WHAT TYPE OF STUDENTS PREFER WHAT COMPONENTS OF A BLENDED LEARNING ENVIRONMENT? A CLUSTER-ANALYTIC INVESTIGATION

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In the teaching of introductory statistics to first year students economics and business, the Maastricht University uses a blended learning environment that allows students to design a individualized environment by attuning available learning tools to personal preferences. The 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. Usage of only the first component is required; the usage of other components can be set according to individual preferences. In this study, we will focus on the intensity of the use of the electronic learning environment ALEKS and investigate the relationship between this and student learning dispositions in a cluster analytic study. Data of about 4650 students taking this course are used. This study aims to contribute on the topic 'development of tools to improve students' learning of statistics'.

INTRODUCTION

In this empirical study, we investigate in a large group of first year university students following an economics or business program, the revealed preferences for using the e-learning component in a blended learning environment for learning introductory statistics. 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 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.

Not much research has been directed to the role of student learning styles and the existence of variability over students, in the area of statistics education. In her USCOTS 2007 plenary session, Utts (2007) provides an overview of several instruments available to measure student learning styles, and some empirical outcomes of the application of these instruments. The 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 on the one side allows students more choice options, so bringing about more variation, and on 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 European/Australiam 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.

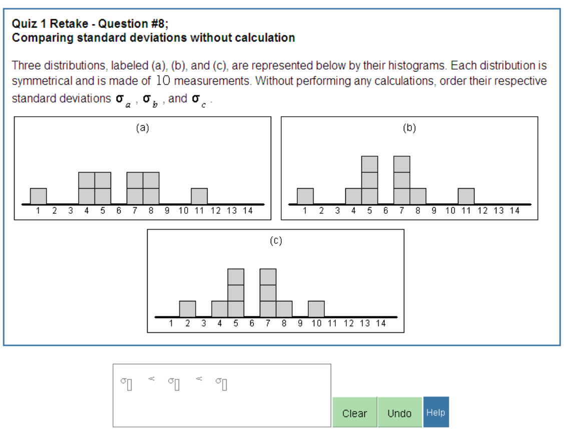
THE ADAPTIVE E-TUTORIAL SYSTEM ALEKS

The ALEKS system, in full *A*ssessment and *Le*arning in *K*nowledge *S*paces, 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, Rienties, Rehm, Dijkstra, Arts, & Blok, 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. The 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.

The core of the system is the adaptive assessment engine that provides in a 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 task: 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 (see Figure 1 for a sample assessment item). 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, of which Figure 2 shows part of, 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.



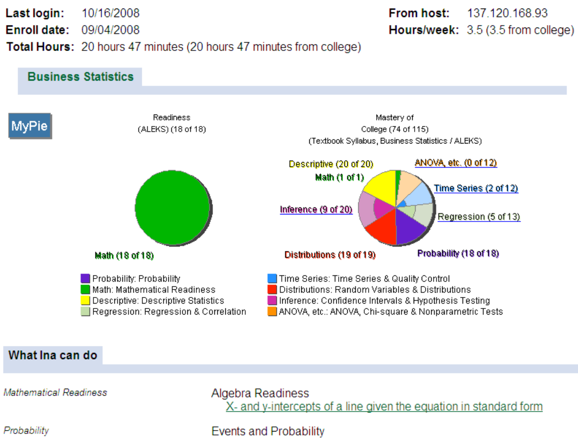


Figure 1. Sample of ALEKS assessment item. Figure 2. Partial sample of ALEKS learning report.

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.

MEASURES

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, as described in the Table 1. 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.

Table 1: Components and scales of the Inventory of Learning Styles

Processing strategies	Regulation strategies	Learning orientations	Learning conceptions, or Mental models of learning
Relating and structuring	Self-regulation of learning processes	Personally interested	Construction of knowledge
Critical processing	Self-regulation of learning content	Certificate directed	Intake of knowledge
Memorising and rehearsing	External regulation of learning processes	Self test directed	Use of knowledge
Analysing	External regulation of learning results	Vocation directed	Stimulating education
Concrete processing	Lack of regulation	Ambivalent	Co-operation

In addition to the ILS, the MSLQ instrument (Entwistle & Peterson, 2004; Pintrich & De Groot, 1990) has been administered in a subset of the population. The MSLQ counts two sections: motivation and learning strategies; in this study, we will focus on this last section. The section learning strategies consists of two main scales, each with several subscales. The cognitive and metacognitive strategies main scale counts the subscales: Rehearsal, elaboration, organisation, critical thinking, and metacognitive self-regulation. The resource management strategies scale counts four subscales: Time and study environment management, effort regulation, peer learning, and help-seeking.

Several course performance indicators are available: subtopic scores (statistics and mathematics), and scores for different assessment instruments applied in the performance portfolio: final written exam, quizzes and project work. In addition, this study applies GPA as the overall measure of student performance in the first year program.

DATA AND STATISTICAL ANALYSIS

Participants in this study were 4655 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 six cohorts, ranging from academic year 03/04 to academic year 08/09. Somewhat more than one third of the participating students are female (36%), against 64% males. About one third of the students (34.1%) are of Dutch citizenship, the remaining 65.9% being international students, mostly from Germany. Distinguishing national from international students is relevant with regard to prior schooling in statistics: Dutch secondary school programs contain statistics as a major topic, several international programs do not.

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 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 through connect hours. Doing practicals is not a requirement, and is especially beneficial for students who lack prior knowledge, need to refresh mathematics or statistics due to schooling discontinuities, and/or experience methods courses as difficult. Therefore, data on practicals are not representative for the whole course.

During the start of the course, and as part of the fulfilment of a required student project for statistics, students filled several self-report questionnaires on learning related characteristics. Participants are from six consecutive cohorts. Therefore, performance measures as quizzes and final exams are scored with equivalent, but not identical instruments. Quizzes are administered in the assessment mode of ALEKS, and are thus strongly tied to the performance in the learning mode. The last performance measure, GPA, is based on scores in all first sits of first year exams.

In order to distinguish different student approaches to the ALEKS supported practicals in statistics, we applied K-means cluster analysis to the following set of input and process data: ALEKS hours: the amount of connect time in the e-tool; Math readiness mastery: mastery in the small slice of items on mathematical foundations of statistics; & Mastery in statistics: mastery in the main seven slices of statistical topics. As a subsequent step, cluster differences with regard to learning dispositions were investigated with ANOVA.

RESULTS

K-means cluster analysis was applied for a range of cluster numbers. A four-cluster solution was opted for, since allowing more clusters would create relatively small clusters. Table 2 contains cluster characteristics of the four clusters, counting 2091, 1031, 199, and 1309 students, respectively. To ease the interpretation of the last row of the table: of all items in the statistics slices, 60% are relevant for our introductory course, implying that a ceiling effect at the level of 60% mastery is to be expected.

Table 2. 4-cluster solution of input and process data on e-tool use.

Final Cluster Centers

	Cluster			
	1	2	3	4
Hours in ALEKS	21.77	9.49	5.09	41.72
%Mastery Math Readiness	99.52	92.73	16.98	99.84
%Mastery Statistics	53.80	19.46	1.21	58.12

On average, students spend 23.9 hours in ALEKS; somewhat more than 25% of total learning time of 80 hours available for introductory statistics. However, strong variability over clusters exists. Both clusters 1 and 4 consist of high performing students, the difference being that cluster 4 students use the e-tool with far greater intensity than cluster 1 students. The relative small cluster 3 is maybe least interesting: these students probably quit the study in or before the first week. Cluster 2 students are those who stayed in the program, mastered math readiness covered in week 1, but opted out for intensive use of the e-tool.

Cluster composition is dependent upon both gender and nationality. Both female students and, to an even stronger degree, international students are overrepresented in cluster 4, and underrepresented in clusters 2 and 3, as is clear from Table 3.

Table 3. 4-cluster break down in terms of gender and nationality.

		Cluster				Total
		1	2	3	4	
Gender	Male	62.8%	70.8%	73.4%	56.2%	63.2%
	Female	37.2%	29.2%	26.6%	43.8%	36.8%
Nationality	Dutch	41.6%	48.6%	55.8%	8.2%	34.1%
	International	58.4%	51.4%	44.2%	91.8%	65.9%

Differences in performance in practicals mirror themselves in differences in academic performances. Figure 3 contains three such academic performances, the first two related to the course under investigation, Exam score and Quiz score for statistics, the third being the overall first year GPA. Students in clusters 1 and 4 perform well, in contrast to students in clusters 2 and 3. Differences are not only statistically significant, but also very substantial.

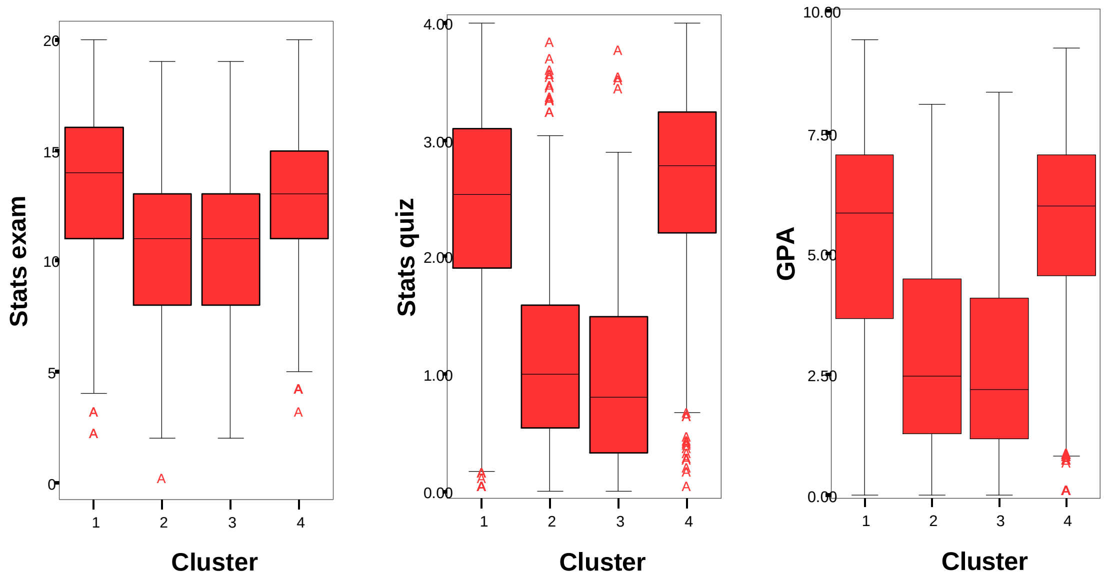


Figure 3. Variation in academic performance indicators over clusters.

Stepping over to cluster differences between student learning dispositions, we again find strongly statistically significant differences, but less substantial ones. Focussing on the three main processing strategies deep learning, stepwise learning, and concrete processing, we find that cluster 4 students always score highest of all clusters, but especially in surface learning: see Figure 4. The highly structured way in which ALEKS guides students through the statistical discipline, and the systematic way of offering practice material and providing feedback, appears to be first of all attractive for students disposed of a stepwise learning approach. Further differences are present in concrete processing, but nearly absent in deep learning.

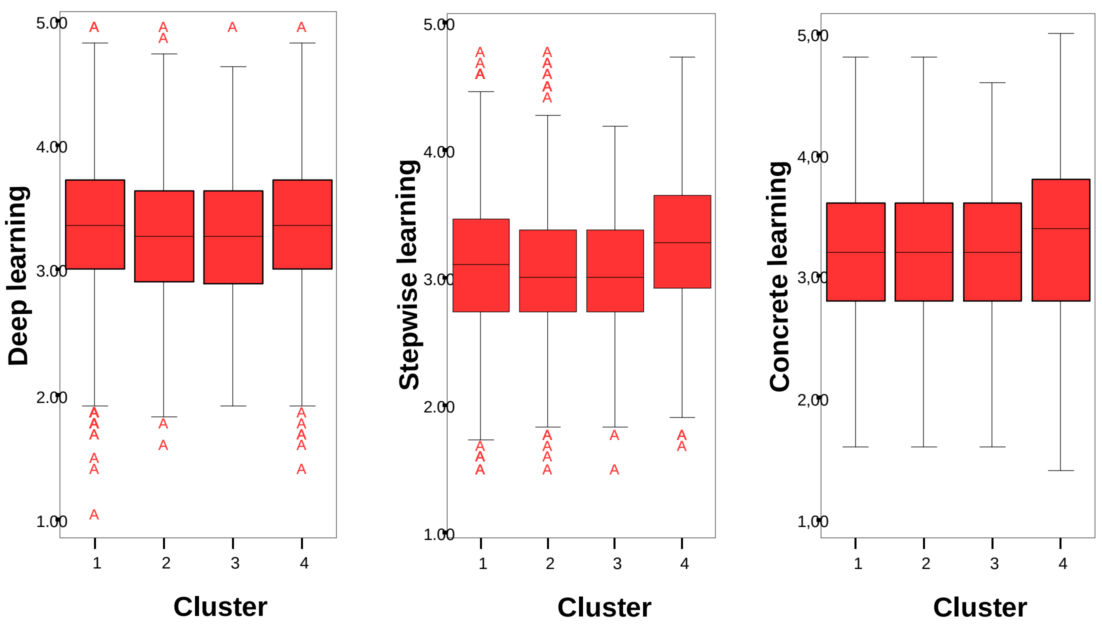


Figure 4. Variation in processing strategies over clusters.

Connected with processing strategies are different preferences in regulating the learning process. Stepwise learners are frequently dependent on external regulation, whereas deep learners are more often able to regulate the learning process themselves. Some students lack any regulation. Figure 5 indicates differences in self-regulation and lack of regulation are very small, but differences in external regulation are substantial. Cluster 4 students score highest on external regulation, followed by cluster 1 students. Remarkably, the only deviant score for lack of regulation is for the cluster 1 group, indicating that high performing students who economise on the use of the e-tool are less troubled by lack of regulation. A similar pattern can be discovered in terms of learning orientations and learning conceptions, or mental models of learning. Of these two categories, we choose to highlight three scales: the ambivalent orientation, indicating a lack of orientation, and the construction of knowledge and intake of knowledge: see Figure 6.

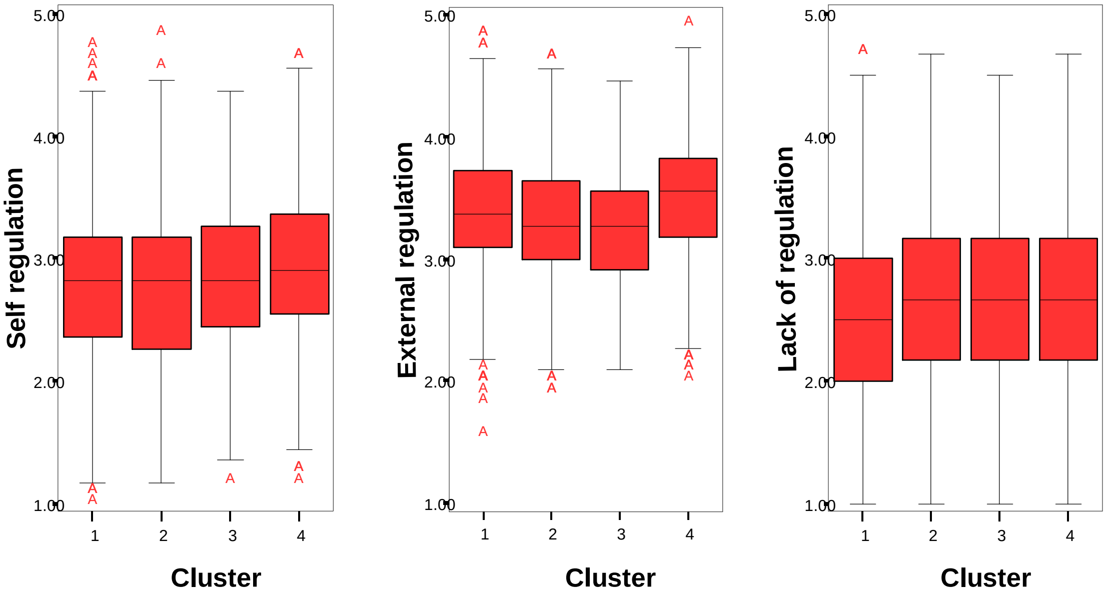


Figure 5. Variation in regulation strategies over clusters.

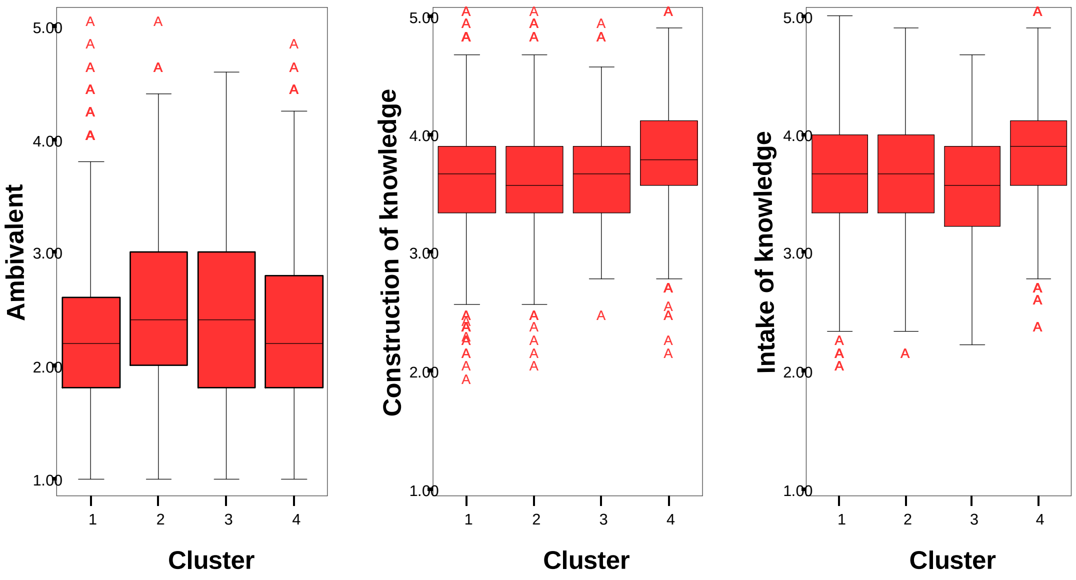


Figure 6. Variation in learning orientations and conceptions over clusters.

Cluster 4 students score higher than all other clusters on both construction and intake, and, together with cluster 1 students, low on ambivalence. Apparently, the e-tool supports both somewhat opposite learning conceptions. Cluster 4 students score higher than all other clusters on both construction and intake, and, together with cluster 1 students, low on ambivalence. Apparently, the e-tool supports both somewhat opposite learning conceptions.

MSLQ learning strategies, administered in two of the six cohorts under study, demonstrate the pattern depicted in Figure 7. Cluster 4 students distinguish from all clusters on the cognitive strategy organisation, and together with cluster 1 students, distinguish with regard to the resource management time and study environment management and effort regulation.

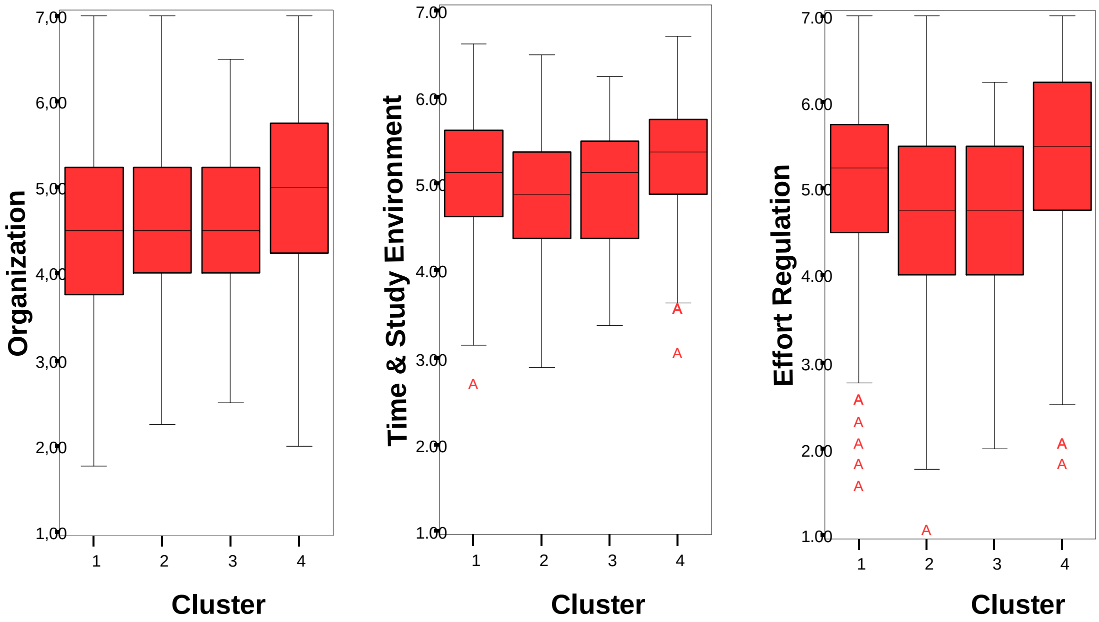


Figure 7. Variation in MSLQ learning strategies over clusters.

Gathering together all empirical data, it appears that the two main clusters, clusters 1 and 4, can be labelled as clusters with a relative (and not outspoken) preference for deep versus surface learning. Cluster 4 students are the conscientious learners: open to external regulation, well organised, strong in effort regulation, eager to both construction and intake of new knowledge, but in a stepwise manner. In contrast, cluster 1 students better confirm the profile of deep learners. Although the program on which this study is based aims to adapt student learning styles as much as possible in the direction of deep learning, academic performances of both types of students are very similar.

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 personal preferences. It appears that not only prior knowledge, but also differences in learning dispositions, account for part of the variation observed in the intensity of using e-learning:

- International students are overrepresented amongst e-learners; differences in prior knowledge can account for some of these effects, but not all.
- Female students are overrepresented amongst e-learners; since female student have better prior knowledge students, there is no cognitive explanation for this.
- E-learners have relative strong preference for stepwise learning.
- E-learners can be both self-regulators and external regulators, where external regulation dominates self regulation in general.
- E-learners tend to be strong in construction and intake learning conceptions.

- E-learners are strong in organisation, such as selecting main ideas from their readings, and skilled in resource management: manage time and schedule well, are willing to try hard on academic work.

This study is somewhat handicapped from the fact that the observation of learning is one-sided: we can measure the intensity of studying with the e-learning tool, but not the intensity of use of other parts of the learning process. Therefore, one cannot totally exclude the possibility that cluster 4 students not only use the e-tool with higher intensity than other students, but do so for all resources. However, given the strong correspondence between the principles on which the e-learning tool ALEKS is based, and the type of learning dispositions of cluster 4 students, it is highly plausible that the e-tool is of greatest support to students that are typically overrepresented amongst the group of students at risk: the less well academically adapted, the students with learning dispositions that are generally regarded as inferior to deep, self-regulated learning. So although accommodation 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 is of great value, especially in difficult service courses as statistics.

REFERENCES

Entwistle, N. & Peterson, E. (2004). Learning Styles and Approaches to Studying. In: *Encyclopedia of Applied Psychology*, C. D. Spielberger (Ed.). Vol. 2, pp. 537-542. Amsterdam: Elsevier.

Falmagne, J.-C., Cosyn, E., Doigon, J.-P., & Thiéry, N. (2006). The Assessment of Knowledge, in Theory and in Practice. In: *Lecture notes in computer science*; vol. 3874, pp. 61-79. [Online: http://www.aleks.com/about_aleks/research_behind].

Ford, N. (2008). *Web-Based Learning through Educational Informatics: Information Science Meets Educational Computing*. Hershey, PA: Information Science Publishing,

Pearl, D. (2005). Cooking for the Buffet - How to Individualize the Multi-Section Course. USCOTS 2005 Conference. [Online: http://www.causeweb.org/uscots/uscots07/program/utts.php].

Pintrich, P. R., De Groot, E. V. (1990). Motivational and Self-Regulated Learning Components of Classroom Academic Performance. *Journal of Educational Psychology*, 82(1), 33-40.

Tempelaar, D. T. (2002). Modelling students' learning of introductory statistics. In: Proceedings 6th International Conference on Teaching Statistics. Cape Town: IASE.

Tempelaar, D. T., Rienties, B., Rehm, M., Dijkstra, J., Arts, M. & Blok, G. (2006). An online summercourse for prospective international students to remediate deficiencies in math prior knowledge: The case of ALEKS. In: *Proceedings WebALT2006* (pp. 23-36). Technical University of Eindhoven: Oy WebALT Inc. [Online: http://webalt.math.helsinki.fi/content/results/docs/proceedings2006/].

Utts, J. (2007). Recognizing and Valuing Variability - In Our Students and Ourselves. Plenary session USCOTS 2007 Conference. [Online: http://www.causeweb.org/uscots/uscots07/program/utts.php].

Vermunt, J. D. (1998). The regulation of constructive learning processes. *The British journal of educational psychology*, 68, 149-171.

Vermunt, J. D. & Vermetten, Y. (2004). Patterns in Student Learning: Relationships Between Learning Strategies, Conceptions of Learning, and Learning Orientations. *Educational Psychology Review*, 16(4), 359-385.

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