# Recommendation Acceptance in a Simple Adaptive Learning System

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*Abstract* - **In the following article we report the current status of our research on integrating a simple, useful adaptive learning system into a university's standard learning management system. In this context, a corresponding instructional design was implemented for a basic mathematics course with the aim of supporting students in their self-study. A rule-based tool was developed for this purpose. The theoretical basis of the design was the Cognitive Load Theory. Based on the principles of this theory, the load on the working memory of the students during learning was to be optimized by appropriate task difficulties. It was expected that the learning performance would be improved. The first results from one of our preliminary studies focusing on learning progress, activity and previous knowledge of different groups of students showed that students who actively worked with adaptive tasks benefited from the system and achieved a greater learning progress than the comparison groups. In the follow-up to this finding, new research questions have arisen for us on the basis of certain limits of the previous study. All of these questions aim to determine whether the positive learning effects can be attributed to the increase in learning activities alone or to following the recommendations or to the interaction of both. In this paper, we present the next research steps in the sense of a framework in order to find the corresponding answers.**

***Keywords - technology-based learning; adaptive learning; recommendation system; cognitive load; learning management system; log files.***

## I. INTRODUCTION

Many areas of our society and social life are increasingly subject to digitalization. This also applies to the area of education and learning. Accordingly, new forms of learning are emerging and gaining importance, such as distance or blended learning concepts or also pure technology-based learning offers. These forms of learning can be distinguished from traditional ones by their flexible characteristics [2]. For example, they enable certain forms of freedom and autonomy, they help to overcome space-time barriers, they open up new opportunities for lifelong learning, or they allow students to complete academic studies even while in full or part-time employment or parenthood. In addition, this flexibility also opens up the opportunity of individualizing or, even more, of personalizing learning on the basis of the heterogeneous characteristics or needs of learners by adapting teaching concepts, curricula, learning contents or tasks to the specific needs of the individuals. In many current training programs, specifically in higher education, it is generally expected that all learners develop the same competences, despite different prerequisites, such as pre-knowledge, learning skills, interests, motivation, social status, life situation, and so on. In addition, the learners in traditional learning offers are given the same or almost no different learning paths or learning support. In contrast to the corresponding traditional "one-size-fits-all" concept, one effective method of achieving learning success is to continuously adapt learning arrangements to the individual needs of students. The importance of adapting learning processes to the individual needs of learners is demonstrated, for example, by a phenomenon known in research on cognitive instruction design as the Expertise Reversal Effect [7][9]. It is shown that, among other things, instructions or specific assistance, which are important for beginners, lose their effect for experts or can even hinder them in their learning. From a technological point of view, adaptive learning environments or adaptive arrangements can be provided within a learning environment by a more or less complex Learning Management System (LMS).

Today, studies on adaptive learning concepts are becoming increasingly common, but practical implementations are still scarce [6][16]. Price et al. [14] argue that there is a gap between research and practice that appears to be systemic in nature and requires change at several levels, including institutional change. FitzGerald et al. [3] in contrast assume that individualization in technology-based learning can be seen as positive and promising, but that its implementation is difficult to realize. While some, such as Murray and Pérez [13], assume that the cause is more to be found in technology-based learning environments, they look to the educational sciences and less to the technological side to drive forward a corresponding transformation. However, in order to bridge the gap between research and practice, we need an interdisciplinary approach with broad-based field studies in appropriate contexts and the further development of sound didactic concepts [15]. In one of our own studies [5] we show, for instance, that a viable adaptive concept for a basic mathematics course (university level) can be realized in a simple way via a standard learning management system (Moodle) using a blended learning scenario during a whole semester. In particular, novices with low pre-knowledge and high learning activity benefit from this concept regarding their learning progress.

On the basis of these results, the present study aims to answer a further question, which has not yet been assessed: whether the positive learning effects found in the preliminary study are attributable to the increase in learning activities or rather to recommendations of the learning system. In the following, the adaptive learning system developed by us is described and the results of the preliminary study are summarized. We then discuss the further research questions and methodological approaches (data collection and evaluation) arising from the limitations of the preliminary study.

## II. Implementation and First exploratory Findings

### A. *Implementation of the Adaptive Learning System and Instruction Design based on the Cognitive Load Theory*

The above-mentioned adaptive learning concept was developed and implemented as part of a degree program for business engineers. For this purpose, we implemented 84 adaptive online tasks and made them available to the students for the autumn semester 2017/18 through the learning platform. The blended learning scenario consisted of 20% learning time as a face-to-face sessions and 80% as self-study. This included literature study on the one hand and the possibility to acquire required skills by intensive practicing with interactive tasks (in this case in adaptive form) on the other hand. The adaptive tasks themselves covered all learning objectives of the course.

Various authors (e.g. [11]) propose a learner model on a theoretical basis for the development of adaptive learning environments. In this context, we focused more on a basic theory of information processing the Cognitive Load Theory [17] as a framework. In this theoretical approach, it is assumed that the working memory has only a limited capacity. Three types of cognitive loads influence its information processing processes. The intrinsic cognitive load (1) arises from the actual learning content respectively from the number of information connections of a learning task. The extraneous cognitive load (2) results from demands outside a learning task and is caused, for example, by the presentation of the learning material or by the teachers themselves. This form of load is increased by unfavorable instructional methods, e.g., by distracting information or unnecessary complexity of a task. The germane cognitive load (3) results from the development of new or the extension of existing cognitive schemata which are stored in the long-term memory. It is regarded as desirable, since new information is built up or the basis for new skills is laid in this context.

Generally, the theory of cognitive load can be applied to any learning context (e.g., offline or online). To improve learning, it is assumed that the intrinsic load should be optimized, supporting measures to promote introduction of germane load and/or minimize extraneous load.

In the present study, we focused especially on the individually adapted improvement of the learning situation with regard to the intrinsic load and the associated extrinsic load [8][10]. Therefore, the difficulty and design of tasks in learning processes were to be planned and regulated in such a way that many resources in the working memory could be kept free for the germane cognitive load and therefore for information processing. Utilizing these assumptions, we designed an adaptive learning process in which learners with low pre-knowledge or low learning performance received much support and guidance when solving mathematical learning tasks so that they were not overburdened by the complexity of the new learning content and information. In contrast, learners with a high level of pre-knowledge or high learning performance received little help and guidance, as superfluous support would disturb them and possibly even impede learning (see the Expertise Reversal Effect [7, 9]). Consequently, mathematical tasks were developed using these learning designs. Each task contained the same mathematical problem and learning goals, but differed in the quantity and type of solution steps and provided different levels of detail or assistance in the case of insufficient performance.

Based on a model by Zimmermann et al. [18], we used three resources to implement the adaptation. These served to continuously measure the characteristics of the learners and the current learning behavior (in the present context learning performance), to compare the measurements with the desired target values, and then, in case of discrepancies, to initiate teaching reactions with the assistance mentioned above. As a first source, results of pre-knowledge tests with which students started their online course activities were used. Depending on the result, the students automatically received feedback on their current knowledge and their classification in our system as "high" performer or "low" performer. Accordingly, they received either detailed tasks with many intermediate steps and much support when classified as low performer or non-detailed tasks with little support for the high performers (see also Figure 1). The second source of adaptation was the solution behavior of the students. The tasks were divided into individual steps or questions depending on performance. When the student answered a question, he immediately received corresponding feedback. In the event of incorrect answers, the student received up to three different types of assistance. The immediate feedback and the corresponding solutions were meant to rapidly close and/or avoid knowledge gaps. The third source of adaptation could be found between the tasks. After each standard task, a transfer task was recommended to the students in order to work on the respective learning objective again. This horizontal learning transfer was supposed to help to test and to stabilize the knowledge. Transfer tasks were similar to standard tasks. They dealt with a similar or slightly different problems than the standard tasks and could be solved with mathematical methods already learned. Depending on their performance, low performers were recommended to perform the detailed standard task again or a non-detailed transfer task, while high performers were suggested to perform either the detailed standard task or a non-detailed transfer task. Under certain circumstances, high performers may also have received a suggestion to proceed to a new task set. In the other cases, however, this only happened with good performance in the transfer tasks. The various adaptive learning paths are shown in an overview in Figure 1. For a more detailed description of the learning system see [5].

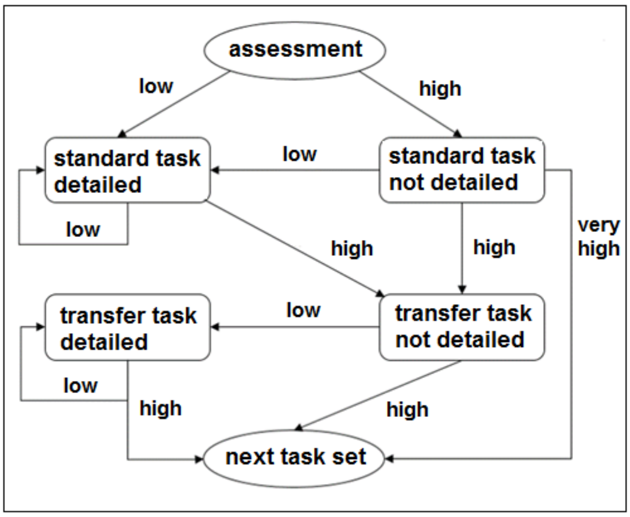


Figure 1. Task Set for a Learning Goal

The entire adaptive system was based on recommendations. Students could follow them or decide not to. Thus, the intention was that the students have to make their own learning decisions, which in turn helped to assess their own learning. The recommendations were guided by a pre-defined set of rules. Defined threshold values for the number of points achieved defined which task was recommended next (see also Figure 1 and for more details [5]).

The entire adaptive learning system was based on a standard Learning Management System (Moodle) without additional plugin. It worked with the conditions/restrictions that were available in the core of Moodle (from version 3.3+ on). A specific advantage of this variant without plugin was a guaranteed stability. Using plugins often lead to problems and revisions due to possible compatibility problems between core and plugin when updating.

### B. *Current Findings and new Research Questions*

In a first explorative analysis [5] of the adaptive concept for a basic mathematics course, we focused on possible performance improvements of students by investigating the relationship between three variables: pre-knowledge (in other words low performer and high performer), online activity (log files), and learning progress. It turned out that students working actively online in the adaptive course achieved significantly better learning progress than the students who did not. The learning progress was defined as the difference between the results of the prior knowledge test, standardized to 100, and the results of the final examination, also standardized to 100. The average learning progress of the "inactive" students was 8.4, that of the "active" ones 32.4 (the difference is significant, verified by a t-test, $p < 0.05$).

In addition, the analysis showed that the active low performers in an adaptive version of the course showed significantly higher learning progress compared to all low performers in a non-adaptive variant of the same course (mean value of active low performer in the adaptive course: 49.2, mean value of all low performer non-adaptive course: 19.0; tested by a one-sided ANOVA with Tamhane post hoc test, $p = 0.01$).

A comparable result with a significant difference was also found when comparing active high performer of the adaptive course with all high performer of the non-adaptive version (mean value of active high performer in the adaptive course: 22.2, mean value of all high performer in the non-adaptive course: -12.1, tested with a one-sided ANOVA with Tamhane post hoc test, $p = .01$, see also [5]).

On the basis of these results, it could be assumed that the adaptive teaching design, implemented in the learning platform, facilitated the learning progress of active online students compared to a non-adaptive design. However, the analysis was limited in that it was not clear whether the improved learning progress was only due to the increased activity or to the enhancement of learning processes through the optimization of cognitive load (assumption in our design) by following the recommendations of the adaptive system.

In order to clarify this question and to continue the work, we therefore formulated the following four research questions for further investigation.

a. How do the students follow the recommendations?
b. Which parameters best predict the following subsequences (Logs) of the recommendations?
c. Which groups follow the recommendations more?
d. How does following the recommendations affect the learning behavior?

In order to be able to answer these questions, we need a complete tracking of the online activities of the students as well as information on the self-monitoring of the students of their own learning activities. With the current work, we also want to check which recommendations are more likely to be accepted by students and which are not, and in this way modify and improve the recommendation system if necessary.

## III. WORK IN PROGRESS

### A. *Collecting Data*

For further investigation and to answer the research questions, we use self-declaration by the students by evaluating their own mathematical knowledge (by asking short questions at the beginning of the course and storing the answers in the database of the learning platform) and also by individual log files or entire sequences of log files with time stamp. Each online action of a user is tracked and registered in a database in the following form: Time stamp of the action, personal identification of the user and event name.

This creates sequences of log files that can indicate what the user has done in what time. This also means that it is possible to track which tasks (steps) were processed at which time in which action sequence, trial amount and also results (e.g., right/wrong). It is also possible to check on the basis of the log file sequences whether the tasks were processed according to the rule based recommendations (see Figure 1) or whether the users performed other online actions in between. In addition, it is also possible to estimate how much time elapsed between the recommendations and the subsequent actions.

With the above data, we will test and validate three methodological assessment procedures to obtain an indicator of "how students follow the recommendations":

1. In the first procedure, we consider only the next entry in the database that follows the recommendation. So, we check whether students go directly to the next recommended task without doing another online activity first. We assume that the students who directly execute the system's recommendations are less self-monitoring in their own learning. The index is calculated as the percentage of recommendations followed.
2. The second method is to look at a sequence of log files after the student has received a recommendation. This involves observing when students follow recommendations and how much online activity they perform before they follow a recommendation [1][4][12]. We assume that these students monitor their own learning behavior more closely and accept a recommendation accordingly or do not follow it after consideration. For this purpose, we want to measure the average number of logs until the student starts the recommended online activity.
3. In the third procedure, as an alternative to the two previous methods, we will use, for students who followed a recommendation, the average time until the student starts a corresponding online activity after a recommendation as an index.

### *B. Data evaluation*

For the first two procedures, we will test the predictive validity and for the third method, we will check whether integration of "time" as an additional parameter results in a better predictive power.

With a focus on all above mentioned research questions, we intend to combine the data resulting from the above-mentioned methods with different groups of students. One criterion for the differentiation of students is their self-evaluated mathematical knowledge at the beginning of their studies. It is then analyzed whether different evaluations have an influence on the acceptance of the system's recommendations. A further goal is to determine how different prior knowledge (measured by the standard mathematical test of the adaptive system) influences the following of recommendations. The same relationships are also explored for the frequency and type (self-monitoring) of online activities (recorded by logs) and learning performance (progress and performance in the final test).

The results of the study should be available by the end of 2019 and published subsequently.

## REFERENCES


[1] A. Abbott, “Sequence Analysis: New Methods for old Ideas,” Annual Review of Sociology, 21(1), pp. 93-113, 1995. https://doi: 10.1146/annurev.so.21.080195.000521

[2] P. Bergamin, E. Werlen, E. Siegenthaler, and S. Ziska, "The Relationship between Flexible and Self-Regulated Learning in Open and Distance Universities," International Review of Research in Open and Distance Learning, vol. 13, no. 2, pp. 101–123, 2012.

[3] E. FitzGerald et al., "Dimensions of Personalisation in Technologyenhanced Learning: A Framework and Implications for Design," British Journal of Educational Technology, 2017. https://doi.org/10.1111/bjet.12534

[4] A. Gabadinho, G. Ritschard, N. S. Mueller, and M. Studer, "Analyzing and Visualizing State Sequences in R with TraMineR," Journal of Statistical Software, 40(4), pp. 1-37, 2011.

[5] M. Holthaus, F. Hirt, and P. Bergamin, "Simple and Effective: An Adaptive Instructional Design for Mathematics Implemented in a Standard Learning Management System," CHIRA 2018 - 2nd International Conference on Computer-Human Interaction Research and Applications - Proceedings, pp. 116 - 126, 2018.

[6] L. Johnson et al., "NMC Horizon Report: 2016 Higher Education Edition." Austin, Texas: The New Media Consortium, 2016.

[7] S. Kalyuga, "Expertise Reversal Effect and Its Implications for Learner-Tailored Instruction," Educational Psychology Review, 19(4), pp.509–539, 2007.

[8] S. Kalyuga, "Cognitive Load Theory: How Many Types of Load Does It Really Need," Educational Psychology Review, 23(1), pp. 1-19, 2011. https://doi.org/10.1007/s10648-010-9150-7

[9] S. Kalyuga, P. Ayres, P. Chandler, and J. Sweller, "The Expertise Reversal Effect," Educational Psychologist, 38(1), pp.23–3, 2003.

[10] S. Kalyuga and A.-M. Singh, "Rethinking the Boundaries of Cognitive Load Theory in Complex Learning," Educational Psychology Review, 28(4), pp. 831-852, 2016.

[11] C. Limongelli, F. Sciarrone, M. Temperini, and G. Vaste, “Adaptive Learning with the LS-PLAN System: a Field Evaluation,” IEEE Transactions on Learning Technologies, 2(3), pp. 203-215, 2009.

[12] Z. Liu, H. Dev, M. Dontcheva, and M. Hoffman, "Mining, Pruning and Visualizing Frequent Patterns for Temporal Event Sequence Analysis," Proceedings of the IEEE VIS 2016 Workshop on Temporal & Sequential Event Analysis, 2016. http://eventevent.github.io

[13] M. C. Murray and J. Pérez, "Informing and Performing: A Study Comparing Adaptive Learning to Traditional Learning," Informing Science, 18(1), pp.111–125, 2015.

[14] L. Price, D. Casanova, and S. Orwell, "Modeling an Institutional Approach to Developing Technology Enabled Learning: Closing the Gap between Research and Practice," INTED2017 Proceedings, pp.5009–5018, 2017.

[15] E. Scanlon, T. O'Shea, and P. McAndrew, "Technology-Enhanced Learning : Evidence-based Improvement," L@S '15 Proceedings of the Second (2015) ACM Conference on

Learning @ Scale." Vancouver, BC, Canada: ACM New York, NY, USA, pp. 229–232, 2015.

[16] S. Somyürek, "The New Trends in Adaptive Educational Hypermedia Systems," International Review of Research in Open and Distributed Learning, 16(1), pp.221–241, 2015.

[17] J. Sweller, "Cognitive Load During Problem Solving: Effects on Learning, "Cognitive Science, 12(2), pp. 257-285, 1988.

[18] A. Zimmermann, M. Specht, and A. Lorenz, "Personalization and Context Management," User Modeling and User-Adapted Interaction, 15(3), pp. 275-302, 2005.