Simple and Effective: An Adaptive Instructional Design for Mathematics Implemented in a Standard Learning Management System

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Abstract: This article shows how an adaptive instructional design in a standard learning management system was realized within the framework of a straightforward technological concept with four components and with the help of simple technological tools for a mathematics module. For this purpose, we have implemented a didactic design with domain-specific online exercises in which the frequency of step-by-step support is automatically adapted to the level of knowledge of the individual students. The consequence of this is that students with lower pre-knowledge and/or a lower learning achievement receive more and other teaching assistance than those with a high pre-knowledge or high performance. In our approach we assume that this indirectly reduces the subjective task difficulties (intrinsic cognitive load) for beginners but also means unnecessary repeating for advanced learners. The design of this teaching method is based on an adaptive feedback mechanism with integrated recommendations. After a presentation of the didactic design and its theoretical and empirical foundations, we report on the first results with a focus on the learning progress of the various student groups. It has been shown that both weaker and stronger students benefit from the adaptive tasks. Online activity is hereby a crucial factor.

1 INTRODUCTION

As a result of the life-long learning required in the modern world, new forms of learning such as distance learning as well technology-based learning are gaining in significance (Bergamin et al., 2012). These concepts and their flexible approaches enable many people to pursue continued academic education in situations in which traditional studies would be difficult to accomplish (e.g. employment or parenthood). From a didactic perspective, flexibility also means taking the individual requirements of the learner into account and incorporating respective measures into the instructional design.

According to the Cognitive Load Theory and in particular to the Expertise Reversal Effect (Sweller et al., 2003), it is important to adapt the learning process to the learner's level of knowledge. Such individualisation of learning possibilities can be achieved through adaptive learning environments and provide students with the chance to better handle the challenges of life-long learning (Boticario and Santos, 2006). In academia for instance, the design of adaptive learning concepts is aimed at delivering an optimal support for learners in consideration of their differing levels of knowledge. Despite different levels of pre-knowledge, learners should be able to finally develop the same competences. At universities, this usually happens less as a result of the learners processing different learning content and more through instructional support or content sequencing adapted to the individual learners.

Today, there is an increasing number of technological possibilities for implementing adaptive learning. Numerous experimental investigations have been carried out to test even the most complex adaptive learning systems. Despite this, practical implementations of adaptive technology-based learning systems in real-life learning settings seem to still be very rare (Somyürek, 2015). FitzGerald et al. (FitzGerald et al., 2017) state that individualisation in technology-based learning can be seen as positive and promising but its implementation is difficult to realize. The application of experimental research into prototypes and the following implementation in everyday scenarios seems to be hard to achieve (Scanlon et al., 2013). Murray and Pérez (Murray and Pérez, 2015) predict that there is still a long way to go before appropriate, sophisticated and intelligent learning systems can be applied in practice. Bridging the gap between research and practice requires results of applied research and specific experience in the implementation and application of relevant technology-based learning systems, well-founded instructional designs and large-scale investigations in university contexts. However such research findings are very scarce (Johnson et al., 2016).

This work seeks to bridge the gap between experimental research and its practial application. In this regard, we address the question of whether there are currently any possibilities for implementing an exemplary adaptive learning system in a classic learning environment (Moodle), based on a cognitive learning approach and on a fairly simple rule-based instructional design but without the use of high-end technology or machine learning algorithms. Drawing on our experience in designing and implementing course modules for online distance learning, we demonstrate in this paper how an offer of adaptive learning can be implemented in practice at university level within a traditional Learning Management System (Moodle). We further explore to what extent instruction design based on the adaptation of task difficulty, online activity and previous knowledge are related and contribute to the improvement of learning progress. Finally, we discuss the possibilities and limitations of rule-based adaptive learning systems in a standard Learning Management System (LMS) in addition to the advantages for students.

2 THEORETICAL BACKGROUND AND DESIGN

2.1 Instructional Implications of the Cognitive Load

Optimal teaching of complex learning content needs to deliberately take account of learners' cognitive load or actively manage it through instructional interventions (Somyürek, 2015). The Cognitive Load Theory *(*Sweller, 1988) can be used as a basis for this. The Cognitive Load Theory strongly focuses on the interplay between two interacting components of the cognitive system: The working memory and the long-term memory. According to the Cognitive Load Theory, the long-term memory is where all our knowledge is stored and has an unlimited capacity. The working memory, by contrast, is used to consciously process new information but is significantly limited in terms of its capacity and durability (Kalyuga, 2011a). Nowadays, we differentiate between two kinds of cognitive load during learning: the intrinsic load and the extraneous load. The intrinsic load is occupied by cognitive processes which are necessary to process learning material and can be affected by the subjective complexity or difficulty of the learning content. The extraneous load is consumed by cognitive processes that are not vital for learning, caused by unfavourable design or presentation of the learning material (Kalyuga, 2011a, b). The extraneous and intrinsic load combined cannot exceed the limited capacity of the working memory (Paas et al., 2003). So, if the extraneous load is filled with unnecessary unfavourable design or presentation of the learning material less intrinsic load can be allocated to processing learning material. If learning activities require too much cognitive capacity (overload), learning is hindered. In addition to the objective difficulty of the learning content and instructional design, the extent of the current cognitive load on the working memory is also determined by characteristics of the learner. As already mentioned, working memory and long-term memory interact with one another. The extensive schemata stored in the long-term memory enable complex learning content to be processed more easily in the working memory because elements can already be collated in higher-order units thanks to the available schemata. This reduces the intrinsic load and enables certain processes to take place routinely. In this way, there is more cognitive capacity left for new content (Kalyuga, 2011a). Consequently, the level of available expertise/knowledge in the long-term memory exerts considerable impact on cognitive load in the working memory (Kalyuga, 2007b).

The influence of this effect on the instructional design can be demonstrated via the so-called Expertise Reversal Effect. This theory postulates that the teaching support which is beneficial for novices can be superfluous or even detrimental to experts and vice versa (Kalyuga, 2007a, b). 'Reversal' here refers to the fact that the relative effectiveness of didactical aspects may reverse for differing levels of learners' expertise (Lee and Kalyuga, 2014). One important application of the Expertise Reversal Effect relates to the degree of the learners' instructional guidance. On the one hand, if novices do not receive sufficient external instructional guidance during complex learning activities, this leads to poor problem-solving strategies or arbitrary trial-and-error attempts. On the other hand, superfluous instructional guidance for experts, forcing the learners to squander their resources to compare and connect what they already know with their own schemata, may also lead to inefficiency through high extraneous load (Kalyuga, 2011a). In this sense, the assumption is that direct instructional guidance can balance out a lower level of knowledge in the long-term memory of novices by clearly indicating how they should proceed in a certain situation while this should be avoided for experts (Kalyuga, 2007b; Kalyuga and Sweller, 2005). For us, this means that learners are to be provided with instructional guidance (e.g. step-by-step instruction) at the start of the learning process (novices) to enable them to handle tasks and optimise the cognitive load. This guidance can then be gradually reduced as they gain more expertise (see, for example, fading scaffold; Merriënboer and Sluijsmans, 2009). The fundamental educational implications of the Cognitive Load Theory and, in particular, the Expertise Reversal Effect have been confirmed by numerous studies. In order to tie in some contradictory research results with theory, Kalyuga and Singh (Kalyuga and Singh, 2016) stress that the validity of this theory is limited to the acquisition of subject-specific knowledge as a learning goal. For other educational goals (e.g. promoting self-regulated learning skills or learning motivation), the assumptions of Cognitive Load Theory (e.g. suitability of much instructional guidance for novices) are not necessarily applicable.

Learners, particularly novices, may feel overburdened by the notion of undertaking the adjustment of their learning (Kirschner and van Merriënboer, 2013). Therefore technology-based adaptive learning support may be an option to enhance effectiveness of learning.

2.2 Adaptivity in Technology-Based Learning Environments

In contrast to the traditional technology-based approaches adaptive concepts allow the learning content, navigation and suitable learning support to be presented in a dynamic environment continually changing based on individual requirements. In principle, adaptive learning support can be provided at the macro level (e.g. at the level of the academic goals of an individual) or at the micro level (e.g. at the level of individual courses or tasks). In this study we focus on this second level. There is a wide range of possibilities how to adapt individual characteristics on a course level (for an overview see e.g. Nakic et al., 2015). Three main factors can be established as basis of adaptation: (1) Stable or situation-related personal characteristics such as gender, culture, style of learning, knowledge or emotions, (2) content-specific characteristics such as topics or task difficulty and (3) context-based characteristics such as learning time or place (Wauters et al., 2010). On the basis of these factors, different dimensions of the learning experience can be adapted. For instance, the level of task difficulty, the level of detail of the explanations, the frequency of hints, or the modus of presentation (video, text, figure...) can be adapted to match the needs (basis of adaptation) of individual students.

In our instructional design we focus on task difficulty, actual knowledge and giving different adaptive support. Depending on the learner's level of knowledge, the system recommends tasks with more or less detailed instructions and thus with different degrees of difficulty. This way less performant learners are given tasks with more support and assistance. The support and assistance is reduced for more efficient learner increasing the difficulty of the tasks. Aiming to reduce the cognitive load.

Based on a model by Zimmermann et al. (Zimmermann et al., 2005), we developed the methods and components for processing and linking learning data with adaptive instructional interventions. We delivered interventions in the form of hints and recommendations integrated in task feedbacks displayed by our learning management system Moodle. Conceptually, the system is based on four components resulting in the adaptation mechanisms. The components themselves use learning data, which must be measured and stored continuously. The first component are the sensors. These use data from tasks worked on by learners, specifically if a certain point has been achieved or not. As an entry point we use the data from a previous knowledge test, which evaluates the expertise with which the learners start the course. Further tests and assessments then form an additional data base for the sensor component. The second component is the analyser. This component collects, evaluates and interprets the data measured by the sensors. The analyser then transfers this information to the third component, the controller. This component determines whether a threshold is met. Depending on the outcome the controller determines if and to what extent the adjustment object (for example a task) is to be changed by one or more educational interventions. The last and fourth component is the presenter, which finally triggers the customized display of the concrete learning objects.

Based on the model with its four components, the learners are classified as "low" or "high" performers, depending on their learning performance. In addition, the result of each individual learning step is registered and compared with a threshold value. Consequently, learners receive instructions and learning support adapted to their learning performance and behaviour.

We chose a rule based operating, adaptive learning system with a fixed set of rules for two reasons: On the one hand our learning scenario and the sensors we use for individual learners do not generate enough data for a high-quality self-learning system and, on the other hand, we chose to keep the adaptation mechanisms transparent for learners in the sense of an "open learner model". We will take up this issue in the conclusion section again.

3 INSTRUCTIONAL DESIGN AND SYSTEM IMPLEMENTATION

Starting in the autumn semester of 2016/17, we have carried out a two-year field study to implement the above-mentioned approach. For this we used the framework of the study module "Mathematics, Statistics and Operation Research" and our university's standard student platform (Moodle). This course covers concepts, terms and methods of one-dimensional analysis. The entire module is organized in a blended learning format. In addition to the participation in five face-to-face sessions, there is a high proportion of self-study, which consists of a mix of online and off-line phases. The learning platform offers students the opportunity to complete voluntary online task sets that have been modified as part of an adaptive instructional design compared to non-adaptive, poorly interactive ones foreseen in the classic form of the course. The students were enabled to work on the modified tasks for the first time in the autumn semester 2017/18.

Distance students in general and students at our university specially tend to have very different previous knowledge and different strategies to acquire knowledge, depending on their education or professional experience. Accordingly, we supported learners with lower current knowledge levels by adapting additional learning support without hindering those with more knowledge through this additional support. The learning process itself is constantly adapted based on a theory-led, rule-based adaptation mechanism to ensure the optimal cognitive load during the completion of tasks. As explained previously the appropriate learning support delivered to the student was defined by four components: the sensor determines is a point has been achieved, the analyser sums up the point total, the controller determines if a specific threshold has been reached and the presenter displays recommendations and other objects of learning support. Our individualised support focuses on three elements:

The first element (initial sensor) is a first knowledge determination, consisting of a set of standard exercises that students complete at the start of the course. Based on the performance in this assessment and a given threshold score, the learners are divided into two groups, “novice" and "expert". Depending on the score the first task of the set appears in a guided (high learning support) or an unguided (low learning support) version.

The second element (step loop) is used to measure the current level of knowledge within a task and to determine the appropriate learning support. In this second element, the default values are determined on the basis of a specification by experts, taking into account the difficulty of the different tasks. When learners reach or exceed the threshold value, i.e. have (partially) answered a question correctly, they receive a different feedback than when they receive an incorrect answer and fall below the threshold value. Such feedback is given after each step in the task. This error-sensitive feedback includes appropriate advice depending on whether there are visible gaps in knowledge or misinterpretations that can be characterized by individual wrong answers (cf. for example Goldberg et al., 2015). Such adaptive feedback prompts serve to clarify possible misunderstandings of learners as quickly as possible, for example by reminding them of forgotten information (Durlach and Ray, 2011).

The third element, the task loop, consists of both standard tasks and transfer tasks. The standard tasks are used to assess to ability to solve a particular problem, while the transfer task has two objectives: On the one hand, the transfer task aims to determine whether a particular problem has been understood and can be solved in its unguided form (see vertical transfer), on the other hand, it aims to evaluate whether the acquired problem-solving knowledge of a previous basic task can be applied to a similar task on the same issue (see horizontal transfer; van Eck and Dempsey, 2002). Within each task set, the system recommends which task a learner should tackle next and in which form (guided/non-guided). The guided version includes numerous small solution steps, while the unguided version is composed of few solution steps.

To promote the acceptance and motivation of learners, we chose a mixed form of adaptation (system controlled) and adaptability (learner controlled). This means that the learners receive recommendations as to which tasks (and in which form) they should ideally complete according to the current level of knowledge. The learner always has the choice whether to comply with these recommendations or not. The recommendations themselves are integrated into the task feedback. At the same time, the sensor data (current state of knowledge) is also made available to the learners in a clear and concise way to promote their own self-assessment skills and the acceptance of the recommendations (see open learning models, e.g. Long and Aleven, 2017; Suleman et al., 2016).

4 ANALYSIS

In order to investigate the impact of our instruction design (based on the adaptation of task difficulty in a mathematical course) on learning progress, we concentrate in a first step on the relationship of online activity and learning progress and in the second step on the connection between previous knowledge and learning progress in a comparison of an adaptive and a non-adaptive course module. To achieve this goal, we have formulated two hypotheses for our exploratory investigations:

H_1: Students who actively perform the tasks of adaptive instruction design have a higher learning progress than those who do not actively engage in these tasks.

H2: Regardless of pre-knowledge, adaptive design leads to higher learning progress for students who are actively engaged in learning tasks.

All statistical operations were performed with IBM SPSS Statistics 23.

4.1 Object of Investigation and Subjects

As we have already reported, for the use of adaptive tasks with a recommendation system in our investigation we chose the mathematics module "Mathematics, Statistics and Operation Research (in the following always named MSOR1)". The module is offered each autumn semester at our university. We chose this module, as it can be called a “problem module”. It is the first math module in the university program and has a high failure rate.

In each semester the students are divided into seven or eight classes. Each class has its own online course. At our university all courses base on a blended learning concept which includes 80% distance study and 20% interaction with tutor either online or face to face. The classes allow students, who usually work in a profession, to choose the best place (and date) for the face-to-face events. This division has no influence on the module content or the online part of the course.

In the autumn semester 2017/18 were implemented 84 adaptive tasks in the module MSOR1. These tasks cover each learning goal several times. However, not all tasks have to be completed by a student. A good student, for example may only need to complete 18 adaptive tasks after having successfully completed the first knowledge assessment (initial sensor). This is if he always follows the recommendations. With these 18 tasks he will have worked on each learning goal once. So the principle differences between the module of 2016/17 and the 2017/18 one are the additional adaptive tasks that were implemented. The remaining module content was the same. The data of 288 students was used for this analysis. 143 students from the adaptive MSOR1 autumn semester 2017/18 module and 145 students from the non-adaptive MSOR1 of the autumn semester 2016/17 (see table 1). The data from this second module was only used for the comparison of learning progress.

Table 1: Dataset

semester	n
Non-adaptive Course (MSOR1, AS 2016/17)	145
Adaptive Course (MSOR1, AS 2017/18)	143
overall	**288**

4.2 Procedure

To start off we compared the students' learning progress in the module MSOR1 of the autumn semester 2017/18. We looked at the students’ log files with focus on the number of tasks completed. Some students did not use the adaptive tasks, but other students worked very intensively with the tasks. Thus, we decided to take the group of students who did not use the adaptive tasks as a control group for this module. We will compare their learning progress with the students, who use the adaptive tasks for their learning.

In a second step will also compare the learning progress between the adaptive course and the non-adaptive course (MSOR1 AS 2017/18 and AS 2016/17 respectively). To achieve this we will focus on learning progress. Finally we will compare the two courses in regard to previous knowledge and online activity.

4.3 Online Activity

Taking into account the number of tasks completed, we divide the participants into three groups to define different activity groups of the adaptive module (table 2). The first group (the control group) is classified as "Inactive". These participants have completed a maximum of three adaptive tasks online, this means less than one per topic. The second group are referred to as "moderate active". These students worked on four to sixteen adaptive tasks. Sixteen completed tasks are just under the minimum number of 18 tasks with which a (good) student needs to address all learning objectives. The third group were named "Active". These students performed at least 17 adaptive tasks.

Students were free to choose whether or not to work on the tasks. While working on the tasks, they were also allowed to freely decide whether to follow the recommendations of the system and the learning support or not.

In our analysis we only account for completed tasks because the recommendation made on task loop is only given after a completed task.

Table 2: Activity groups with students per group (n), mean and standard deviation of tasks completed.

group	n	mean tasks	SD tasks
Inactive	68	0.46	0.94
Moderate Active	41	9.00	3.22
Active	34	30.09	14.8
overall	**143**	**10.0**	**13.95**

The number of tasks completed by a student in the module has a high correlation (Pearson's r = .926) with the total online activity in the module (number of logs). From the number of tasks processed, we therefore assume a high level of online activity.

4.4 Pre-Knowledge, Learning Progress and Online Activity

In the following step we try to explain the relationship between the online activity and the learning progress in the adaptive module. For this purpose learning progress was defined as the difference between the results of the pre-knowledge test and the final test, both standardized to 100.

Table 3: Learning progress of groups.

group	n	mean learning progress	SD learning progress
Inactive	22	8.40	29.11
Moderate Active	36	21.49	32.32
Active	32	32.36	22.05
overall	**90**	**22.15**	**29.40**

Table 3 shows the distribution of the learning process among the three groups. Only students who completed both the pre-knowledge assessment and the final test could be included in the analysis.

A t-test was performed that shows a significant difference with regard to learning progress between the "Inactive" and the "Active" group (t (52) = -3.442, p = .001, n = 54). The variance homogeneity, tested with Levene's test, was given (F (1, 52) = 1.126, p = .293, n = 54). The comparison of the "Moderate Active" group with the "Inactive" and the "Active" group failed to show a significant difference in the t-test (t (56) = -1.552, p = .126, n = 58) and (t (66) = -1.600, p = .114, n = 68 respectively). Variance homogeneity, as tested with Levene's test, was given for both tests (F (1, 56) = 0.303, p = .584, n = 58) and (F (1, 66) = 3.196, p = .078, n = 68 respectively). The results show that, in line with our first hypothesis (H_1), more online activity leads to more progress for students who actively participate in the adaptive learning module than for those who do less. It is also to note, that the non-adaptive course of the autumn semester 2016/17 was non-interactive and did not allow online activity. In view of this fact, no direct comparison between the adaptive and non-adaptive course modules is possible with regard to the correlation between learning progress and online activity.

The same pre-assessment and a comparable final test were used in both courses, allowing for comparison of learning progress of both modules. The comparability of the final test was determined by a comparison of the pass-grades students obtained in this final test. The mean values and the SD are close to each other (autumn semester 16/17: Mean = 5.07, SD = .644. Autumn semester 17/18: Mean = 5.24, SD = .707.). This allows the learning progress of different levels of previous knowledge i. e. different starting positions to be compared between the courses. Students were divided into "novices" (less than 50% correct) and "experts" (more than 50% correct) depending on the achieved points in the initial assessment.

Table 4 and 5 show the mean of the initial assessment (pre-knowledge test) and the mean score on the final test separated by semester.

Table 4: Mean pre-knowledge test (standardized to 100).

semester	n	mean pre-knowledge test	SD pre-knowledge test
Non-adaptive Course (MSOR1, AS 2016/17)	92	54.83	18.48
Adaptive Course (MSOR1, AS 2017/18)	103	45.96	23.93

Table 5: Mean final test (standardized to 100).

semester	n	mean final test	SD final test
Non-adaptive Course (MSOR1, AS 2016/17)	124	56.67	25.59
Adaptive Course (MSOR1, AS 2017/18)	118	61.82	31.14

A t-test showed a significant difference in the previous knowledge test between MSOR1 HS16/17 and MSOR1 HS17/18 group (t (189.149) = 2.911, p = .004, n = 195). The variance homogeneity, checked with Levene's test, was not given (F (1, 193) = 7.252, p = .008, n = 195), therefore the corrected t-value was chosen.

The t-test did not show any significant difference between both semesters on the final test (t (226.681) = -1.403, p = .162, n = 242). The variance homogeneity, also checked with Levene's test, was not given (F (1, 240) = 12.135, p = .001, n = 242), therefore the corrected t-value was chosen. This results shows, that the final tests had comparable difficulties.

In a further step the course participants of adaptive course (MSOR1 AS 2017/18) were divided into six groups with regard to online activity and previous knowledge. To compare the courses (adaptive vs. non-adaptive), the two groups ("novices" and "experts") of the traditional course from the autumn semester 2016/17 were also taken into account. The results of the learning progress in the corresponding eight groups are listed in Table 6.

Table 6: Pre-knowledge level and learning progress.

group	n	mean learning progress	SD learning progress
Adaptive Course, MSOR1 , AS 2017/18			
Active Novices	12	49.23	21.39
Moderate Act. Nov.	19	29.11	35.55
Inactive Novices	14	16.19	30.76
Active Experts	20	22.24	15.52
Moderate Act. Exp.	17	12.97	26.79
Inactive Experts	8	-5.24	21.24
Non-adaptive Course, MSOR1, AS 2016/17			
Novices	34	19.04	21.64
Experts	51	-12.12	28.73
overall	**175**	**11.56**	**31.65**

In the following analysis we excluded the group of inactive novices and inactive experts of the adaptive course, since the non-adaptive course is used as a control condition compared to the adaptive course. We applied a one-sided ANOVA with Tamhane post-hoc testing assuming unequal variances, as the variance homogeneity tested with Levene's test was not given (F (7, 167) = 3.467, p = .002, n = 175). The one-sided ANOVA shows significant group effects (F (7, 174) = 11.979, p < 0.001, n = 175). The post hoc test leads to significant differences between active novices (Mean = 49.23) of the adaptive course and the novices (Mean = 19.04) of the non-adaptive course (p = .013) as well between the active experts (Mean = 22.24) of the adaptive course and the experts (Mean = -12.12) of the non-adaptive course (p < 0.001). These results indicate in line with our second hypothesis (H_2) that for students who are actively involved in adaptive learning tasks regardless of their pre-knowledge, adaptive design leads to a higher level of learning progress compared to non-adaptive design. However, we also have to note that no significant differences were found between moderate active novices (Mean = 29.11) of the adaptive course compared to novices (Mean = 19.04) of the non-adaptive course (p = 1.000) and also between the moderate active experts (Mean = 12.97) of the adaptive course and the experts (Mean = -12.12) of the non-adaptive course (p = .072). From our point of view, this result indicates that a certain online activity level is necessary for the adaptive instructional design to be effective.

In addition, we have found a significant difference between the learning progress of active novices (Mean = 49.23) and active experts (Mean = 22.24) of the adaptive course (p = .035). A difference was also found in the non-adaptive course for the novices (Mean = 19.04) and the experts (Mean = -12.12) (p = .001). This can be understood by the novices having a larger learning progress than the experts in both courses.

Besides the significant differences mentioned here, however, we also point out that the differences between the active novices (Mean = 49.23) and the inactive novices (Mean = 16.19) and between the active experts (Mean = 22.24) and the inactive experts (Mean = -5.24) cannot be shown as significant (between novices p = .102 and between experts p = .192) despite the high differences between the mean values. We assume that large individual differences and the real small number of test persons play a role here.

5 DISCUSSION OF THE FIRST EXPLORATIVE RESULTS

In this article we presented an adaptive instruction design which was implemented in a standard learning management system as a relatively simple concept. The theoretical part of the instruction refers to the Cognitive Load Theory and the Expertise Reversal Effect. On this basis we developed adaptive task sets and combined them with a recommendation system. The practical application took place in a mathematics module (AS 2017/18) at our university.

The first results on effects related to students' different prior knowledge, online activity and learning progress show some positive effects of the adaptive design used, although not all results are unambiguously. We have also found some unclear results, such as the insignificant differences between the active and inactive novices and between the active and inactive experts in the adaptive course, even though there are very high differences in the mean values. Hence it has also become apparent that some further clarifications are necessary and will also require further in-depth research.

All in all the students from the adaptive course scored significantly worse in the pre-knowledge test than their fellow students from the non-adaptive course. This is not due to the adaptive design, as at the time when the students fill out the pre-knowledge test no adaptive measures have been taken. But rather simply that one year students had a higher starting level than the next. It is also evident that at the end of the adaptive course more students (54.2 %) passed this examination on their first attempt than after the non-adaptive course (37.0 %), despite a similarly difficult final examination.

As mentioned previously, the results show a clear improvement in learning progress with increasing online activity in which students actively work through online tasks. The better results of both the novices and the experts with high online activity indicate this. However, this result cannot unequivocally be attributed to the instructional design. Higher online activity could lead to better results independently of learning design. Or the better results could effectively be due to the instructional design and the compliance of the recommendations. To clarify this question further investigations are required. Furthermore, the significant differences can only be seen in the comparison of very active students and inactive students. This means that a certain level of activity is necessary. In fact, the question arises as to why moderately active participants did not benefit significantly from the instructional design but also did not differ significantly from the active participants. It is possible, that they do benefit a bit, but by not committing to the recommendations the benefit is only limited. We also found that 47.6 % of students (in the AS 2017/18) were not active online. Unfortunately, it was not possible in our study to control further learning activities (such as learning offline, face to face discussions, etc.). These learning activities could have had an impact as well.

Further, we found a significant difference between novices and experts in terms of learning progress in both the active group of the AS 2017/18 group and the AS 2016/17 group (control). In both instances the novices showed a more prominent learning progress. The interpretation that this cannot be attributed to adaptive tasks can be justified, as the same difference can be seen in both adaptive and non-adaptive courses. In this context, however, it would be interesting to examine more precisely the learning paths of the individual students in order to determine whether the learning progress can be traced back, among other things, to more success or more and earlier positive feedback, especially in the case of the novices and thus also be attributed to motivational factors. Another possible explanation could be, that the experts started at a point where their potential to improve was just too small. Such a ceiling effect would lead to similar result.

6 CONCLUSIONS

Returning to our three-part research question, whether it is possible to implement an adaptive learning system based on a cognitive learning approach in a classical learning environment (1), to what extent the cognitive factors and technical components mentioned in previous parts contribute to improving learning progress, taking into account the design of the corresponding instructional design (2), and which possibilities this opens up and which limits are set (3), the following conclusions can be drawn:

The instructional design used in this project refers to findings of cognitive load theory and the associated Expertise Reversal Effect. This approach points out that the teaching support helpful to beginners (low level of knowledge) can be superfluous or even harmful to experts (high level of knowledge) and vice versa (Kalyuga, 2007a, b). We have shown that adaptive interventions used for the adaptive learning design of online tasks in mathematics are possible. The consideration of the difficulty of the tasks and the previous knowledge, as well as the students' intermediate solutions in the step loop and the distinction between guided/unguided tasks with a correspondingly elaborated feedback, as selected here, seems to represent a useful and achievable adaptation approach (see e.g. also Brunstein et al., 2009; Hsu et al., 2015; instructions with feedback: e.g. van der Kleij et al., 2015). However, during the development of the design we were also able to note that there are numerous other possibilities for design adaptations and interventions. In this respect, there is the option of further designs can be varied or extended. Some of these methods are much more complex in concept and design, but potentially bring further advantages. For example, the differentiation with regard to the level of knowledge and the associated level of didactic guidance could be refined (e.g. adding a medium level of competence and a medium level of didactic guidance). In this sense we have deliberately concentrated on a rather easy to implement version. Of course there is no standard optimal adaptive teaching design in the field of adaptive learning, but the specific learning objectives and characteristics of the teaching and learning environment should be taken into account. The adaptive, elaborate feedback used here is suitable for learning objects where certain misunderstandings are based on false answers and can be recognized. The distinction between guided and unguided teaching according to the level of knowledge seems to be easy to implement, especially for tasks in mathematics teaching, which require basic previous knowledge.

By confirming our two hypotheses, we were also able to show that high online activity leading to clear learning progress can be realized with both a low and a high level of pre-knowledge. As already mentioned, we have not yet evaluated data on the acceptance and use of the recommendations. In principle, the students were free to decide whether they would follow the recommendations contained in the feedback on the tasks (and on the previous knowledge test). It was also up to the students to decide whether they want to perform a task one time, perform it several times or skip it.

Based on our theoretical assumptions about the concept of the adaptive design, a significant learning effect should be demonstrated for students who have followed the recommendations. In principle, one can assume that learners following such recommendations invest more learning effort or practice more in a well thought-out adaptive system. Therefore, it should also be carefully examined whether more learning effort and practice goes hand in hand with greater learning efficiency. However, it must be taken into account that the design of the user interface has a considerable influence on the learning behaviour and thus also on the learning progress of the students. In particular, the presentation of learning content and the handling of the learning system, lead to an extraneous cognitive load (Sweller et al., 2011). In fact, we have not taken the relevant questions into account in this study. In our further research, however, we will look into these issues more closely. In addition to the Cognitive Load Theory (CLT) for instance various findings from the application of Cognitive theory of Multimedia learning (CTML) can be used (see for an overview Mayer, 2009).

Overall, we have repeatedly been challenged by the fact that technological feasibility alone is no guarantee of the didactic quality of the system. As such, it is therefore appropriate to check and, if necessary, optimise the functioning of implemented components using, for example, empirical learning analytics for the purposes of quality assurance as for instance the measurement performance of the sensors (e.g. normal distribution of the number of points reached in a task, degree of difficulty of the task, etc.) and dependent threshold values are fundamental for the quality of the adaptation system. Although not shown in this paper due excessive length, we validated the measurement performance of the sensors in various smaller test runs and the non-adaptive course which was carried out in the autumn semester 2016/17. Another element for measuring the accuracy of sensors is the awareness of the students in carrying out seriously the assessments. A problem for a reliable and valid measurement is that it requires a careful and serious completion of the tasks by the users. Failure to do so (e.g. quick or unenthusiastic clicking on answer options without proper thinking or trial-and-error strategies) can reduce the reliability of the adjustment basis and thus the informative value of the entire adjustment process. However, it seems difficult to force a serious completion of the tasks when time-consuming sensors are connected with relatively high mental effort. Automatic sensors (such as face scanners or eye-trackers), which will probably be available in everyday learning situations in the future, could solve this problem, since no significant additional time and effort is then required for learners to obtain valid measurements. Such "objective" measurement parameters would function relatively autonomously. A quick recognition of inappropriate (unscrupulous) behaviour would then be possible and instructive interventions could be displayed.

Taking up the third part of our research question, we note that there is currently a controversial discussion about the way adaptive learning systems are controlled. In the concept presented here, we applied a theory-based, rule-based adaptation mechanism and avoided the frequently propagated self-learning mechanism of systems based on artificial intelligence. One reason for this is that simple, theory-based mechanisms are generally understandable for learners if the mechanisms are clearly communicated (Long and Aleven, 2017; Suleman et al., 2016). They can also promote secondary learning objectives such as self-assessment or self-regulation by learners. Mechanisms acquired purely from data technology are often less systematic and logically difficult for learners to understand, since they cannot be assigned to a specific didactic theory. Another reason against self-learning mechanisms was our limited data volume per course module with approx. 100 students. The debate on whether the control mechanism should be rule-based or self-learning is fundamental and advocates of self-learning systems currently seem to dominate the literature. For the reasons mentioned above, careful consideration is necessary to determine in which learning scenarios and for which learning objectives rule-based or self-learning control mechanisms are to be used. In our case it would have made less sense to control the selection of our adaptive, elaborate feedback in the step loop by artificial intelligence, since the formulation of the elaborated feedback itself is based on theory-led rules. Essa (Essa, 2016), for example, argues that artificial intelligence generally seems unsuitable for a step loop adjustment. A combination of rule-based systems with artificial intelligence could also be a useful mechanism. Further research is needed to obtain concrete information on the advantages and disadvantages of the various control mechanisms.

Finally, we hope that the work presented here will help bridge the gap between research and practice and we would like to use our experience to motivate university and distance teachers to test the implementation of rule-based, adaptive designs.

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