in comparison Arriba-Pérez *et al.*, 2016). A recent similar project proposal reports about the problems and issues on the use of commercial wrist wearables in education and about supporting technologies for smart education in the context of new smart universities (Arriba-Pérez *et al.*, 2017).

2.2.2 Self-Reporting Methods

Self-reporting data can enhance the findings achieved with the physiological data. As mentioned before the data acquired with wearables can provide insights into when and in which context motivation changes. But it does not explain why these changes happen. Self-reports can fill this gap. They can offer an understanding of the reasons why critical motivational incidents arise.

Gathering physiological data also contributes to an advanced implementation of self-report data. Due to the continuous measurement of physiological data, patterns in motivational changes become apparent. This helps to identify appropriate time intervals in which questionnaires should be administered.

Since this methodology is the main focus of the current paper, a detailed explanation of suitable self-report instruments can be found in chapter four Methodology.

2.3 Adaptive Educational Systems

There are two ways in which a system can adapt to the user. First, users can change settings that influence presentation and content themselves. In this case the system is adaptable. The other way for a system to react to user needs is by forming a user model, which predicts demands. According to these predictions the system follows a set of rules to change its appearance and content. This is meant by adaptivity. (Mödritscher, 2007)

The user model can contain different information about the person interacting with the system. It is continuously updated and serves as a basis for all adaptation. Once the system registers a change in the user model, it will react and try to adapt itself according to the changes.

Kobsa et al. (2001) categorize the information in a user model as user characteristics, usage data and environment data. Environment data is gaining relevance due to the variety of devices on which systems can operate today. Not only does the screen size impact a system, but also the environment in which it is being used. Furthermore, systems can collect different information about when, how long or how often a user is interacting with them. This usage data can provide insights into problematic interactions. (Kobsa *et al.*, 2001)

The heart of a user model consists of the user characteristics which describe the user’s needs and preferences. These information change according to the type of adaptive system and its goals.

Rachbauer mentions the following five groups for educational systems (see Table 1).

Table 1: Information that could be included in a user model (Rachbauer, 2009).

individual characteristics	examples
cognitive capabilities	learning, intelligence, concentration, memory
knowledge	domain specific knowledge, general knowledge
goals	learning goals
preferences	learning styles
physical characteristics	disabilities

Adaptation can be achieved by different methods and techniques. Methods are more abstract than techniques. While techniques include an adaptation algorithm, methods represent a general concept. (Koch, 2000)

Brusilovsky distinguishes two methods for adaptation. Adaptive presentation describes all changes to the content and the presentation of a system. This includes the usage of images, videos or animations as well as text. On the other hand, adaptive link support guides the user through a system by changing links. (Brusilovsky, 1998) Each of these methods encompasses multiple techniques. An overview of all techniques can be found in (Brusilovsky, 1998) and (Knutov *et al.*, 2009).

For this paper the link annotation technique is especially relevant. This technique highlights appropriate links to relevant content for the user. This highlighting could be implemented as different colours, small icons or additional tooltips.

3 POTENTIALS OF WEARABLE TECHNOLGY IN CONTEXTS OF EDUCATIONAL SCIENCE

To exclude usability of wearables as an influencing variable on the learning process, a first formative usability evaluation of current consumer-wearables was conducted in 2016 at the Ilmenau University of Technology. In this study 30 students tested four fitness-trackers and one smartwatch. The user study evaluated the devices in terms of usability and user experience by means of self-reports, focus groups and requirements definition (Schneider *et al.*, 2017).

The usability tests were based on a functional analysis for identifying benchmark tasks that served for the creation of representative user tasks with focus on performance, ease of use as well as usability metrics like efficiency and effectiveness (Hartson and Pyla, 2012). The usability of all devices was rated very positive. Especially the smartwatch exceeds the fitness tracker in terms of user experience, because of the wider scope of functionality and the more appealing user interface. As other studies have shown, present wristband-wearables currently seem to be a convenient extension to a user´s smartphone (Min *et al.*, 2015). Most wearable users seem to be early adopters (Lyons, 2015). Trends like quantified self in combination with revealing a true added value could have the potential to increase user acceptance.

4 METHODOLOGY

Engineering studies are characterized by extensive basic knowledge, which is acquired in the first semesters, and then in the following semesters should be linked with domain-specific knowledge. Therefore, three chairs of the Ilmenau University of Technology worked together with associations and companies to develop an e-learning platform for micro-nano-integration. The goal was to make the difficult to grasp area of micro- and nanotechnology available for education and training. The resulting NanoTecLearn platform was intended to specifically support companies in qualifying employees in the field of micro-nano-integration (Krömker *et al.*, 2017, 2015).

This knowledge platform serves as a case study for the SensoMot project. It is intended to shift the application area towards university learning. Within this scope the platform will be transformed into an adaptive version that adjusts its instruction based on the current learning motivation (see Figure 2).

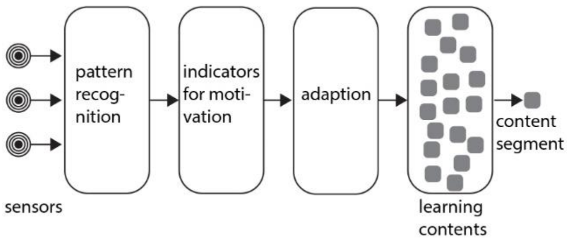

Figure 2: SensoMot process chain: Sensor data is condensed by means of pattern recognition to indicate motivational states, which are used for the adaption of learning content (Schneider *et al.*, 2017, p.269).

NanoTecLearn provides a very good foundation for an adaptive system since it offers learners different approaches according to their knowledge background and learning preferences.

Learners with a stronger inclination towards physics and mathematics can use interactive formulas to get a deeper understanding of a topic. Users with a higher interest in chemical and biological examples can view and interact with samples (see Figure 3).

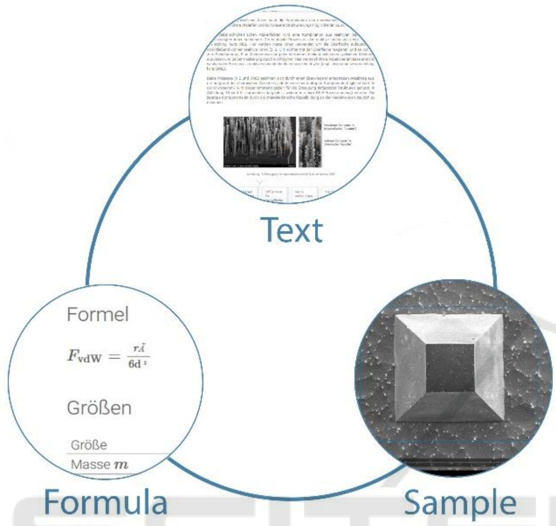

Figure 3: Formula, Sample and Text in NanoTecLearn.

NanoTecLearn was also evaluated in terms of usability. Especially the design of the platform was received very positively. Therefore, negative effect on motivation by design error can be eliminated.

4.1 Studies for Identifying "Critical Motivation-Incidents" During an E-Learning Session

Before updating the conventional NanoTecLearn platform to an adaptive educational system, the motivational disposition of the learner population, the motivational status quo of the instructional design and motivationally critical instants of time during an e-learning session should be examined. Several studies will be conducted. The main study will be oriented towards Rheinberg´s framework (see section 2.1) and will focus on task specific aspects of current motivation like interest or challenge that are capable of predicting the learning outcome in self-regulated comprehension-learning settings (Rheinberg *et al.*, 2001). According to the framework these aspects are said to affect learning outcome indirectly through the mediating variable emotional functional state (Rheinberg *et al.*, 2000).

The learner´s current emotional condition will be measured at central transitions during the e-learning session as micro-analytic experience sampling-like procedure (Csikszentmihalyi and Larson, 1987). Emotions are measured according to Schallberger´s dimensional model (Schallberger, 2005).

Also, qualitative interviews will be conducted after the e-learning session to further investigate motivationally critical phases and possible reasons for their appearance. The data will form an important foundation for the design and implementation of the adaptive version of NanoTecLearn. The study will also evaluate the current e-learning regarding the ARCS-components. Additionally, a guideline inspection considering ARCS-strategies will be performed in cooperation with e-learning experts.

In a parallel online study the learner population will be examined concerning their overall study interest, aspects of learning strategies (Schiefele and Wild, 1994) and the prevalent dominance of intrinsic or extrinsic motivation.

The identification of critical motivation-incidents shall assure a high-quality adaptation in terms of providing an added value regarding tutorial support of the e-learning platform that meets the users´ needs. Being a key factor in education, fostering learners´ motivation can be an important first step in the personalisation of learning systems (Baumstark and Graf, 2014).

4.2 Prototypical Design of the Adaptive NanoTecLearn Platform

The e-learning system described in this paper will use adaptive link annotation according to changes in the motivation of the learner. As a starting point, a prototype was created that represents a segment of the NanoTecLearn platform.

The prototype was implemented with a prototyping tool for websites and mobile apps (see https://www.justinmind.com/).

Since there is currently no functional adaptation algorithm that can detect motivational changes in sensor data, the prototype uses self-reports via buttons as indicators for motivation. The user will need to choose, whether her interest and self-efficacy are increasing or decreasing (see Figure 4 and 5). The buttons are linked to parts of the booklet that should either improve or maintain the current level in interest and competence.

At this point several questions need to be approached. The current prototype will react if one and only one of the factors interest or competence changes.

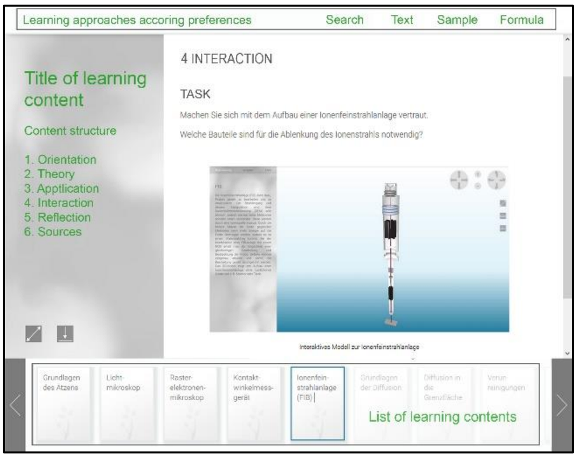

Figure 4: Schematic structure of the NanoTecLearn-Prototype.

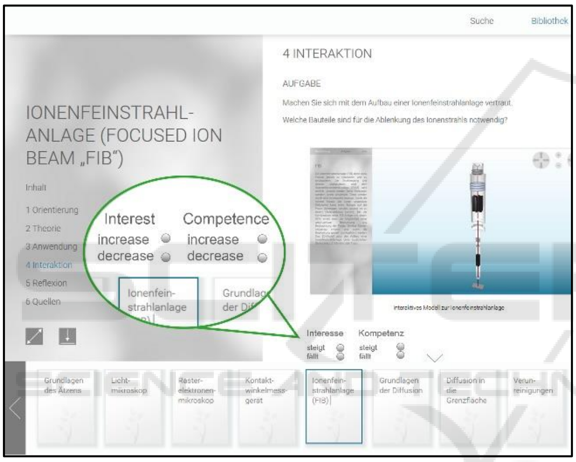

Figure 5: Example for the integrated self-report-mechanism within the NanoTecLearn-Prototype.

Ideally the system should also adapt if both change in the same direction. This could be achieved by adding scores for interest and competence.

Depending on the final score, different links are being highlighted. This process would lead to problems, if interest and competence change in different directions and each change would require a different content section to compensate for that change.

Another challenge to be discussed is when and how many links are going to be highlighted. Some chapters on the NanoTecLearn platform are long and might take a learner several minutes to read. If a change in the user model occurs and the system reacts immediately, the learner might leave a section without completely reading it. This way important information could be missed. Therefore, the system should only act once a section has been finished.

This requires signals that indicate a user is no longer working on a section. Average reading time and the current display might be such signals.

Once the user has finished a section she will consider which section to work on next. This is when link annotations will help to find relevant information according to the user's current motivation. In the NanoTecLearn platform this is achieved by presenting different approaches to knowledge. Either the user reads a text explaining a theory or she could interact with samples or formulas. Highlighting all relevant information will be confusing, so a selection will be necessary. The optimal solution would be to just highlight a single link.

Due to the navigational structure of the NanoTecLearn platform consisting of two layers, it might be acceptable to allow one annotation per layer. One of the layers represents different learning segments and the other one different chapters within a segment. This allows the system to direct the learner towards more information on one topic or towards a completely different topic. Additionally, one can change between different approaches (formulas or samples) as mentioned before.

5 SUMMARY AND CONCLUSION

Learning motivation is an essential condition for successful learning in e-learning environments. Both, learner characteristics and the design of the learning situation, determine whether learners are engaged and focused on a learning activity.

If a lack of motivation or motivational blocks are detected early on, learning processes can be modified and learning content can be adapted to the needs of the learner.

This paper outlines briefly the sensory recording of motivation indicators by means of wearables for the adaptive control of learning contents of an e-learning platform on the one hand and the need of self-reporting methods on the other hand. Wearables are used to collect physiological data of the learners, which allow conclusions about psychological parameters such as stress or motivation. The future algorithm of the educational software will perform various adaptations based on this data collection. For example, the form of learning or the presentation of the learning content can be adapted. Corresponding learning scenarios are prototypically developed and evaluated for university teaching using the example of "nanotechnology" as well as for vocational distance learning in technical education in "mechanical engineering".

The usability and user experience of current available wearables have proven to be good in user tests. The acceptance and potential of the technology is focussing in the opinion of the users particularly on the fitness and lifestyle aspect of the devices. The examination of the suitability and acceptance in the learning context is still pending and will depend on the meaningful embedding of the technology in the learning process. The benefit of physiological measurements is the production of unbiased, quantitative outcomes. Currently, however, there is no conventional market sensor available, that fully meets the requirements of the project. Although the wearables market is growing rapidly, those with open interfaces tend to decline.

For this reason, another approach through self-reporting methods is necessary to fully understand the reasons why critical motivational incidents arise in e-learning. This approach was particularly addressed in this paper in order to be able to offer highly accurate adaptation in the future and to estimate whether adaptation can yield to better learning outcome.

In following steps of the project there should be a shift within the acquisition of motivational data from self-reports towards unobtrusive physiological measures via suitable wearable sensors requiring a functioning mechanism of machine learning-based pattern recognition. Due to the analysis of studies performed by another project partner in the SensoMot project, it will be possible to identify suitable physiological indicators for motivation. This will then allow the selection of a wearable that allows the measurement of this indicator. Moreover, improving the NanoTecLearn platform regarding critical motivational incidents and their reasons as well as designing the adaptation and evaluating its effects on learning motivation is of central scope.

In the long run, the overall objective is to increase learning success through a higher learning motivation in adaptive e-learning environments and to lower dropout rates in engineering science.

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