USING BLENDED LEARNING ENVIRONMENTS IN TEACHING INTRODUCTORY STATISTICS TO A STRONG DIVERSITY OF STUDENTS: THE ROLE OF BACKGROUND FACTORS

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In the teaching of introductory statistics, the Maastricht University uses a blended learning environment that allows students to attune their use of available learning tools to personal preferences. The blended learning environment consists of small-group tutorials designed according to problem-based learning principles, a sequence of overview lectures and seminars, independent learning based on learning goals set in tutorial sessions, and an electronic learning environment: the adaptive e-tutorial ALEKS. Participation in tutorial sessions is required; the usage of other components can be set according to individual preferences. In this contribution, we will focus on student background characteristics that influence the intensity of the use of the e-tool, using data of 3000 students. We conclude that the adaptive e-tutorial not only supports students with weaker statistical background, but also less academically prepared students.

INTRODUCTION

In this empirical study, we investigate the revealed preferences for using the e-learning component in a blended learning environment for learning introductory statistics in a large group of first year university students following an economics or business program. This blended learning environment consists of tutorials based on the problem-based learning principle, lectures, independent learning and an electronic learning environment based upon knowledge space theory: ALEKS (Tempelaar, Rienties, Rehm, Dijkstra, Arts et al., 2006). Except for the tutorial sessions, for which attendance is required, students can set the intensity for each of the components of the blended learning environment according their personal preferences. Some of these preferences become revealed, e.g. by measuring connect-time in the e-learning mode. This study aims to explain patterns in these revealed preferences by individual differences in learning styles or approaches to studying, subject attitudes, and achievement motivations.

Not much research has been directed to the role of student learning approaches, the existence of variability over students, and its relationship to the use of e-learning tools in a blended learning environment. A recent study into learning styles and e-learning environments (Vigentini, 2009) reports on an empirical investigation into the relationships between learning approaches, intensity of e-learning, and academic performances, and finds weak evidence for the existence of such relationships. In the area of statistics education, some studies focus on the design of courses using blended learning to accommodate individual differences in learning. For example, Utts (2007) provides an overview of several instruments available to measure student learning styles, and some empirical outcomes of the application of these instruments. Main theme of her contribution is the mismatch that more often than not exists between learning styles of students and preferred styles of lecturers. To avoid such mismatch, Pearl (2005) proposes a buffet system in which students are assessed on their learning styles, and subsequently are matched to an educational setting that best accommodates individual student preferences. In such a setting, accounting for student variability takes place when the student is assigned to one unique educational setting; after this assignment, the instructional format is fixed.

In this contribution, we investigate the relationship between revealed student learning preferences and learning styles in a setting that at the one side allows students more choice options, so bringing about more variation, and at the other side is not neutral with regard to learning styles: some are regarded as better fitting a university study than others, bringing about the goal of adapting student preferences (see also Tempelaar, 2002). The style instrument we use in this study can be characterized as typical for the European/Australian tradition of learning style research (Entwistle & Peterson, 2004), and assesses students' learning dispositions with regard to information processing, approaches to learning, learning conceptions and learning orientations.

In C. Reading (Ed.), *Data and context in statistics education: Towards an evidence-based society. Proceedings of the Eighth International Conference on Teaching Statistics (ICOTS8, July, 2010), Ljubljana, Slovenia*. Voorburg, The Netherlands: International Statistical Institute. www.stat.auckland.ac.nz/~iase/publications.php

THE ADAPTIVE E-TUTORIAL ALEKS

The ALEKS system, in full Assessment and Learning in Knowledge Spaces, is an intelligent tutoring system based on principles of knowledge space theory, a branch of artificial intelligence (Falmagne, Cosyn, Doigon & Thiéry, 2006; Ford, 2008; Tempelaar et al., 2006). The ALEKS system combines adaptive, diagnostic testing with an electronic learning and practice tutorial in statistics, business statistics and several other domains relevant for higher education. First pillar of ALEKS is the description of all such domains by a hierarchic knowledge structure that specifies the interdependencies between the individual items spanning the domain. This knowledge structure indicates what knowledge states are feasible, and what are inconsistent. All these feasible knowledge states together constitute the knowledge space.

Second pillar of the system is the adaptive assessment engine that provides in an efficient way a probabilistic estimate of the knowledge state of any individual student. Based on that assessment, the system offers material that the student is best able to learn at a given time. In fact, the student can choose from two types of tasks: those belonging to the outer fringe, and those belonging to the inner fringe of the student's knowledge state. The outer fringe consists of new activities, not practiced before, for which the student masters all prerequisite items (new items ready to learn). The inner fringe consists of items the student has practiced before, but for which the mastery level is estimated as less than complete (items suggested for review).

The ALEKS assessment module starts with an entry assessment in order to evaluate precisely a student's knowledge state for the given domain (e.g. Business Statistics). Following this assessment, ALEKS delivers a graphic report analyzing the student's knowledge within all curricular areas for the course, based on specified standards. The report also recommends concepts on which the student can begin working; by clicking on any of these concepts or items the student gains access to the learning module. All problems of the assessment module are algorithmically generated, and require that the student produce authentic input. The assessment is adaptive: the choice of each new question is based on the aggregate of responses to all previous questions. As a result, the student's knowledge state can be found by asking only a small subset of the possible questions (typically 15-25). Assessment results are always framed relative to specified educational standards that can be customized with a syllabus editor (part of the instructor module). Both the assessment and learning modules are automatically adapted to the chosen standards.

The learning report provides a detailed, graphic representation of the student's knowledge state by means of pie-charts divided into slices, each of which corresponds to an area of the syllabus. In the ALEKS system, the student's progress is shown by the proportion of the slice that is filled in by solid colour. Also, as the mouse is held over a given slice, a list is displayed of items within that area that the student is currently 'ready to learn', as determined by the assessment. Also, as the mouse is held over a given slice, a list is displayed of items within that area that the student is currently 'ready to learn', as determined by the assessment.

At the conclusion of the assessment ALEKS determines the concepts that the student is currently ready to learn, based on that student's current knowledge state. These new concepts are listed in the report, and the learning mode is initiated by clicking on any highlighted phrase representing a concept in the list. The focus of the learning mode is a sequence of problems to be solved by the student, representing a series of concepts to be mastered.

SETTING AN PARTICIPANTS

Participants in this study were 2980 first year university students in two programs based on the principle of problem-based learning: International Economics and International Business Studies. Data has been collected in three cohorts: 07/08, 08/09 and 09/10. Somewhat more than one third of the participating students is female (36%), against 64% males. About one third of the students (28%) is of Dutch citizenship, the remaining 72% being international students, mostly from Germany. In the first term of their first academic semester, these students took two required, parallel courses: an integrated course organizational theory & marketing, two subjects from the behavioural sciences domain, and an integrated methods course mathematics & statistics. The methods course is supported by 'practicals'. Those for statistics are based on the e-learning environment ALEKS, and allow for the measurement of user intensity operationalized as the number of connect hours into the system. Doing practicals is not a requirement, and is especially beneficial for students who lack prior statistics education or need to refresh statistics due to schooling discontinuities, and/or experience methods courses as difficult. Therefore, data on practicals are not representative for students' learning efforts in the whole course.

INSTRUMENTS

The Inventory of Learning Styles (ILS) instrument, developed by Vermunt (see Entwistle & Peterson, 2004; Vermunt, 1996; Vermunt & Vermetten, 2004), has been used to assess preferred learning dispositions. Vermunt distinguishes in his learning styles model four domains or components of learning: cognitive processing strategies, metacognitive regulation strategies, learning conceptions or mental models of learning, and learning orientations. Each component is composed of five different scales. The two processing strategies Relating and structuring and Critical processing together compose the 'deep learning' strategy, whereas Memorizing and rehearsing, together with Analysing, compose the 'stepwise learning' strategy (also called surface learning in several theories of learning). The fifth processing strategy is Concrete learning. Similarly, the two regulation scales Self-regulation of learning processes and Self-regulation of learning content together compose the strategy 'self-regulation', hypothesised to be prevalent in deep learning students. The two regulation scales External regulation of learning processes and External regulation of learning results constitute the 'external regulation' strategy, supposed to be characteristic for stepwise learners. The fifth regulation strategy signals absence of regulation: 'Lack of regulation'.

In addition to the ILS, attitudes toward the subject statistics based on Eccles' expectancy-value theory (Eccles, 2005; Wigfield & Eccles, 2000, 2002; Wigfield, Tonk, & Eccles, 2004) are measured with the instrument Survey of Attitudes Toward Statistics (SATS), developed by Schau and colleagues (1995; also see Dauphinee, Schau & Stevens, 1997; Hilton, Schau & Olsen, 2004). Expectancy-value models take their name from the key role of two components in the motivation to perform on an achievement task: students' expectancies for success, and the task value, that is the value they attribute to succeeding the task. Two expectancy factors deal with students' beliefs about their own ability and perceived task difficulty: Cognitive competence and Difficulty, and two subjective task-value constructs encompass students' feelings toward and attitudes about the value of the subject: Affect and Value. Recently, the instrument is incremented by two more attitudes scales: Interest and Effort, where the last scale represents the willingness of the student to invest time and other efforts in learning the subject. The naming of the Difficulty scale is somewhat counterintuitive, since in contrast to all other scales, lower scores and not higher scores correspond to higher levels of conceived difficulty. Therefore, the scale is mostly addressed with 'lack of Difficulty' in the next sections. Attitudes are measured twice: in the begin of the course, and at the end; in the modelling step, we transform these scores into start values, and growth values.

A third group of students' background factors is based upon Grant and Dweck (2003) inventory of profiles for achievement goals. That instrument distinguishes six goal types: outcome, ability, normative outcome, normative ability, learning, and challenge-mastery.

Beyond activity in the e-tool (connect time 'HoursALEKS' and final mastery 'MasteryALEKS'), general learning intensity proxied by the number of clicks in the BlackBoard learning environment (BBClicks), and course performance indicators are available, achieved with different assessment instruments being part of the course performance portfolio: quizzes in statistics (StatsQuiz), and the score in the final written exam (StatsExam).

RESULTS

On average, students spend 23.5 hours in ALEKS; somewhat more than 25% of total learning time of 80 hours available for introductory statistics. In this amount of time spent on e-learning, students achieve an average mastery level of 46.5% of available items in ALEKS (where 60% mastery is the maximum score, since part of the module content is beyond the goals of the course). The adaptive entry test the ALEKS module starts with, determines the entry point of any student in the module. For that reason, ALEKS time and ALEKS mastery will be different indicators, due to both differences in average time spent in doing an item, and differences in the level of the entry point. The first course performance indicator, the score in the quizzes, is by composition related to the e-tool indicators, and especially mastery in ALEKS: quizzes are administered in the ALEKS-tool, and quiz items correspond to practice items. The second performance indicator, score in the written exam, is unrelated to the e-tool.

For all five outcome variables, multiple regression models are estimated using student background factors as explanatory variables, with the first regression playing the role of benchmark. Table 1 contains the beta's (in bold: beta's significant at 5% level) or standardized regression coefficients of these models, with in the last row the percentage of explained variation (R^2). In the top of the table, three indicator variables are included: Gender (indicating female students), Dutch secondary education, and Math at advanced level in secondary education. The dummy indicating Dutch secondary education is significant in most regressions, and is the most powerful predictor of both HoursALEKS and ALEKSMastery. That is an expected outcome, in fact even the prime reason to introduce the e-tool: Dutch secondary math education is very different from math education in many European countries, with a large share of teaching time devoted to statistical topics. For that reason, the use of the e-tool is not much added value for students educated in the Dutch system, explaining the large negative beta's in the equations explaining hours of use and mastery. A similar, but weaker role is played by the dummy variable MathMajor: students from these advanced tracks may both have more prior knowledge, and more talents, making them less dependent on the use of the e-tool. Other important predictors of connect time are the learning goal orientation, the ambition to acquire new knowledge and skills (also called mastery orientation), and the attitudes Cognitive Competence and Effort, both as Planned value and Growth: the willingness to invest a lot of efforts, and certainly time, in one's study.

Table 1. Beta's, standardized regression coefficients, of five regression models

	BBClicks	HoursALEKS	ALEKSMastery	StatsQuiz	StatsExam
Gender (Female)	-0.030	0.019	**0.063**	0.023	**0.046**
DutchEducation	**-0.102**	**-0.351**	**-0.209**	**-0.177**	0.030
MathMajor	**0.064**	**-0.055**	**0.039**	**0.085**	**0.144**
Relating and structuring	-0.046	-0.042	0.014	0.008	0.053
Critical processing	-0.014	-0.036	0.044	**0.052**	**0.097**
Memorizing and rehearsing	-0.008	0.000	-0.031	-0.029	**-0.067**
Analysing	0.023	**0.106**	0.039	0.040	**0.002**
Concrete processing	**-0.081**	-0.026	**-0.055**	**-0.078**	-0.042
Self-regulation of learning processes	-0.012	0.026	**-0.049**	**-0.076**	**-0.096**
Self-regulation of learning content	**0.077**	-0.004	-0.043	**-0.051**	**-0.082**
External regulation learning processes	-0.016	-0.032	**-0.054**	**-0.045**	-0.042
External regulation of learning results	**0.062**	**0.052**	**0.079**	**0.077**	0.040
Lack of regulation	0.006	**0.047**	0.039	**0.043**	0.025
OutcomeGoal	-0.026	0.026	-0.010	-0.005	**-0.054**
AbilityGoal	0.036	-0.022	-0.029	-0.029	0.025
NormativeOutcomeGoal	0.062	0.030	**0.090**	0.054	**0.134**
NormativeAbilityGoal	**-0.149**	-0.053	**-0.103**	**-0.082**	-0.027
LearningGoal	0.049	**0.063**	**0.077**	**0.110**	0.046
ChallengeMasteryGoal	0.021	0.047	**0.079**	0.054	-0.012
Affect	0.053	-0.063	0.071	**0.103**	0.039
CognitiveCompetence	-0.029	-0.018	**0.112**	**0.193**	**0.309**
Value	-0.005	**-0.056**	-0.010	0.036	**0.108**
DifficultyLackof	0.029	0.005	0.009	-0.012	**-0.072**
Interest	0.005	**0.082**	-0.057	**-0.092**	**-0.133**
EffortPlanned	**0.142**	**0.175**	**0.248**	**0.260**	**0.079**
AffectGrowth	0.019	-0.001	0.049	**0.118**	**0.065**
CognitiveCompetenceGrowth	0.004	0.005	**0.076**	**0.100**	**0.166**
ValueGrowth	-0.039	**-0.056**	-0.044	**-0.056**	0.010
DifficultyLackofGrowth	**0.068**	**0.055**	**0.092**	**0.065**	-0.018
InterestGrowth	0.020	0.051	-0.012	-0.006	-0.039
EffortGrowth	**0.184**	**0.175**	**0.289**	**0.312**	**0.158**
R-square	10.1%	26.4%	26.0%	34.2%	24.1%

The outcome variable that is unrelated to the use of the e-tool is the score in the final exam: StatsExam. Its main predictors are first the MathMajor dummy, the two attitudes scales Cognitive Competence and Value, and Critical Processing, the most outspoken aspect of deep learning. Amongst the goal orientations, it is the Normative Outcome Goal, striving for good performance with a normative goal that best predicts this achievement measure.

The two e-tool related achievement measures, ALEKSMastery and StatsQuiz, take an intermediate position. Like connect time, the dummy indicating Dutch secondary education has a negative impact. But learning approaches act more similar as in the score in the exam, as do subject attitudes (besides planned effort). With regard to goal orientation: both patterns are inherited, that is, both Learning Goal and Normative Outcome Goal do predict ALEKSMastery and StatsQuiz.

DISCUSSION AND CONCLUSION

Students investigated in this empirical study learn statistics in a blended learning environment that allows them to adapt the use of different learning resources according to personal preferences and dispositions. It appears that differences in learning dispositions, achievement motivations and subject attitudes account for a substantial part of the variation observed in the intensity of using e-learning. But that is as well true for course performance indicators, and the intensity of learning in general, as measured by BBClicks. When contrasting the five regression models, some striking differences show up.

- The dummy variable having taken Dutch secondary education (with a lot of statistics in its program) has a strong negative impact on the intensity of use of the e-tool, and a strong positive impact on the course performance Score in exam. This pattern was the mere reason to introduce the e-learning tool: aimed at students with no or few prior schooling, it is no surprise that these students use the tool more frequently, achieve higher mastery in the tool and higher score in the quizzes, to bridge the gap in knowledge caused by prior education differences, as measured by the final exam.
- Critical processing, the most outspoken aspect of the deep learning style, is a strong predictor of score in Exam, but is unrelated to any aspect of the use of the e-tool. Apparently, the e-tool does not discriminate between different profiles of learners with regard to learning approaches, and in this way is especially helpful for the more surface oriented learners. The negative beta of Memorizing and rehearsing, the most outspoken aspect of surface learning, in the Exam regression, but not in other regressions, signals a similar effect.
- Intensive e-learners are characterized by stronger external regulation, especially with regard to learning results.
- With regard to achievement goals: a strong learning or mastery orientation is important to be successful as e-learner, but no guarantee for success in the exam. In contrast: high-performing students tend to be performance goal oriented.
- Intensive e-learners exhibit a rather weak profile with regard to subject attitudes, compared to high-performing students: relative low in Affect, Cognitive Competence and Value. This is compensated by somewhat higher Interest levels, and much higher Effort levels.
- Student background factors explain a very limited part of the variation in general learning intensity (10%). In contrast: 30% of variation in e-learning intensity is explained by the same background factors.

The picture that emerges of the intensive e-learner is that of a learner aware of her or his lack of knowledge, being learning and mastery goal oriented, being relative weak in subject attitudes, but willing to invest a lot in remediating this shortage, and having an orientation toward external regulation. Some of these differences in the profiles between e-learners and academically successful students might be an artefact of a drawback of this study: the fact that the observation of learning intensity is one-sided, in that we were able to measure the intensity of studying with the e-learning tool, but not the intensity of using other components of the blended learning environment. Therefore, one cannot totally exclude the possibility that e-learners not only use the e-tool with higher intensity than other students, but do so for all components of the blended learning environment. However, given the strong correspondence between the principles on which the e-learning tool ALEKS is based, and the type of learning dispositions of these e-learners, it is highly plausible that the e-tool is of greatest support to students of this specific profile. So although accommodation of individual differences should not go at the cost of the ultimate goal of raising students to the desired level of self-regulated deep learners, the availability of a blended learning environment encompassing different components that are able to support different types of learners seems of great value, especially in difficult service courses as statistics.

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