13th International Congress on Mathematical Education
Hamburg, 24-31 July 2016

LEARNING BEHAVIOUR, ACADEMIC SUCCESS IN ENGINEERING MATHEMATICS, AND LECTURERS' RATINGS

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Understanding and exploring which factors actually facilitate passing written exams is a first step towards supporting first-year students. In our survey, 508 engineering students described their learning behaviour concerning lectures, homework, tutorials, time management, superficial learning, and effort. The data was evaluated in connection with academic performance and university course. Additionally, 10 lecturers who had worked with engineering students in the last five years attributed examination success to the same categories. Our findings stress the importance of weekly assignments, invalidate the notion that future engineers can pass mathematics exams with the help of surface learning techniques, and reveal differences between engineering courses.

INTRODUCTION

The transition from secondary to tertiary education is considered problematic for mathematics (e.g. Liston & O'Donoghue, 2009, Gueudet, 2008). This prompted various studies on how to support first-year students (cf. Biehler, Hochmuth, & Rück, 2013, for Germany). Recently, a research focus on learning strategies has emerged (Dehling et al., 2014). Obstacles vary, but engineering students are expected to quickly master a range of routines. Many studies share the aim of finding a feasible way to improve students' academic performance. Our study contributes to this field.

THEORETICAL BACKGROUND AND RESEARCH QUESTIONS

The obstacles first-year students have to overcome in mathematics have been categorized by de Guzmán, Hodgson, Robert, and Villani (1998) into epistemological / cognitive, sociological / cultural, and didactical difficulties, stressing the range of relevant aspects. Theoretically, transition processes (particularly those from secondary to tertiary education in mathematics) have been described as entering a new world (Tall, 2004), or as resembling a rite of passage (Clark & Lovric, 2008). Quantitatively, Rach (2014, p. 219) identified, among others, mathematical competence and school qualifications as predicting as much as 38% of academic success (in terms of passing a first-year module in calculus), whereas Dieter (2012) and Heublein (2010) explored reasons for failure, listing difficulties to meet the standards and lack of motivation on top. Our research adds insight into what is predictive of academic success for first-year engineering students. We wonder:

RQ1: What structure does the data collected possess?

RQ2a: What are the connections between self-assessed learning behaviour and academic success?

RQ2b: Are there differences for distinctive engineering courses?

RQ3: Can we describe clusters of students with varying learning behaviour? Do they show differences in acedemic achievement?

RQ4: In how far do lecturers' ratings reflect or oppose our findings from the data?

METHODOLOGY

We opted for items covering learning behaviour under the following aspects: weekly assignments (a1 to a8, 8 items), lectures (l1 to l5), tutorials (t1 to t4), deep learning (d1 to d8), surface learning (s1 to s4), and effort (e1, e2). The items were taken from Wild and Schiefele (1994), Himmelbauer (2009) as well as from Trautwein, Lüdtke, Schnyder, and Niggli (2006), via Rach (2014), and rated on 4-point Likert scales with extreme points *not true* (1) and *true* (4). Three lectures were involved, yielding 508 data sets. Additionally, 10 lecturers with recent experience in engineering mathematics rated the percentage of the influence of the different categories on academic success. For them, the categories were complemented by a seventh, *intelligence / talent*, and an open eighth.

73% of the engineering students surveyed were male. The average age was 20.15 years (SD=3.53 years). 66% attended an advanced mathematics course at school, 54% went to a preparation course before university, and 15% did neither. 44% got average marks (or worse) in mathematics at school.

To explore the structure of the questionnaire, we employed descriptive statistics, conducted explorative factor analysis and calculated Cronbach's α to measure internal reliability. Multiple linear regression was used to explore the influence of the different categories of learning behaviour on academic success, separately for two of the courses, whose written examinations differed in so far as one included multiple choice tasks. For each participant, the items in the respective scales were combined by calculating their means. These scores were used as predictors to calculate their influence on the outcome variable, *academic success*, represented by assessment points. Furthermore, k-means cluster analysis was employed to identify different learner types who might show different patterns of academic success. Standardization of scale scores proved helpful. Two clusters emerged, and their average examination scores were calculated. Lecturers' ratings were combined by calculating descriptive statistics, including medians.

RESULTS

Factor	Items	Respective loadings	α	% var.
Weekly	a1, a2, a4, a5, a6, a7,	.57, .52 .36, .68, .62, .73,	.75	12%
Continuous effort	e1, e2, d4, d7, d8, t3,	.43, .61, .61, .59, .66, .47,	.72	10%
Lectures	l1, l2, l3	.85, .71, .76	.72	7%
Surface learning	s1, s2, s3, s4	.64, .66, .71, .48	.57	7%
Deep learning	d1, d2, d3, d5, d6	.34, .66, .49, .42, .69	.56	7%
Tutorials	t2, t4, a3	.76, .30, .64	.53	5%

Table 1: Final factor descriptions and loadings, total variance explained 48%.

Item t1 (I regularly attend maths tutorials) was answered very homogeneously, resulting in M_{t1}=3.80, reducing its descriptive potential. The explorative factor analysis (principal component, varimax rotation) showed that scale adaptations were needed. The number of factors was varied between four and nine. In the end we decided to delete two items (t1 for reasons stated above, l4 to improve internal reliability) and to extract six factors. Thus, we were able to retain five out of the original six categories. One factor description had to be changed to *continuous effort*. The other scales kept their names see table 1. Sampling proved good (KMO=.84), and Bartlett's test of sphericity ($X^2(406)=3257.72$, p=.000) indicated correlations between items that were sufficiently large. The internal reliability meets the accepted standards (α > .7) for three of the six categories.

	CEE				ME			
Predictor	b	SE b	β	Sig.	b	SE b	β	Sig.
(Constant)	25.95	18.09		.15	-30.04	23.85		.21
Weekly assignments	21.50	4.16	.48***	.00	28.20	5.86	.47***	.00
Surface learning	-7.27	3.09	-.19*	.02	-3.03	4.57	-.06	.51
Deep learning	-7.46	4.16	-.15	.07				
Continuous effort	-2.77	4.01	-.06	.49				
Lectures					5.80	3.23	.17	.08

Table 2: Regression model with four resp. three predictors and outcome variable *academic success*, constructional and environmental (CEE) / machine (ME) engineering, $R^2=.27$ resp. $R^2=.32$.

Correlations between the resulting factors were <.48, allowing linear modelling. Preliminarily integrating all six factors into a linear model gave insight into the significance and relevance of separate factors, with $R^2=.28$ (constructional and environmental engineering, CEE) and $R^2=.32$ (machine engineering, ME). For CEE, a four factor model was accepted, see table 2. For the ME course, three factors accounted for $R^2=.32$, which is the same as in the six factor model, see table 2.

Scale centres	A	U	V	T	O	E	# Students	Exam CEE	Exam ME
Cluster 1	-.75	-.55	-.22	-.66	.42	-.65	181	47.78	53.82
Cluster 2	.56	.41	.17	.50	-.32	.49	145	52.70	77.70

Table 3: Cluster analysis (k-means) for two clusters, standardized score values.

Attempts with different numbers of clusters led to a two-cluster solution whose details are given in table 3. Students in cluster 2 can be described as busying themselves more with their weekly assignments, showing more continuous effort, preferring deep learning strategies over surface learning, and making more out of tutorials, when compared to the students from cluster 1. Unsurprisingly, they score higher in their examinations. This particularly applies to the ME course.

The ratings given by lecturers ranked *weekly assignments* highest (M=26.17, SD=13.65, median=22.50), *effort* second (M=15.60, SD=6.19, median=15.00), and *intelligence / talent* lowest (M=7.06, SD=7.09, median=5.00).

SUMMARY AND DISCUSSION

Concerning the structure of the data (RQ1), we were able to identify six factors characterized as *weekly assignments*, *continuous effort*, *lectures*, *surface learning*, *deep learning*, and *tutorials*. This agrees with the survey design, but internal reliability of only three scales could satisfy.

Analysis of the impact that the surveyed learning behaviour has on academic success (RQ2a) stressed the importance of *weekly assignments*, which had the strongest positive influence for both engineering courses. There were differences, though (RQ2b): For constructional and environmental engineering, *surface learning* had a (significant) negative impact, but so has *deep learning* (albeit not significantly). For machine engineering, *surface learning* has only a very weak (and insignificant) negative impact on academic success, and *deep learning* does not contribute relevantly at all. Here, delectably, *lectures* impact positively. All in all, the factors described in our model explain no more than 27% respectively 32% of the outcome variable *academic success*.

Clustering (RQ3) resulted in two distinctive groups that were characterized as students showing desired learning behaviour (cluster 2), as opposed to those showing irregular or spurned learning behaviour (cluster 1). This produces the anticipated effect on their examinations outcomes, which is much weaker, though, for those students who were confronted with multiple choice questions.

In lecturers' ratings, the main difference to our findings from above lies in the high ranking of *effort*. The ranking of *weekly assignments* as highly influential on academic success seems universally accepted. Teaching concepts should therefore accept this feature as central, spending appropriate time and thought on the design and conceptualisation of tasks.

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