

A Crowdsourcing-based Learning Approach to activate Active Learning

Agnes Koschmider¹, Mario Schaarschmidt²

Abstract: Usually students consume learning material and write an exam at the end of the lecture. Such a process follows a summative learning pattern, which can be considered a standard approach at universities. Studies in educational theory indicate, however, that active involvement – instead of passive consumption – should be fostered in learning since active learning proved to be superior to passive learning. To benefit from active learning arrangements, we implemented an active involvement of students into the exam preparation for an introduction to Information Systems course at the University of Cologne. Students were asked to design exercises and provide solutions to selected topics. Subsequently, they received feedback to their submissions, which supports the self-assessment on the subject. An empirical evaluation shows general agreement for such active involvement of students and also indicates that students participating in the task creation are more likely to pass an exam than students denying the participation. This paper presents our crowdsourcing-based learning approach and discusses challenges for its implementation.

Keywords: active learning, learning map, crowdsourcing, information systems education

1 Introduction

Paper-written exams are still the first choice at universities. Due to a reduced effort for the marking of exams, electronically-based examinations (e-exams) are becoming increasingly common [Wi16]. Although a significantly reduced time for marking of e-exams favors them against paper-written exams, still, e-exams have to cope with the challenge that they do not foster individual capabilities of learners. Looking at the process of preparation of e-exams from a role perspective (student, teacher), a variety of activities are undertaken by the lecturer him/herself, who thus takes an active role. The students remain passive, which means that only their passive learning is addressed. According to the Center of Research and Learning (2016) active learning “*is a process whereby students engage in activities, such as reading, writing, discussion, or problem solving that promote analysis, synthesis, and evaluation of class content*”. Studies comparing active against passive learning show that active learning outperforms passive learning in various dimensions such as learning success [We12].

A novel approach of student involvement has been tried at the University of Cologne as a specificity of active learning. Students received the opportunity of an exam bonus for the lecture “Foundations of Information Systems” in the summer term 2016. Their task

¹ Institut AIFB, Karlsruher Institut für Technologie, 76128 Karlsruhe, agnes.koschmider@kit.edu

² ZIHET, Universität Koblenz-Landau, mario.schaarschmidt@uni-koblenz.de

was to design exercises *and* solutions to selected topics and to assign complexity scores to each exercise. One lecturer or teaching assistant was responsible for the marking of a single exercise and accompanying solution proposal and for communicating feedback to students. Peers could also review the submissions of others. About 100 students participated and submitted five exercises and solutions to topics such as Event-Driven Process Chain (EPC), Python, SQL, UML, ERM and HTML. An empirical evaluation that we conducted at the end of the term supports our crowdsourcing-based learning approach and shows that students that participated were more likely to pass an exam than students denying participation. Particularly, the following reasons justify this result from the empirical study:

- The continuous design of exercises and solutions in the semester is a representative of formative learning, which fosters active learning since peers build a map of the learning material already when designing exercises and solutions.
- Lectures received feedback concerning lacks of understandability that pop-upped within the evaluation of exercises and solutions. After the marking of all tasks it became evident that particular topics were not well understood. Lectures can use this feedback in order to recap topics and to improve the teaching [LN05]. Thus, misunderstanding in the learning material is clarified along the course.

Beside the positive effect of passing an exam, the approach of exercise and solution design by students can be used as a foundation to implement individual and individualized e-exams. The large set of exercises forms a repository and is suitable to provide e-exams at individual time and considering individual preferences of students with respect to visualization of exam questions. Moreover, the evaluation shed light on various factors for future intention to participate again in such a bonus program, thus suggesting aspects on how to successfully design such a crowdsourcing-based approach.

This paper of piloting a crowdsourcing-based learning approach is organized as follows. The next section relates our approach to existing approaches in the areas of crowdsourcing and active learning. Section 3 compares the as-is and to-be process of exam preparation and thus demonstrates the benefits of a crowdsourcing-based learning approach. Section 4 presents the results of an empirical evaluation study in the summer term 2016, and Section 5 discusses our lessons learnt. The paper concludes in Section 6 with a discussion on future directions to fully implement such an approach.

2 Related Work

Crowdsourcing refers to spreading tasks to a mostly unknown workforce of professionals or everyday people [Ho06]. The concept has been widely adopted such as for idea generation [Le09]. In line with these applications, crowdsourcing-based learning is related to distributing learning tasks and a suitable approach to support e-assessment and peer evaluation, which are two well established learning instruments. E-assessment

refers to formative, self-assessing of online exams where the lecturers provide the (exam) question pool [De09]. Open question pools of other universities might be integrated in order to broaden the view of the learning material [LN11]. However, the active learning effects are not fully exploited in e-assessment. Within a crowdsourcing-based learning approach, the learners design exercises and solutions and also revise the quality of questions of other peers. Consequently, with such a learning approach their active learning is addressed.

Mutual feedback by students is referred by peer evaluations, which can be considered as a specialization of e-assessment. Students mutually evaluate the achievements of their peers. Numerous empirical studies showed positive effects for this learning instrument [Bo01, LL15]. This finding also resonates with [Sc15], who recommends peer reviewing for seminar papers. A crowdsourcing-based approach goes beyond peer assessment. Learners are requested to design exam exercises and thus to build a map of the learning material [No10]. Their task is to assess the quality of their peers. Moreover, they also have to indicate and evaluate complexity scores of exercises and they must familiarize themselves with representation of exam tasks, which might be different to the own preferences (e.g., visual vs. text). Approaches in favor of using crowdsourcing in the learning process can be found in the literature and they support our approach. For instance, [We12] recommends crowdsourcing in combination with personalized online education in order to reach full potentials of online education. [An11] points to positive effects of crowdsourcing for judging of answers by peers. [CM12] found out that crowdsourcing can offer additional richness for accreditation and assessment.

To sum up, crowdsourcing in learning is in its infancy particularly when it comes to practical use in learning. Initial empirical studies, however, indicate positive effects compared to conventional learning. Thus, these studies justify our research of a crowdsourcing-based learning approach. The initial idea of our crowdsourcing-based learning approach thus without any presentation of evaluation, discussions and lessons learnt has been published within a short paper [KB16].

3 As-is and to-be process of exam preparation

To elucidate the benefits of the crowdsourcing-based learning approach we now compare it with the common as-is process of exam preparation. The as-is process starts with the preparation of exam questions by the lecturer based on a selected set of topics. Subsequently the questions are composed to an exam where quality assurance (i.e., acknowledging the correctness of the way exam questions are proposed along with ensuring suitable solutions) is subject to lecturers. At a predefined time, the exams are written either on paper or at a computer-based system and the exam is supervised by the lecturer or research assistants. Next, the exams are marked either by a system (in case of a multiple-choice-based e-exam) or by hand (in case of paper-written exams). Finally, the results are published.

Against this “conventional” exam process, we suggest the following process (*to-be*), which is inspired by crowdsourcing [Ho06]. Instead of writing exams that are predefined by lecturers, students provide exercises and solutions for exams. They indicate levels of difficulty and scores for the questions. The evaluation of exercises and solutions is mutually conducted by the students. The students also mutually benchmark, validate the scores of the exercises and solutions and improve exercises based on a star rating, which is common to them (e.g., classification for hotels, restaurants or services in the internet). The benchmark can be done using a system being equipped with corresponding features. The final quality of the exam questions and solutions, however, is still subject to the lecturer. He/she decides if exercises are still not mature enough or not appropriate as exam questions and drops them out of the system. When an exam should be conducted, then the system composes an exam out of the students’ exercises. Comparing the as-is against the to-be process it becomes evident that learners are more involved in the exam process in the crowdsourcing-based learning approach. The to-be process has been partially implemented within the lecture “Foundations of Information Systems” in the summer term 2016. A bonus of at least 15 points (17% of the total exam score) was granted to students if they submitted exercises and solutions to 5 out of 6 topics such as EPC, Python, SQL, UML, ERM and HTML. Around 120 to 150 students attended the lecture on a regularly basis. For each task (i.e., each round of submitting questions and solution), students received a document summarizing the task, which also highlighted associated learning targets. In particular, for EPCs, for example, we stated that “*students should already have understood the syntax and semantics of the Event-Driven Process Chain and have to apply the modeling notation correctly.*” This learning target excluded exercises towards the syntax of EPC such as “Right or wrong: an EPC consists of rectangles”. After this initial clarification, example exercises, solutions, and possible difficulty scores were communicated to the students as well as a tool recommendation. The students had one week of time for submission. One lecturer or teaching assistant was in charge of marking a topic in order to detect cheating and duplicates in the question pool. Examples of very good and comparatively bad question-solution pairs were discussed in the next session. Individual feedback could be provided upon request. In addition, topics were recapped where a lack of understandability was identified.

To validate our crowdsourcing-based approach demonstrated on the process of exam preparation the next section presents results of an empirical study.

4 Evaluation

The evaluation of the crowdsourcing-based learning approach is split into two separate parts. Part 1 involves the analysis of students’ success in both the bonus program as well as the final exam as such. Part 2 consists of a post-exam survey among students to identify drivers and barriers of participation and future intention to participate in such a program.

Concerning part 1, we analyzed exam and bonus program results. For reasons of anonymity, we only compared exam and bonus program results, but did not merge them with the survey in part 2 or any other demographic (e.g., age, semester). Officially, 227 students were registered to the course, of which approximately 120-150 participated on a regularly basis (based on simple counting by the lecturer). Students could choose among two exam dates, one two weeks after the last session and the other at the beginning of the next semester. Our analysis is limited to students who participated in the first exam. Ninety students took part in this exam. Of these students, 83 participated in the bonus program, meaning that they submitted at least one out of five exercises. The students could receive 15 bonus points in total. On a descriptive basis, the following aspects are notable (without providing theoretical explanations):

- Ten students did not pass the exam, of which seven did not participate in the bonus program.
- Students who scored 1.0 or 1.3 in the exam (the two best possible grades in the German system) received 13.28 bonus points (SD = .3) on average.
- The average grade of those students who had received 14 or 15 bonus points, got a median grade of 1.7 (Note: Possible grades are 1.0, 1.3, 1.7, 2.0, 2.3, 2.7, ... 5.0, i.e., not passed)
- Students who would not have passed the exam without applying bonus points got 10.4 bonus points on average.

Part 2 of our evaluation is based on a survey among course participants. First, shortly after the course has ended, we discussed the perceptions concerning the bonus concept as such with a group of selected students as well as course tutors. Their perceptions helped to identify questions of concern and helped to abandon questions that were not perceived as relevant by the target group. We also discussed the entire bonus program-approach as well as the evaluation with experts in didactics and learning.

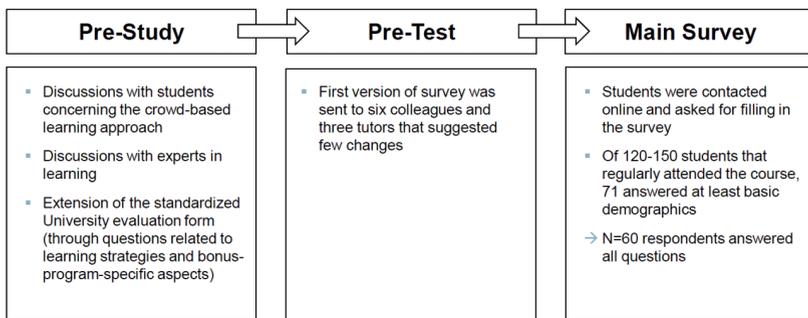


Fig. 1: Process of survey-based evaluation

Based on these insights, we developed a first version of a questionnaire, which consisted of university-wide standardized questions pertaining to the course and the lecturer, enriched by questions related to the bonus program and exam. Finally, students were contacted online through the course management system and were asked to complete the

questionnaire. This invitation was sent out three weeks after the first exam was held. We sent out one reminder one week later. Of the 227 students registered in the course system, 84 started to answer questions, but only 60 completed the entire survey. The entire process of Part 2 of our evaluation is depicted in Figure 3.

Among the 60 students who completely filled in the questionnaire, 34 (56.7%) were women, which reflects the course structure quite well (Note: 95% of the students were enrolled in business administration). Respondents' average age was 22 years and the mean semester they studied in was 4.23. We also asked about their average grades received prior to taking the course. Respondents indicated to have an average grade of 1.67 (in a German system were grades start with 1 [best] until 5 [not passed]). We also assessed the effort a student invested in a) preparing the exam and b) preparing exercises for the bonus program. Respondents indicated to have invested a total of about 60 hours for exam preparation, and about 3.5 hours per exercise they submitted. Table 1 provides an overview on descriptive aspects of the sample.

	#	%	Mean	SD
Gender				
Male	26	43.3%		
Female	34	56.7%		
Age			22.18	2.30
Semester			4.23	1.94
Average grade (self-rated)			1.67	.94
Effort for exam preparation (in hours; total)*			60.68	40.96
Effort for bonus program participation (in hours, per exercise)			3.52	2.62

*Only $N=40$ students who attended the first exam answered this question.

Tab. 1: Descriptive evaluation results

Another reliable indicator of this crowdsourcing-based learning approach's success (apart from the ratio of failed exams) is the students' future intention to participate in the program. The survey therefore also contained an item that asked whether or not students would participate again in such a bonus program. Of the 60 respondents, 51 agreed to be willing to participate again, while only nine indicated to not be willing to participate again. While the overall number of 85% agreement on future participation seems promising, we were also interested in what drives or impedes future intention. Based on discussions mentioned above, we decided to focus on a distinction between bonus program specific aspects of future intention and aspects that were related to students' learning strategies and achievement goal orientations. For goal orientation, we relied on the conceptualization by Ames and Archer [AA88], who distinguish mastery goal orientation from performance goal orientation. Students that favor a mastery goal performance are driven by the willingness to develop new skills and abilities. They value the process of learning itself regardless of the final outcome. With a performance goal

orientation, in contrast, students value normative high outcomes such as achieving success with little effort or outperforming others. [AA88] differentiate both forms of achievement goals in terms of eight dimensions. We adopt three of these eight dimensions based on the applicability to our research context: aspects of success, reasons for satisfaction, and focus of attention. For each facet, we adapted one item for both achievement goal orientations (see Table 2). In addition, we integrated two items on deep learning strategies, also inspired by Ames and Archer [AA88].

Question	Factor 1	Factor 2	Factor 3
1 I rate success in my studies as the reception of good grades. [PER1]	.829		
2 I am satisfied with my studies when I am better than others. [PER2]	.864		
4 I rate success in my studies as my personal improvements. [MAS1]		.526	
5 I am satisfied with my studies when I have worked hard [MAS2]		.778	
6 I focus my attention primarily to my own learning progress. [MAS3]		.656	
7 During the course “_____”, I tried to pursue a deep learning strategy [LS1]			.852
8 I set my own goals for the course “_____”.			.796

*Note: Item 3 was not included in this analysis, because it revealed a low factor loading of below .5. Values below .4 are not displayed

Tab. 2: Factor analysis on goal orientation and learnings strategy

To analyze the psychometric validity of our measure of achievement goal orientation and learning strategy, we conducted an exploratory factor analysis with Varimax rotation and Kaiser normalization. The results of this assessment are shown in Table 2. Based on Eigenvalues > 1 , three distinct factors emerged. We had to exclude one item that represented “focus of attention” due to low factor loadings. After removing it, none of the items cross-loaded onto other factors (i.e., no crossloading of above .4). All other loadings remain stable and above .5. Thus, the three factors represent performance goal, mastery goal and deep learning strategy quite well and can be used for further analyses.

Next, we tested a model of bonus program-specific and student learning-related aspects of students’ future intention to participate in a bonus program again (see Figure 4). In addition to the three factors that stem out of the factor analysis (i.e. student learning-related aspects), we integrated two aspects that relate to the design of the bonus program as such, both measured with a single item based on discussions with students and tutors. We note that according to [BR07], the application of single item measures is appropriate, when the underlying aspects can be represented by a single item. The first item relates to

the difficulty of designing an exercise along with a solution (i.e. task difficulty) and reads: “I perceived developing exercises generally as difficult”. The second item pertains to fairness in the sense of a ratio between effort and outcome (i.e. adequate effort) and reads “The effort required to develop exercises stood in an adequate relation to the result in form of extra points”.

As the questionnaire started with standardized questions concerning the course as such, which were designed to align with the German system where ‘1’ indicates ‘very good’, we anchored the additional questions concerning the bonus program and learning strategies with ‘1’ = fully agree to ‘5’ = fully disagree to not bemuse participants. However, to better be able to interpret results in relation to the dependent variable future intention, which was coded ‘0’ = future intention NO and ‘1’ = future intention YES, we reverse coded all items prior to putting them into analyses. Based on this procedure, we observed that task difficulty ($M = 3.52$, $SD = 1.05$) was rated a little higher than adequate effort ($M = 2.82$, $SD = 1.21$), indicating that the tasks were generally perceived as demanding.

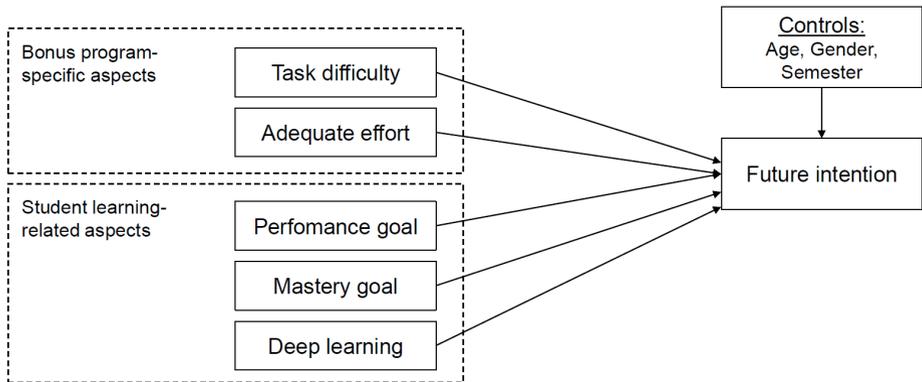


Fig. 2: Conceptual model

As our dependent variable is of a dichotomous nature, we applied logistic regressions to assess the effects of the antecedents of future intention to participate [HL04]. The logistic regression including all study participants ($n = 60$) expressed the predicted values as probabilities and the predicted proportion of students willing to participate in the future as the logistic model $\exp(X)/(1+\exp(X))$, where X is a linear function of the independent variables. As the results in Table 3 indicate, the overall model predicting future intention revealed good fit, as indicated by appropriate R^2 values. In addition, the [HL04] measure of overall fit was not significant ($\chi^2 = 5.412$; $df = 8$; $sig. = .713$). Finally, we can expect that 86.7% of all cases classified correctly, thus indicating an acceptable overall model fit. Table 3 provided the results for the test of factors affecting future intention to participate. None of the controls, that is, age, gender, and semester, showed a significant influence on future intention. In addition, neither performance goal orientation nor mastery goal orientation revealed any significant relationship with the dependent variable. Finally, of the two aspects reflecting bonus program-specific facets,

namely task difficulty and adequate effort, only adequate effort had a significant predictive power ($B = 3.03$, $\text{Exp}(B) = 20.586$); meaning that a one-unit increase in adequate effort increases the likelihood of future intention by 20.586.

	B	S.E.	Wald	Sig.	Exp(B)
<i>Co-variables</i>					
Age	.33	.37	.77	.380	1.385
Gender	-.83	1.21	.47	.493	.436
Semester	.38	.37	1.07	.300	1.465
<i>Predictor variables</i>					
Task difficulty	-.06	.49	.02	.895	.937
Adequate effort	3.03	1.22	6.17	.013	20.586
Performance goal	.26	.66	.16	.689	1.301
Mastery goal	.49	.60	.68	.410	1.637
Deep learning strategy	.52	.48	1.20	.274	1.684
Constant	-11.15	8.79	1.61	.205	.000
N	60				
Cox & Snell R ²	.319				
Nagelkerkes R ²	.558				
-2 log-Likelihood	287.714				

Tab. 3: Logistic regression results; DV: Future intention

5 Lessons learnt

The evaluation results show that students are satisfied with our approach of crowdsourcing-based learning on various dimensions, as indicated by a high number of students that are willing to participate in the bonus program again and an overall satisfaction level with course as such (including the impression of how well the lecturer performed) of 2.2 on a scale from 1 to 6. There are several lessons learnt on which we like to report. First, according to our first implementation of a crowdsourcing-based learning approach, bonus points are a sufficient incentive for students to participate in a crowdsourcing-based learning arrangement. Of course, setting this incentive too high will stimulate participation but not necessarily activate active learning among the entire group of learners to the same degree an “adequate” bonus would do. As adequate effort was rated comparatively moderate ($M = 2.82$, $SD = 1.21$, on a 5-point scale), we are confident to have balanced our demands and related bonus in a “fair” way. Nevertheless, future research could investigate how different incentives in form of bonus points affect satisfaction and learning success.

Second, the implementation of the approach was new to us. Therefore, we used comments of students after each round of exercises to continuously improve the approach. However, offering this opportunity when little teaching resources available is demanding, as the time between two waves of submitted bonus works is relatively short to implement changes to a satisfying degree.

Third, according to our impressions, students need as much documentation as possible. A detailed description of the task and an example exercise and solution for each task must be handed to the students. If students have to grade exercises (i.e., assigning a complexity score) then comparative example exercises with scores must be handed as well. Otherwise, students tend to submit “simple” exercises with high complexity scores and are disappointed when not receiving full points. Our evaluation schema benchmarked the design of the exercise (appropriateness of complexity score vs. complexity of the exercise) and the design of the solution (correctness, detailed documentation). Additional points were granted if the submitted exercises differed from the example exercise pointing to creativity of the student.

Finally, within several discussions with experts and administration staff, we learnt that our crowdsourcing-based learning approach is particularly useful when exams are only marked with “pass” and “failed” and not with grades like 1.0, 1.3, 1.7, 2.0, 2.3, 2.7, ... 5.0. The assessment schema “pass” or “failed” is currently superior as it does more comply with current German exam requirements (e.g., requirement that each student must receive an exam that equals other exams in terms of complexity).

6 Conclusion and Future Directions

This paper presented a crowdsourcing-based learning approach for active learning including an evaluation study. The approach has been illustrated on the process of exam preparation. Students were asked along the complete semester to design exam exercises and solutions for selected topics of the lecture “Information Systems”. The self-creation of exam exercises is the foundation of a crowdsourcing-based learning approach. Our empirical evaluation has shown that an exam bonus is a sufficient incentive. However, the effort required to develop exercises should be in an adequate relationship to the result in form of bonus points. However, several technical, conceptual (exam design), and administrative challenges must be solved to unravel the full potential of the approach.

The first challenge to be addressed is the comparability of the automatically generated exam questions. The current course content management system allows to generate an exam from predefined questions or to compose the exam from randomly selected questions but is limited when it comes to assigning complexity scores. To make the (automatically composed) exams comparable, the self-assessed complexity of exercises by students can be taken into consideration as well as statistical measures, which rate the fulfillment of learning objectives per question type. According to [SG06] students are able to grade in a similar way as teachers when the scoring rubric is trained to them. In our context, a star rating system with a scale from 1 (= low) to 5 (=high) seems to be an

appropriate grading system since the use of the rating system is known by students (and also no training effort would be necessary). Thus, first the student self-assesses his/her exercise and then peers assess the complexity of the exercise resulting in an average star value, which gives a rough picture of the complexity of the exercise. The average star value is considered in the composition of exams.

The second challenge addresses the effort for *quality assurance* (revision) of questions by the lecturer. This effort should be reasonable (lower) compared to the effort for marking of paper-written tests. Students already reduce the revision effort of the lecturer when revising the exercises of their peers (they improve the language as well as the concepts). The effort decreases from one student to the next. The final quality assurance, however, should be a task of the lecturer. A future direction would be to investigate influences of the review process on quality of the revision of exercises. In addition, research could ask if there is a correlation between the number of revision cycles and the knowledge and expertise of students.

The third challenge of the crowdsourcing-based learning approach is the compatibility between automatically generated exams and University's examination regulations. It is likely that changes to examination regulations are necessary before individual exams can be offered to students. These changes affect Intellectual Property (IP) (i.e. who is the user of the exercises and who the owner?). Students create an exercise and the solution. Then peers revise the exercises and solutions. Finally, the lecturer approves the quality (this might also lead to adaptations of question/answer pairs). Consequently, a discussion might arise that the final exercise (which was iteratively revised) belongs to several parties (the student, peers and lecturer) and how these groups enforce their IP rights. Similar discussions arose around "owners of peer reviews" ([Be10, Cr15]) and studies have been conducted to find answers. Comparative analysis investigating correlations between student exercise quality and the final review quality are still outstanding, but would be fundamental to a crowdsourcing-based learning approach. Thus, we call for future research that combines crowdsourcing-based active learning with IP issues.

Bibliography

- [AA88] Ames, C.; Archer, J.: Achievement goals in the classroom: Students' learning strategies and motivation processes. *Journal of Educational Psychology* 80/3, S. 260–267, 1988.
- [An11] Anderson, M.: Crowdsourcing Higher Education: A Design Proposal for Distributed Learning. *Journal of Online Learning and Teaching*, 7/4, S. 576–590, 2011.
- [Be10] Bernstein, D.: Peer Review and Evaluation of the Intellectual Work of Teaching. *Change. the Magazine of Higher Education* 40/2. S. 48–51, 2010.
- [Bo01] Boud, D.: Introduction: Making the Move to Peer Learning. in: *Peer learning in higher education*, Kogan Page, S. 1–14, 2001.
- [BR07] Bergkvist, L.; Rossiter, J.R.: The predictive validity of multiple-item versus single-item measures of the same constructs. *Journal of Marketing Research*, 44/2, S. 175–184,

2007.

- [Ce16] Center of Research and Learning: Active Learning. University of Michigan, Center for Research on Learning and Teaching, 2016, <http://www.crlt.umich.edu/tstrategies/tsal>, Stand: 18.07.2017.
- [CM12] Corneli, J.; Mikroyannidis, A.: Crowdsourcing education on the Web. A rolebased analysis of online learning communities.” in: Collaborative Learning 2.0: Open Educational Resources, IGI Global, S. 272–286, 2012.
- [Cr15] Crotti, D.: The Problem(s) With Credit for Peer Review, 2015, <https://scholarlykitchen.sspnet.org/2015/06/17/the-problems-with-credit-for-peer-review/>, Stand: 18.07.2017.
- [De09] Dermo, J.: e-Assessment and the student learning experience: A survey of student perceptions of e-assessment. *British Journal of Educational Technology* 40/2, S. 203–214, 2009.
- [HL04] Hosmer Jr, D. W.; Lemeshow, S: Applied logistic regression. John Wiley&Sons, 2004.
- [Ho06] Howe, J.: The rise of crowdsourcing. *Wired Magazine* 14/6, 2006.
- [KB16] Koschmider, A.; Buschfeld, D: Shifting the process of exam preparation towards active learning: A crowdsourcing based approach. GI-Jahrestagung 2016, S. 1017–1022, 2016.
- [Le09] Leimeister, J. M.; Huber, M.; Bretschneider, U.; Krmar, H.: Leveraging crowdsourcing: activation-supporting components for IT-based ideas competition. *Journal of Management Information Systems*, 26 /1, S. 197–224, 2009.
- [LL15] Lehmann, K.; Leimeister, J.M.: Theory-Driven Design of an IT-Based Peer Assessment to Assess High Cognitive Levels of Educational Objectives in Large-Scale Learning Services. In: ECIS 2015, Münster, 2015.
- [LN05] Lomas, L.; Nicholls, G.: Peer Review and Evaluation of the Intellectual Work of Teaching. *Quality in Higher Education* 11/2, S. 137–149, 2005.
- [LN11] Lai, Y. C.; Ng, E.: Using wikis to develop student teachers' learning, teaching, and assessment capabilities. *The Internet and Higher Education* 14/1, S. 15–26, 2011.
- [No10] Novak, J. D.: Learning, creating, and using knowledge: Concept maps as facilitative tools in schools and corporations. Routledge, New York, 2010.
- [Sc15] Schlagwein, D.: Students as Reviewers and Lecturers as Editors: The Peer Review with Scaffolded Assignments Model. ICIS 2015, AISNet, Fort Worth, 2015.
- [SG06] Sadler, P.M.; Good, E.: The Impact of Self- and Peer-Grading on Student Learning. *Educational Assessment* 11/1, S. 1–31, 2006.
- [We12] Weld, D. S.; Adar, E.; Chilton, L.; Hoffmann, R.; Horvitz, E.; Koch, M.; Landay, J.; Mausam, C.H.L.: Personalized Online Education - A Crowdsourcing Challenge, 2012.
- [Wi16] Wibowo, S. et al.: A Pilot Study of an Electronic Exam System at an Australian University. *Journal of Educational Technology Systems* 45/1, S. 5–33, 2016.