Chapter # - will be assigned by editors

MONITORING THE USE OF LEARNING STRATEGIES IN A WEB-BASED PRE-COURSE IN MATHEMATICS

A comparison of quantitative and qualitative data sources

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Abstract: With the increasing heterogeneity of first year students' mathematics knowledge, preparatory courses are frequently used by universities to overcome large knowledge differences at the start of tertiary education. Collected at a very early stage, pre-course data could be valuable resources for learning analytics, but little is known about their informational value. This issue is explored based on quantitative and qualitative evaluations of data collected from a web-based pre-course in mathematics (demographic, test results, survey answers, log files, and interviews). The quantitative analyses revealed a dominant influence of cognitive variables, results in a diagnostic pre-test being the strongest determinant of first year mathematics achievement, which in turn was highly predictive of overall study success. Pre-course participation had a significant but relatively small moderating effect on this relation, suggesting that only students who actively participated in the course managed to improve their starting position at university. The study discusses the difficulties of collecting data from open web-based learning environments, from missing data to interactions between cognitive and meta-cognitive variables. It is argued that qualitative information strongly contributes to understanding the sometimes counterintuitive results of such analyses. Suggestions are made for the design of pre-courses that support "at risk" students' use of learning strategies.

Key words: e-learning, evaluation, learning strategy, mathematics, predictors

1. INTRODUCTION

One of the challenges tertiary institutions have to face is the growing diversity in first year students' educational backgrounds and knowledge levels. Not all undergraduates seem to be adequately prepared for the demands of their course; in technical degree programs many students have knowledge gaps in secondary school mathematics and some even struggle to apply basic (Armstrong & Croft, 1999) or "extremely basic" (Ballard & Johnson, 2004) rules. Such deficits are a considerable threat to academic achievement in STEM subjects (science, technology, engineering, and mathematics) (Croft, Harrison, & Robinson, 2009; Knospe, 2011).

Technical faculties have met this problem by providing preparatory and bridging courses in mathematics, offered face-to-face (Abel & Weber, 2014), online (Krumke, Roegner, Schüler, Seiler, & Stens, 2012) or in blended versions (Biehler, Fischer, & Wassong, 2012). High participation rates suggest that these are welcomed by students (Bargel, 2015). Web-based learning environments have been found particularly useful when addressing heterogeneous groups of learners and students who not (yet) live near the campus. They also allow to collect learner data at a very early point in time, in the "liminal phase" between secondary and tertiary education (Clark & Lovric, 2009).

Such data are considered relevant from different perspectives. First, mathematics test results can be used to predict tertiary achievement in engineering and, based on these observations, develop “early warning systems” for “at risk” students (Greller & Drachsler, 2012). Second, analyzing learning behavior during the pre-course may help identifying effective and less effective uses of learning strategies. Such observations could result in suggestions for individual learners and thus support their transition to tertiary education. Third, analyses of pre-course outcomes inform practitioners of “what works” and thus contribute to the growing body of literature on “transition pedagogy” (Kift, Nelson, & Clarke, 2010).

The evaluation of preparatory courses, however, can be conceptually and methodologically challenging. Being extra-curricular activities, pre-courses are not mandatory and students are free to participate or withdraw at any time. Such threats to internal consistency may be increased in web-based environments which, compared to traditional face-to-face courses, are characterized by poorer learner commitment (Ashby, Sadera, & Mcnary, 2011; Smith & Ferguson, 2005; Street, 2010) and lower answer rates (Cook, Heath, & Thompson, 2000; Fan & Yan, 2010; Tourangeau, Conrad, & Couper, 2013). Finally, organizational and technical barriers may prohibit relating pre-course learner data to subsequent student performance.

This study measured learner behavior in a web-based pre-course in mathematics and related these outcomes to achievement in five engineering courses at Baden-Wuerttemberg Cooperative State University Mannheim (subsequently abbreviated DHBW for Duale Hochschule Baden-Württemberg). Funded by the joint research project *optes* (www.optes.de), the team at DHBW Mannheim successively developed, revised and re-evaluated the course program consisting of diagnostic self-tests, interactive learning modules, and additional support structures.

Using the theory of self-regulated learning as a theoretical framework, the interplay between students’ pre-conditions when entering the course, their learning behavior, and the learning environment was accounted for in quantitative and qualitative analyses. By exploring which variables positively influenced pre-course learning gains or academic achievement, this study aimed at

- Identification of variables that distinguish between successful and less successful pre-course participation of “at risk” students.
- Clarifying if and how data collected from web-based pre-courses can contribute to the emerging field of learning analytics (Greller & Drachsler, 2012; Scholes, 2016).
- Making suggestions for the support of “at risk” students in the transition phase between secondary and tertiary education.

2. LITERATURE REVIEW

It is generally agreed upon that secondary and tertiary achievement are strongly correlated with each other (Hattie, 2009) and that this relation is of particular relevance in engineering (Ackerman, Kanfer, & Beier, 2013). Thus cognitive predictors like secondary school GPA (Hell, Linsner, & Kurz, 2008; Söderlind & Geschwind, 2017), school grades in mathematics (Liston & O'Donoghue, 2009; Faulkner, Hannigan, & Gill, 2010) as well as placement tests in mathematics (Zhang, Anderson, Ohland, & Thorndyke, 2004; Ehrenberg, 2010; Carr, Bowe, & Ní Fhloinn, 2013) have been found significantly related to measures of academic achievement, like tertiary grade point average (GPA) or retention in STEM subjects.

To isolate the impact of remedial courses from the effect of these cognitive predictors and to quantify their effects has been found difficult. For the UK, Lagerlöf and Seltzer (2009) as well as Di Pietro (2012) found only weak or no effects of participation in a remedial mathematics course on “at risk” students’ achievement in economics. Similar observations were made at US-American universities by Ballard and Johnson (2004), Moss and Yeaton (2006) and Bettinger and Long (2009).

Greefrath, Koepf, and Neugebauer (2016) found that participation in A-level mathematics classes as well as results in a placement test were the strongest predictors of first year mathematics performance in computer science and electrical engineering at two German universities. Participation in a blended pre-course positively affected placement test scores, but not necessarily first year exam grades. The authors suggested that the influence of the pre-course was not strong enough to overpower the dominant role of prior knowledge. Similar observations were made in studies on face-to-face courses by Polaczek and Henn (2008) as well as Abel and Weber (2014).

These studies, however, did not evaluate students' learning activities during the course. Closing knowledge gaps in a relatively short period of time demands a lot of effort and is also likely to be influenced by the course's design. Vuik, Daalderop, Daudt, and van Kints (2012), for example, performed a quantitative evaluation of a web-based course for aerospace engineering and computer science students. In their study pre-course participants outperformed non-participants in their first mathematics exam, particularly when they had been classified "active participants".

When interpreting such results it needs to be considered that the ability to benefit from preparatory courses is dependent on prior domain knowledge, as well. High performing students are more likely to make effective use of learning strategies, to plan and structure the learning process, and to self-evaluate the outcomes of this process (Weinstein, Zimmermann, & Palmer, 1988; Pintrich, Smith, Garcia, & McKeachie, 1991). The concept of self-regulated learning provides a theoretical framework that accounts for the complexity of the learning process and interactions between learner characteristics (e.g. prior knowledge, age, or gender), environmental factors (e.g. design of the course), and the mediating effects of learner behavior (e.g. use of learning strategies) (Azevedo, 2005).

Evaluations of students' use of metacognitive strategies have shown, for example, that time management and organizational strategies are good predictors of academic achievement (Entwistle & McCune, 2004; Barnard, Lan, To, Osland Paton, & Lai, 2009; Barnard-Brak, Lan, & Paton, 2010; Carson, 2011; Credé & Phillips, 2011; Broadbent & Poon, 2015). Inexperienced students and students with poor domain knowledge seem less able to structure and plan the learning process and are more likely to procrastinate (Plant, Ericsson, Hill, & Asberg, 2005; Michinov, Brunot, Le Bohec, Juhel, & Delaval, 2011). The learning environment may positively affect this group's learning behavior by providing external guidance and structure (Azevedo & Cromley, 2004; Artino & Stephens, 2009).

Task strategies like rehearsal or self-monitoring have been found less consistent predictors of achievement; while Morris, Finnegan, and Wu (2005), Samson (2015) and Tempelaar, Rienties, and Giesbers (2015) found that taking self-tests positively affected learning outcomes, two meta-studies reported contradicting results (Broadbent & Poon, 2015) or no effects (Credé & Phillips, 2011).

The effort students put into their learning may also be dependent on motivational aspects like task interest or task value: attitude towards the subject has repeatedly been found to correlate with performance (Robbins et al., 2004; Richardson, Abraham, & Bond, 2012). As mathematics is not the prior study interest of engineering students negative attitudes could be an obstacle for successful pre-course participation (Meyer & Eley, 1999).

The motivation to learn may also be influenced by social interaction with peers and lecturers. Help seeking refers to a learner's ability to activate social resources (Newman, 2002; Karabenick, 2004). As suggested by Zimmerman and Moylan (2009), it indicates a high level of self-regulation if learners seek out help from others to improve their learning. Not all students, however, are able to benefit from help seeking or from peer learning activities, making it difficult to quantify the effects of social environment on achievement (Barnard et al., 2009; Broadbent, 2017).

Finally, students' ability to self-reflect and evaluate the learning process is an essential characteristic of successful learning processes (Zimmerman, Moylan, Hudesman, White, & Flugman, 2011). Learning environments may induce or suppress self-reflection; an extremely high workload, for example, is likely to evoke surface approaches to learning and a stronger focus on grades and scores (Dweck, 1986).

3. METHOD

A multi-method case study was conducted, using quiz and survey results, log files, interviews, and administrative data. Based on Yin's case study framework, the research design was a holistic single case, one university's implementation of a web-based pre-course in mathematics for engineering students (Yin, 2009). The first part of the study used mainly quantitative methods to gain data from whole student cohorts. In-depths insights were captured through a set of guided interviews at the end of the study.

3.1 Pre-course design

Prospective students were able to access the web-based pre-course in June, the first semester started in October. Students could find the course on the university's homepage but were also informed via mailing lists, encouraging them to register and take the diagnostic pre-test. This two hour self-test covered ten mathematical fields, from Arithmetic to Vectors, each addressed by four to six items (see curriculum as suggested by SEFI mathematics working group, 2013, as well as cosh cooperation schule:hochschule, 2014). After submitting the test participants received a diagnostic feedback, suggesting learning contents if test scores per mathematical field fell below a predefined threshold. All learning modules were open for self-study, combining texts, graphs, animations and videos, examples and exercises. At the end of each module students could take a subject-related final test, consisting of 10 to 15 randomized items. Students who wanted additional support in their learning could enroll in either a weeklong face-to-face course or a one-month e-tutoring course.

The complete interactive learning material, animations, tests and surveys were developed by the team at DHBW Mannheim. The technical environment used for this project was the open source learning management system (LMS) Moodle 3.1. Some considerable changes to the LMS's design were made in order to improve usability. The feedback based on students' results in the diagnostic pre-test was significantly improved by a plug-in developed by Dreier (2014) for his student research project in computer science.

At the beginning of the semester, all first year engineering students participated in another diagnostic test, or post-test, taken at the university's computer labs. The post-test covered the same ten mathematical fields and was of similar difficulty (for a more detailed description of course and tool development process see Derr, Hübl, & Ahmed, 2015). The difference between post-test and pre-test result, the gain score, then indicated the learning outcome per student. Figure 1 shows an overview of the different pre-course elements and data sets.

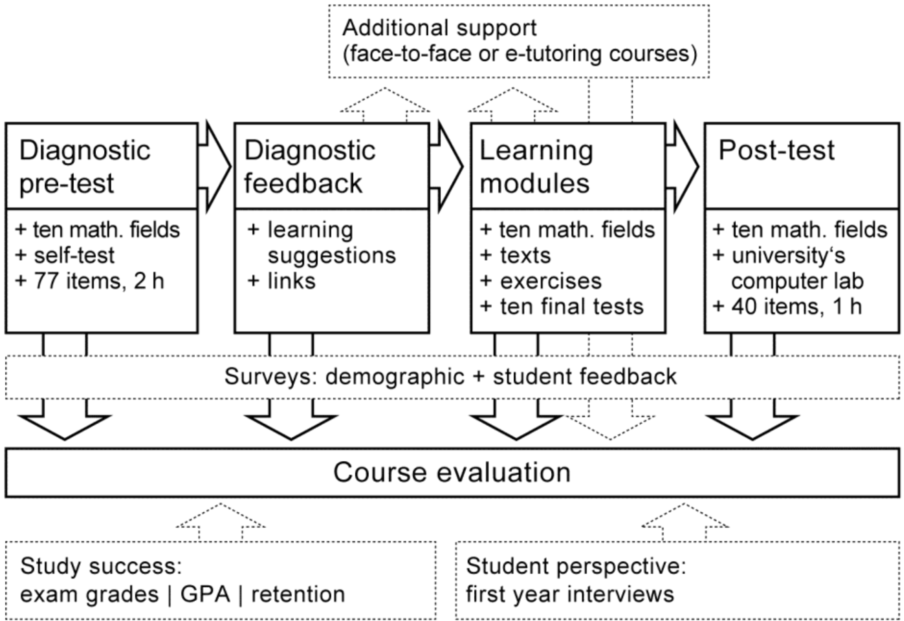

Figure 1. Overview of the design of the pre-course and the data collected for course evaluation

3.2 Data collection

In this report data and results obtained from the years 2014 to 2016 are summarized, but some earlier evaluations will be referred to, as well. Relations between students' prior knowledge, first year performance, and graduation, for example, were analyzed using anonymized administrative data from three complete cohorts who graduated between 2014 and 2016. Table 1 gives an overview of the data. Participants were students from five degree programs (computer science, electrical engineering, industrial engineering, mechatronics, mechanical engineering). Each year between 70 and 80 per cent of all first year students registered on the web-based platform and participated in the diagnostic pre-test (see Table 1). These students were ascribed to the group of pre-course participants (regardless of their learning activities on the platform).

Nearly all first year students participated in the post-test. The first year examination Mathematics I was taken six months later.

The student perspective was based on interviews with nine purposefully selected first year students who had participated in the pre-course and had been considered to be "at risk" based on their pre-test results.

Table 1. Summary of collected data

Interest	Dataset	2014	2015	2016
Pre-course participants				
Prior knowledge in mathematics	diagnostic pre-test	603	551	596
Demographic and attitude towards mathematics	survey	593	535	582
Use of learning strategies	survey	200	117	122
Learning activities	survey and log files	603	551	596
Pre-course learning gains	post-test minus pre-test	603	551	596
Pre-course evaluation	survey	205	117	122
Non-participants				
Prior knowledge in mathematics	post-test	105	156	171
First year students		708	707	767
First year mathematics achievement	exam grades (Mathematics I)	674	660	747
Student experience	interview			9
*Final year students**				
Study success	grade point average	589	650	554

*cohort of 2011 graduated in 2014; cohort of 2012 graduated in 2015; cohort of 2013 graduated in 2016

3.3 Data analysis

3.3.1 Quantitative data

Test results and questionnaire data were inputted into SPSS V 23. Descriptive analyses and single linear regressions were used to analyze and control for interactions between predictive variables. A *p*-value of less than .05 was considered statistically significant; *p*-values of less than .01 or .001 were reported if applicable.

3.3.2 Qualitative data

The interest of the final interview study was to learn about “at risk” students’ experiences in the pre-course and during their first months at university and relate these observations to findings made in the quantitative evaluations. It was expected that the qualitative results would clarify and enrich those outcomes. At the same time, the interviews were to show if further themes that had not yet been addressed would emerge.

The single interviews, ranging from 25 to 35 min, were conducted using a semi-structured interview technique that allowed responding to the situation at hand. A list of open-ended questions was used to guide the interview but varied in order, wording or focus (Robson, 2011). All interviews were digitally recorded, transcribed verbatim by one of the authors, checked for accuracy, and loaded into MAXQDA V12. Each transcript was coded by examining the raw data and identifying statements referring to the study interest. The analysis was performed at two levels, within each case and across cases (Stake, 1994).

3.4 Ethical considerations

The university's data privacy official gave ethical approval. Pre-course participants were informed of the purpose of the study and agreed that their data were collected, anonymized, and evaluated. Students aged under 18 provided parental consent. Tests and questionnaires were completed voluntarily and anonymously. The interviews with first year students were prepared by giving short information about background and goal of the study in selected first year mathematics lectures. An e-mail invitation with an attached information sheet was then sent to all potential participants. Students willing to participate were asked to respond to the researcher by email. Students attended the face-to-face interviews voluntarily and were informed that all data were treated confidentially. The pseudonyms used were Anne, Ben, Chris, Daniel, Eric, Frederic, Julia, Marc and Nora. All data were kept securely and anonymized.

3.5 Limitations

Pre-course participation in this project was free for all entering engineering students, causing a bias that needs to be accounted for in all interpretations.

Regarding the evaluation of tracking data it needs to be considered that only learning activities in the university's LMS could be monitored, but students may also use external links, social networks, learning tools, or apps (Pardo & Kloos, 2011; Tempelaar et al., 2015).

Missing information may also have weakened the representativeness of the scales used in this study. While response rates in the e-tutored courses were acceptable to good (between 64% in 2014 and 38% in 2016), they were relatively poor in the self-study group (27% in 2014 and only 16% in 2016). Distributions in the group of respondents (prior knowledge, first year performance) were not significantly different from the general student body, but it can be assumed that students who participated in the evaluation survey had different mindsets and feelings towards the pre-course than those who did not (Nulty, 2008; Tourangeau et al., 2013).

4. RESULTS

4.1 Prior knowledge in mathematics and study success in engineering

Using data collected from three previous cohorts (entering 2011 to 2013), the first year examination Mathematics I was identified as a significant predictor of study success at the end of the engineering degree program. In a linear regression this exam alone explained up to 43% of the variance in cumulated grade point average (GPA) at the end of the course and thus was considered a good early indicator of study success.

Based on these observations, students' prior knowledge in mathematics was found the strongest determinant of Mathematics I. In a multiple regression results in the diagnostic pre-test outperformed all other person-related variables (including gender, age, gap between school and university, German federal state, type of secondary school, mathematics grades at secondary school, and secondary GPA). In 2014, for example, a student with a pre-test mean score of 40 was predicted Mathematics I grades .6 higher than a similar student with a pre-test mean score of 20 (see Table 3).

Secondary school grade point average (GPA) was the second best predictor of first year mathematics performance (plus .4 grades in Mathematics I for each increase of 1.0 in GPA in 2014). By comparison, the influence of demographic and other school-related variables was weaker and much more inconsistent (for a more detailed quantitative report see Derr, Hübl, & Ahmed, 2018).

4.2 Effects of pre-course participation on first year performance

After having established the relevance of prior knowledge in mathematics for study success in engineering it was investigated if participation in the pre-course would show a moderating effect on this relation. Each year between 70 and 80 per cent of first year students participated in both tests. The average pre-test score (in %) in this group varied between 49.1 (2015) and 51.1 (2016); the average post-test score ranged from 53.9 (2015) to 56.6 (2015). By comparison, students who had *not* participated in the pre-test achieved a post-test mean score between 42.7 (2015) and 47.3 (2014). Between-group difference was significant (p < .01) but in both groups a large variance in test results could be observed (see Figure 2, Table 2).

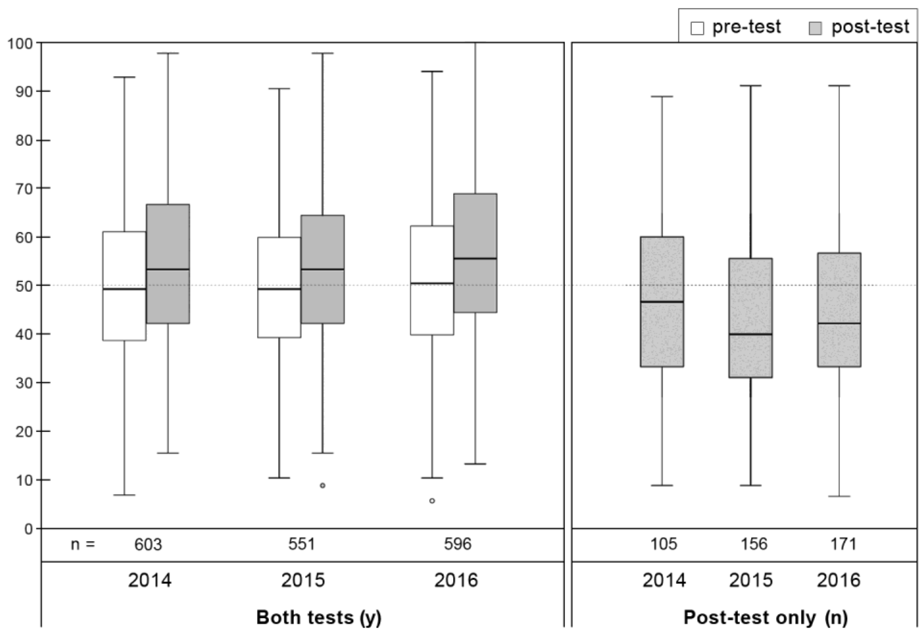

Figure 2. Pre-post-test scores (2014-2016) pre-course participants (= participation both tests) versus non-participants (participation post-test only)

Table 2. Pre-post-test scores (2014-2016) pre-course participants (y) and non-participants (n)

	Both tests (y)						Post-test only (n)		
	2014		2015		2016		2014	2015	2016
	pre-test	post-test	pre-test	post-test	pre-test	post-test			
n	603	603	551	551	596	596	105	156	171
mean	49.7	55.2	49.1	53.9	51.1	56.6	47.3	42.7	43.7
median	49.4	53.3	49.4	53.3	50.6	55.6	46.7	40	42.2
variance	255.4	304.9	215.4	266.5	262	304.4	330.4	288.8	288

The average gain score (post-test minus pre-test) across cohorts was 5.3 (median = 5.7), with a maximum value of 61.8 and a minimum of -40.1. Students with poor pre-test results (mean score < 50), thus considered the “at risk” group, had an average gain score of 8.1 (median = 7.3; max. = 61.8; min. = -25.3).

Added to the multiple regression predicting first year mathematics performance, the gain score significantly contributed to the model. Compared to the dominant role of prior knowledge, this effect was not very strong; a noticeable change in Mathematics I was only predicted for students with very high learning gains. For example, in 2014 a student with a gain score of 20 was predicted an increase in Mathematics I grades by .28 (*B* = .014), compared to a similar student with a gain score of Zero.

Table 3. Regression analysis Mathematics I (2014-2016)

	2014			2015			2016		
	B	*SE B*	β	*B*	*SE B*	β	*B*	*SE B*	β
1 Gender[a]	.17	.12	.06	.03	.12	.01	.16	.11	.06
2 Age (years)	.05	.04	.09	-.04	.05	-.07	-.04	.04	-.07
3 Gap school / university (years)	-.07	.06	-.08	.12	.06	.16	.17	.05	.25
4 Federal State[b]									
Rhineland-Palatinate	.05	.11	.02	.10	.12	.05	.04	.11	.02
Hesse	-.05	.11	-.02	-.05	.12	-.02	-.13	.12	-.05
NRW	-.07	.14	-.02	.10	.15	.03	-.23	.14	-.08
Bavaria	.37	.15	.11*	.16	.14	.06	-.14	.16	-.04
5 Type of school: Gymnasium[c]	.13	.16	.06	.45	.16	.21**	.40	.16	.18*
6 Secondary school mathematics grades	-.06	.14	-.02	.39	.16	.18*	.09	.16	.04
7 Secondary school GPA	.38	.10	.20**	.36	.11	.20**	.62	.10	.36**
8 Pre-test score (%)	.03	.00	.49**	.02	.00	.24**	.02	.00	.26**
9 Gain score (%)	.01	.00	.18**	.01	.00	.13*	.01	.00	.03*
R^2 / R^2 adj.	.35 / .33			.27 / .25			.31 / .29		
F for change in R^2	17.47**			10.21**			13.64**		

B = unstandardized beta coefficient; *SE B* = standard error; β = standardized beta coefficient; *p < .01; **p < .001
[a]baseline: male; [b]baseline: Baden-Wuerttemberg; [c]baseline: vocational school
Mathematics I exam grades measured on a scale from 1 to 5

The quantitative analyses also indicated that pre-course participants on average were able to improve their starting position at university. Students who had *not* participated in the pre-test or the pre-course program showed significantly poorer first year mathematics performance and more failures. The difference between participants and non-participants accounted for distances between .5 and .6 grades in Mathematics I (on a scale from 1 to 5) and ANOVA suggested significant between-group differences for all three cohorts (see Table 4).

Table 4. Mathematics I grades (2014-2016) pre-course participants (y) and non-participants (n)

	2014		2015		2016	
	y	n	y	n	y	n
n	578	96	519	141	583	164
mean	2.8	3.3	2.7	3.3	2.7	3.2
median	2.8	3.3	2.7	3.4	2.7	3.2
variance	0.97	1.24	0.90	0.96	1.01	1.08

ANOVA: 2014: $F(1, 672) = 28.3$, $p < .001$; 2015: $F(1, 658) = 39.7$, $p < .001$; 2016: $F(1, 745) = 29.1$, $p < .001$

The student perspective, as well, suggested a favorable interpretation of pre-course participation; all interviewees claimed that they had benefitted from the course. While these outcomes are only a spotlight and lack representativeness the many positive comments indicate that additional mathematics support was strongly needed and welcomed by students entering tertiary education.

> "And if I hadn't taken part in this pre-course I would have thought: 'Why was he able to just leave out the brackets there?' Because that part isn't explained any more ... And that's why [...] to follow the lecture it really does help." [Frederic]

> "Yes, it was pretty helpful, that you could find out, yeah, okay, that is where you're lacking a bit of knowledge, because otherwise I would have walked right into the first lecture and would have been struck dead. And with this course it wasn't so bad." [Ben]

It also emerged that students were quite aware of the relevance of mathematics for their course and that their first year experience had increased this awareness.

> Julia: "Many pre-course contents were useful later and I thought 'oh, thank goodness I repeated that'."
> Interviewer: "Can you name an example?"
> Julia: "There was this lecture in maths where I noticed that ... Wait, it was prime ... some ization."
> Interviewer: "Prime factorization?"
> Julia: "Exactly. Because then I thought, goodness, where could you possibly need that? And then it was needed in this proof and I was quite happy that I had done that." [Julia]

> "The basics in maths, those aren't highly complicated calculations. You have to be able to solve them quickly and not ponder for three hours." [Nora]

4.3 Drivers of successful pre-course participation

In order to identify variables that helped distinguish between successful and less successful pre-course participation analyses of variance on gain score were performed for different sets of independent variables. All investigations were carried out with a special focus on the group of "at risk" students, thus controlled for prior domain knowledge (=results in the diagnostic pre-test). Variables that showed a significant influence on the gain score were also added to the multiple regression predicting first year achievement in mathematics.

4.3.1 Attitude towards mathematics

Two subscales from the Trends in International Mathematics and Science Study TIMSS were used to investigate the relevance of students' attitudes towards the subject for pre-course learning outcomes (Kadijevich, 2006, p. 41f; Mullis, Martin, Foy, & Arora, 2012, p. 333f). It had been hypothesized that high scores on items like “I am interested in mathematics” (from the subscale “Liking mathematics”) or “I learn things quickly in mathematics” (from the subscale “Self-confidence in learning mathematics”) would positively affect pre-course learning gains.

The scales correlated with each other, thus replicating previously reported relations between mathematics liking and self-confidence (Parsons, Croft, & Harrison, 2009). It should be noted, however, that the results were skewed and that only a minority of students expressed outright negative feelings towards the subject. Very positive attitudes were mainly observed for students with very good results in the diagnostic pre-test. Both attitude scales were unrelated to pre-course learning gains.

In the interviews, all participants stated that they had liked mathematics at school and that they had been good at it. This was remarkable as, based on their pre-test results, all interviewees were in the “at risk” group.

4.3.2 Time management and organizational strategies

Seven items from the subsets “Cognitive and metacognitive Strategies” and “Resource management strategies” of the LIST inventory were related to pre-course learning gains (Schiefele & Wild, 1994). LIST is a German adaptation of the Motivated Strategies for Learning Questionnaire MSLQ (Pintrich et al., 1991). The answer patterns in this analysis were quite irregular; students who “strongly agreed” to items like “I always followed a certain learning schedule” also had high or very high pre-test scores, whereas the rest of the data showed non-linear distributions. The time management and organizational scales thus only allowed to distinguish between students with a very proficient use of learning strategies and the rest of the sample. All seven items were unrelated to the gain score and thus failed to differentiate between more and less successful pre-course participants.

In the interviews students found it difficult to describe how they had planned and structured the learning process. It became apparent that those who had participated in the e-tutored course [Anna, Ben, Marc, Nora] had acted upon the schedule provided by this course while those who studied alone did not follow a certain plan. One exception was Frederic, who had worked through the complete pre-course alone and had managed to complete one learning module per week. In the interview he admitted that he might have benefitted from a course on “learning to learn” and on the issue of time management, but was also skeptical if he would find the time for “yet another course”:

> “And something like that could be useful, maybe a small lecture for time management. But I don’t know if anyone would stick to it, if anybody would really do it [...]. It’s probably difficult to carry out, you just think: ‘Yeah, sure’ but then ... you forget about it.” [Frederic]

4.3.3 Time on task

Different sources to measure quantitative aspects of learning were available, like students’ answers to the evaluation questionnaire (number of learning modules, weeks, hours per week) and the LMS’s log files. Self-reported study time per week, for example, was moderately correlated with outcomes; students who spent more hours learning on average had poorer pre-test results and also higher learning gains. Similarly, the number of learning modules a student had accessed was positively related to the gain score. However, ANOVA or single regression with these variables did not account for significant differences. The interviewees’ accounts of their time on task varied strongly, from “about a day, taken all together” [Chris] to about ten hours per week over a period of ten weeks [Frederic].

4.3.4 Task strategies

Task strategies like reading or rehearsal were measured by tracking the number of learning module pages students had accessed and by the number of (randomized) self-tests submitted at the end of each learning module.

A high number of learning module page views could be ascribed to a higher gain score, but this relation was very weak and not significant. By comparison, the number of test attempts could be related to a significant increase in gain score. Transformed to a four-step ordinal variable, with ‘no test attempts’, ‘1-4 attempts’, ‘5-8 attempts’, and ‘9 and more attempts’, this variable significantly differentiated between higher / lower achievement in the pre-course ($p < .05$).

Summarizing pre-course participation from 2014 to 2016, students with no test attempts on average had the poorest learning gains (gain score = 3.8) and students with 9 and more attempts had an average gain score of 10.4 (Table 5). The effect of this variable was even stronger when the sample was reduced to the “at risk” group (see Table 6).

Table 5. Pre-course gain score of all pre-course participants (2014 -2016) by number of test attempts

	Total (pre-course participants)	Number of test attempts			
		none	1 to 4	5 to 8	9 and more
n	1750	973	490	132	155
mean	5.3	3.8	6.0	7.5	10.4
median	5.6	3.8	6.4	8.1	9.2
variance	162.3	154.1	142.1	221.0	185.0

ANOVA: $F(3, 1746) = 2.8$, $p < .05$

Table 6. Pre-course gain score of "at risk" group (2014 -2016) by number of test attempts

	Total (pre-course participants)	Number of test attempts			
		none	1 to 4	5 to 8	9 and more
n	906	490	274	64	78
mean	8.0	6.4	8.2	13.1	13.8
median	7.3	6.3	7.5	11.3	11.0
variance	160.1	155.7	131.1	174.2	214.8

ANOVA: $F(3, 902) = 11.9$, $p < .001$

4.3.5 Additional face-to-face or e-tutoring support

Two additional support programs were provided: a weeklong face-to-face course and a one-month e-tutoring program. On average, 15 per cent of pre-course participants enrolled in the face-to-face course, 15 per cent in the e-tutoring course, and 70 per cent studied alone.

Students who participated in an additional program had below-average pre-test results. The gain score was significantly affected by the type of course a student had chosen to attend. In 2014, for example, face-to-face course participants had an average gain score of 3.5 ($n = 91$) whereas students who completed the e-tutoring course had an average gain score of 6.7 ($n = 85$). The highest learning gains were achieved by students who had participated in both course types, e-tutoring and face-to-face, with an average gain score of 9.1 (*n* = 28). While learning gains of students in the e-tutoring course were highest, the differences between the different groups were not significant (ANOVA: df1 = 3; df2 = 599; F = 1.578; p = .194).

Descriptive analyses suggested that in the face-to-face course students had even poorer pre-test results and more often had attended vocational schools. Although these differences were not significant there was a tendency that the e-tutoring course was more often chosen by higher performing students. In any case, e-tutoring participants showed much more online learning activities and submitted significantly more test attempts.

It is suggested that the more structured design of the e-tutoring course positively affected students' activity level and was much more efficient than the shorter and less binding face-to-face course that had not demanded the submission of course work.

> "... because, you only got a certificate after submitting all exercise sheets. And I thought that was quite all right because you were somehow forced to do some problems. Because, in hindsight I guess they do help, even if you're not always in the mood to do them." [Ben]

> "I did two courses, one e-tutoring course and one in-class. And I was surprised, because I liked the online course better and I gained much more from it. ... In retrospect I would say that the online course helped me more than the face-to-face course. Despite that, I'm happy that I did both." [Anna]

4.3.6 Social interaction, help-seeking, peer learning

It had been hypothesized that the number of online interactions as an indicator of help seeking would be positively correlated with pre-course learning gains (Macfadyen & Dawson, 2010). The number of forum posts in the e-tutoring course, however, was unrelated to learning gains. The e-tutoring groups were highly heterogeneous regarding communication preferences, and the case numbers were too small for statistical interpretation. Analysis of single cases, as well, did not suggest that a high (or low) number of forum posts was related to achievement.

In the interviews it emerged that students had found it more helpful to learn alone during study preparation. However, social resources and help seeking emerged as highly relevant for the first weeks and months at university. Studying in groups was described as important to understand mathematics problems at tertiary level.

> "Studying in groups is what helps me the most, solving all kinds of problems, and talking it through with somebody, discuss it." [Anna]

> "Well, mostly I prefer studying on my own. But especially in maths I find it makes sense to study in groups. There will always be one person knowing something the others don't. And then the next person gets an idea the others would NEVER have. Yes, I really do think it helps." [Julia]

It also became apparent that not all students had positive attitudes towards learning in groups. Frederic, for example, only chose to participate in a study group after he had failed his first Mathematics I attempt. Ben and Marc found it difficult to benefit from group learning.

> "Well, in general [I prefer studying] alone, because I can concentrate better, because especially when I study in a group, I have often experienced that you easily let yourself be distracted, stray away and then in the end you have been sitting there for four hours and have hardly learnt anything." [Ben]

4.3.7 Self-evaluation and self-reflection

The significant impact of the variable "test attempts" suggested that taking self-tests at different points in time positively affected achievement. The evaluation also revealed that opportunities to practice were highly welcomed by learners. The pre-post-test design in particular helped students to relate their prior knowledge to their individual learning gains. In the interviews it was investigated how interviewees interpreted their test results. Feedback in the form of grades or scores may evoke competitive behavior (Black, Harrison, Lee, Marshall, & Wiliam, 2003) and thus distract students from reflection. The qualitative analyses indeed revealed that some students considered their pre-test result a "negative surprise" [Marc], resulting in feelings of insecurity and a strong motivation to achieve better post-test scores [Frederic].

> "And in the pre-test I think I wasn't THAT good, I only had 40% or so. And then I just, until it really got started, up to then I just did all of the exercises. There was always a test after every exercise and then I just went through everything, and always solved all of the problems. And then there was this post-test again, here at the university and then I even managed to get 75%." [Frederic]

It thus was disappointing for this student that after his efforts in the pre-course he still struggled during his first year and also failed the Mathematics I exam.

5. SUMMARY AND DISCUSSION

5.1 Identification of variables that distinguish between successful and less successful pre-course participation of "at risk" students

In order to evaluate the effects of pre-course participation on engineering study success some underlying presumptions had to be confirmed. First, the relevance of prior knowledge in mathematics for academic achievement in engineering was established by relating pre-conditions (educational background, demographic, prior domain knowledge) to tertiary performance. In these analyses results in a diagnostic pre-test in mathematics emerged as the most dominant predictor of the first year exam Mathematics I. In previous analyses of complete cohorts, Mathematics I had been identified as the best predictor of final year GPA in all five courses.

This study thus contributed to the existing body of literature that placement tests are good predictors of academic achievement in engineering (Zhang et al., 2004; Ehrenberg, 2010; Faulkner et al., 2010; Carr et al., 2013; Abel & Weber, 2014; Greefrath et al., 2016) and that below-average pre-test scores can be considered a risk factor.

To some extent this risk could be reduced by pre-course participation. Pre-course participants showed better Mathematics I results than non-participants and the gain score (difference between post-test and pre-test) significantly contributed to a multiple regression predicting this exam. At the same time, there was a large variance in the data, suggesting that not all students were able to benefit from the course.

From the set of potentially influential factors only one variable emerged that significantly differentiated between successful and less successful pre-course participation of the "at risk" group: Students who repeatedly engaged in self-assessments showed significantly higher learning gains than those who did not. Added to the multiple regression this variable could also be related to a small but significant increase in Mathematics I performance.

Affective and meta-cognitive variables showed only weak or no correlation with learning gains of "at risk" students. Students' attitude towards the subject, for example, seemed to be rather a covariate of prior domain knowledge (Robbins et al., 2004; Richardson et al., 2012) than a factor influencing learning gains.

Two scales addressing the use of time management and organizational strategies were also unrelated to learning gains, an outcome that was inconsistent with the literature (Weinstein et al., 1988; Entwistle & McCune, 2004; Richardson et al., 2012; Broadbent & Poon, 2015). Descriptive analyses revealed interactions with prior domain knowledge; mainly students with a high pre-test result were likely to make use of such strategies whereas for the majority of the sample the data were inconsistent and lacked linearity. Martin (2012), as well, found that mainly high performing students would make use of organizational strategies in an e-learning environment. Based on similar observations, Eley and Meyer (2004) hypothesized that students' sometimes contradicting answers to learning strategy items were representative of the complex and irregular development from an ineffective to a proficient learner.

It is argued that for students with broad knowledge gaps, the "at risk" group, effort-related variables might be more relevant than for other learners (Plant et al., 2005). In our study test attempts showed the strongest impact on this group's achievement. As task strategies like rehearsal and repetition are of particular relevance for the acquisition of basic skills such an outcome may not be surprising: rehearsal helped students to apply mathematical rules more confidently and thus enabled them to follow their first year lectures (Armstrong & Croft, 1999; Meyer, 2000; Ballard & Johnson, 2004).

At the same time, taking self-tests is a means to monitor and evaluate the learning process (Winne, 2004; Zimmerman & Moylan, 2009). Repeatedly engaging in self-tests thus may also be interpreted as an indicator of a higher level of self-reflection.

The qualitative analyses allowed the cautious interpretation that students who participated in study groups in their first year at university were more likely to reflect their learning and to be able to manage the transition to tertiary education. It is thus argued that social interaction and peer learning are indeed highly relevant to evoke self-reflection in "at risk" students, even though such a connection could not be made based on the quantitative analyses.

5.2 Contribution of data collected from web-based pre-courses to the field of learning analytics

It was demonstrated that educational technology is an appropriate way to address learners with heterogeneous knowledge levels by providing them with tools to calibrate and self-monitor their learning (Winne, 2004). Formative self-assessment was found a fundamental driver of the web-based learning process in mathematics. Students highly appreciated opportunities to practice and to monitor their learning (Spector, Ifenthaler, Sampson, & Yang, 2016; Schumacher & Ifenthaler, 2018). The data collected from the pre-post-test design delivered consistent information and allowed to relate prior knowledge and learning gains to measures of academic achievement, thus establishing external validity.

Considering the contribution of pre-course learner data for the field of learning analytics, the most consistent results were obtained from cognitive variables, namely test scores (diagnostic pre- and post-test). The number of test attempts was significantly correlated with pre-course learning gains and thus outperformed other tracking data, like time online, number of page views, or clicks. It is suggested that this variable is a good indicator of effort and engagement in web-based learning environments, which is in agreement with previous research on e-learning (Morris et al., 2005; Samson, 2015; Zacharis, 2015; Tempelaar et al., 2015; Ledermüller & Fallmann, 2017).

The web-based surveys used to collect information on affective and meta-cognitive variables showed less consistent results and particularly failed to explain learning outcomes of the "at risk" group. It may be hypothesized that the sometimes skewed answer patterns were influenced by social desirability. It also has been suggested that in web-based environments surveys are answered less conscientiously (Cook et al., 2000; Nulty, 2008; Fan & Yan, 2010; Tourangeau et al., 2013) and that high performing students find it easier to answer metacognitive items, resulting in interactions between cognitive and meta-cognitive predictors (Case, 2004; Thiessen & Blasius, 2008). Concerns thus might be raised regarding the general idea of "measuring" the use of learning strategies with the help of Likert-scaled items in e-learning environments; probably more sophisticated ways to evaluate e-learning are needed to adequately describe the complex construct of self-regulated learning (Winne & Jamieson-Noel, 2002; Hadwin, Winne, & Nesbit, 2005).

Although some of the data collected from the pre-course were significantly related to first year performance, this study also showed the limitations of predictive models. The multiple regression accounted for 35% of the variance in Mathematics I at most. Thus many students succeeded in spite of a poor pre-test result and there also remained a number of students who performed reasonably well in the pre-test yet failed their course (Robinson & Croft, 2003). The literature suggests that indeed many more factors are involved when it comes to study success (Heublein, Richter, Schmelzer, & Sommer, 2012; Ackerman et al., 2013).

Making individual suggestions based on pre-course data thus does not seem advisable and even may have counterproductive effects. Students with a positive prediction might be provided with a false sense of security (Clark & Lovric, 2009) whereas students with poor prior knowledge might try to avoid the "stigmatization" of being "at risk" (Case, 2004).

It is suggested that quantitative pre-course evaluations have "blind spots" as they fail to inform if students' learning activities remained on the surface or resulted in deeper understanding or self-reflection. It is argued that the current state of technology does not allow to adequately address students who struggle with the learning process and that human tutoring is needed to identify misconceptions. A claim is therefore made to not overemphasize the role of predictive modeling for the individual student.

At the same time, the outcomes of such course evaluations are considered highly relevant for practitioners in this area. Students, as well, should be informed of the outcomes of these analyses and the relevance of basic skills on subsequent achievement at an early point in time.

5.3 Suggestions for the support of "at risk" students in the transition phase between secondary and tertiary education

Based on the observations made in this project we draw the following suggestions for the design of preparatory courses in mathematics:

1. Raise entering students' awareness (in this case for the role of basic knowledge in mathematics) by providing information about the curriculum and tools for self-diagnosis. The results of pre-course evaluations should be made accessible for students; reviewing and discussing data from previous cohorts, for example, can be highly informative and evoke reflection (see example at www.optes.de).
2. Provide an environment to practice and self-monitor learning, fostering the use of task strategies like repetition, rehearsal, and re-activation of existing knowledge.
3. Provide external guidance like weekly schedules, submission dates, and immediate feedback by e-tutors.
4. Introduce students to the use of a set of learning strategies. These should include planning and structuring, self-reflection and analysis and interpretation of test results, but also social aspects like help seeking and how to benefit from group work.

Further research should reveal how e-portfolios can be implemented in mathematics courses and help induce self-reflection (Burks, 2010; McDonald, 2012). Some hands-on-experiments have already been carried out in the optes project, suggesting that it is quite demanding to meaningfully connect cognitive and meta-cognitive learning in an engineering context. It will also have to be explored more deeply how to address not only different levels of domain knowledge but different needs regarding scaffolding and guidance in e-learning environments (Hannafin & Hannafin, 2010).

Finally, our results also draw attention to the issue of increasing heterogeneity in first year students' entry qualifications (Luk, 2005; Ecclestone, Biesta, & Hughes, 2010). Short-term remedial programs like the pre-course described in this study may help to re-activate school knowledge and thus ease the transition to university, but they are certainly not sufficient instruments when it comes to broad and fundamental gaps in knowledge. For many students a prolonged study preparation would be needed, providing the domain and meta-knowledge that is required to successfully study engineering.

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