The course structure dilemma: Striving for Engineering students' motivation and deep learning in an ethics and history course

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INTRODUCTION

Engineers exert a decisive impact on the societal consequences of innovations when designing and implementing technologies. Engineering education prepares students for their future role by also offering them non-technical courses such as history or philosophy. Students – especially Bachelor's students – seem to consider these courses less important compared to the technical courses of their major and thus, engage with them as little as possible. This increases the risk of these courses not achieving their primary objective. It is therefore

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important to explore motivation and deep learning in ethics and history courses and how to improve these in engineering education.

1 CONTEXT OF THE STUDY

A medium-sized Dutch university offers its students four courses of five ECTS (European Credit Transfer and Accumulation System) each on the topic 'User, Society and Enterprise ('USE') to address their future role as social responsible engineers. In the USE-sequence, Bachelor's students learn about the user, society, and enterprise aspects of technology and innovation. In the fourth academic quarter of their first year, all 2000+ students take the compulsory USE basic course providing an introduction to USE with ethics and history of technology. In their second or third year, students choose one USE course sequence from a list of sixteen, such as *Decisions Under Risk and Uncertainty* [1], *Patents and Design Rights and Standards* [2], or *Technological Entrepreneurship.*

The USE basic course is a complex course and has gone through continuous course redesign efforts during the five years of its existence. In 2015-2016, it was taught to 1864 engineering students of a diverse set of thirteen major programs, including Applied Mathematics, Electrical Engineering, Medical Sciences, Industrial Engineering and Sustainable Innovation. Lectures were provided in eight parallel streams in English or Dutch, each of which could accommodate about 250 students. For their assignment, students were given a choice of eight cases (e.g. *Sustainable Energy Technologies*, *Health Robotics* or *Self Driving Cars*). They worked in interdisciplinary groups of four students (from four different departments) on a case in which they used the ethics and history theories to improve an existing technology. Students worked on their assignment using a wiki platform, where they could see each other's ongoing work and gave feedback through this platform. Because of the organisational challenge of grading the large number of students efficiently within a very short time frame, the final exam was a multiple-choice examination. Students could prepare for the final multiple-choice exam with six multiple-choice on-line interim tests. The final grade was determined as follows: final multiple-choice exam counted 50%, assignment 40%, and interim tests 10%.

Analysis of the 2015-2016 version revealed that students showed low enjoyment of the course, reflected to a low overall evaluation score, in addition to self- reported low motivation for the course. An average workload had been strived for and been achieved, but the study time increased because students felt they had to write vast amounts of text (about one page per student per week). Analyses further showed that (1) students' perception of low competence was crucial for the assignment, (2) the course set-up should be simplified, (3) the course materials were crucial to students, (4) students from different majors and with different basic needs reacted very differently to the course set-up, so students' differences were important to take into account, and (5) learning approaches should be considered next to study time only.

This article shows how these conclusions were addressed in the redesign of the 2016-2017 version using theories for deep learning and motivation, its results, and what can be concluded from this redesign.

2 THEORETICAL BACKGROUNDS

2.1 Learning approaches

In order to improve students' learning, we focused in the 2016-2017 redesign on students' learning approaches, which describe their intentions when facing a task and the accompanying learning activities. Marton and Saljo [3] distinguish two approaches in students' learning: a deep and a surface approach. Students with a deep approach to learning are intrinsically interested and try to understand what they study. A deep approach describes students who intend to understand the meaning of the text or task, who try to relate new information to prior knowledge, to structure ideas into comprehensible wholes, and to critically evaluate knowledge and conclusions they encounter. A surface approach describes students who use rote learning, memorizing and repeating the learning content and analysing learning tasks (dividing the learning content into smaller parts and performance of tasks in a more or less prescribed order) with primary objective to pass the test. Apart from the deep and surface approaches in learning, other researchers have identified strategic approaches to learning [4]. A strategic approach to learning describes students' motivation to achieve high grades with the use of organized study methods and efficient time management.

It is important to note that students' approaches to learning are not characteristics of the learner but of their relationship with the learning environment, including aspects like course content, activities and interaction with teachers. This means that a student can adapt their approaches to learning depending on the demands and opportunities of the learning environment. Teachers can change the way students approach learning by changing the way in which they teach their courses. The following factors encourage students' deep learning [5]:

- Relevance of the course: Perceived interest in and being challenged by the subject content.
- Relevance of the course to students' professional practice.
- Workload which is not perceived as excessive by students.
- Teaching behaviors that are associated with deep learning: structuring the course, providing materials, illustrating lectures, answering students' questions, giving feedback.
- Perceived supportiveness of the context: giving support and encouragement for student learning, making the goals and standards clear throughout the course.
- Students' autonomy to make choice within the course (choosing topic of assignment).
- Student involvement in their own learning, using strategies such as group work or negotiation of topics.
- Usefulness of the course book.
- Perceived assessment as assessing higher levels of cognitive processing. Students tend to employ deep approaches or deep learning strategies when they believe that this is the purpose of the assessment.
- Students' motivation; motivation influences the direction, intensity, persistence, and quality of the learning behaviors. Intrinsic motivation can encourage students to adopt a deep learning approach

2.2 Self-Determination Theory

Low students' intrinsic motivation was also suggested by the previous evaluation as a point of improvement and the literature suggests a clear and positive influence of motivation on deep learning (see e.g. [6]). In order to improve student motivation, we looked at the Self-Determination Theory (SDT). SDT divides motivation into several types [6] situated on an internalisation or self-determination continuum, ranging from amotivation, which is the state of lacking the intention to act, to intrinsic motivation which is the state of acting because of inherent interest, satisfaction and enjoyment. To give an example, amotivated students do not perform a given task and do not worry overly much about their learning outcomes. At the other end of the continuum, according to SDT, an electronics student, who is intrinsically motivated just likes to build electronic devices and play around with them, because it is an inherently enjoyable task for him. Within this continuum we also find identified regulation, which reflects a conscious valuing of a goal, such that the action is considered as personally important and entails self-endorsement, self-knowledge and cognitive view of one's own functioning [7]. For example, a student in design might not be very interested in informatics in itself. However, if she identifies herself as becoming a good engineer, she acknowledges that informatics is nevertheless essential for her and she will therefore be driven to study informatics. SDT provided some insight on how to redesign a course in order to foster identified or intrinsic motivation to students by a) emphasizing the relevance of the course to students' interests, b) fostering students' sense of competence to succeed the course by providing clear guidance and c) fostering students' autonomy to make decisions and manage their learning.

3 INTERVENTION PROCEDURE

Based on the 2015-2016 analyses and the theories of learning approaches and motivation, the 2016-2017 redesign clearly divided the history and ethics part of the course. Each part consisted of separate lectures and three tutorials and had clear learning objectives throughout the course. There was a clear and one-to-one structure of lecture and assignment. The word count (of the reading materials and the assignment) was strongly reduced hoping students would not perceive this as excessive any more. In every part, the two first tutorials were devoted to guiding the students through the assignment and the last one was a feedback tutorial. The approach of the cases was retained. The redesign aimed to maintain student autonomy to make choices within the course and to preserve or increase the perceived relevance of the course to students' professional practice.

The two parts had different approaches, mostly in terms of the amount of guidance provided to students for the assignments in the first two tutorials and the type of feedback provided at the third tutorial. In the history part, an open approach was adopted aimed at higher levels of cognitive processing*. The open approach entailed less guidance through the assignment*. During tutorials, sources of policy documents and a description of how to scan these documents for relevant information was provided without providing detailed steps for the document analysis and the development of the assignment. The feedback was given orally during poster sessions, where students summarised their analysis until that moment. Poster session aimed to encourage discussion between different groups and between tutors and students for the more in-depth understanding of concepts. In general, in the history part students' were encouraged to be autonomous and self- directed in their learning. In the ethics part on the other hand, *structured approach was adopted, with emphasis in clarifying learning objectives and increasing students' perception of competence by guiding students and* providing them with a structured methodology to do the assignment that was repeated in the lectures, in several elaborated examples in the book, in the study guide and in the tutorials. A clear and very detailed rubric with 2200 words for six different steps was provided Students gave written peer feedback online on the first draft of the assignment (using the rubric) and further discussed this orally in the last feedback session.

4 RESEARCH QUESTIONS

The research questions are as follows:

RQ1: Which approach (open or structured) gives the best results in terms of motivation, learning approaches, relevance and students' overall evaluation?

RQ2: Which course features contributed most significantly to students' learning approaches and what was the role of motivation?

5 METHODOLOGY

5.1 Questionnaire

Table 1. Variable names and items.

Name	**Item**
ClearGroup	It was clear what was expected in the individual part of the assignment.
Lectures	The lectures provided clear input for the assignment.
StudyGuide	The study guide was a help to know what I had to do in the assignment.
Activities	The activities in the tutorials helped me to make the assignment.
Sources	The sources provided were helpful to do the assignment.
Rubric	The rubric helped me to understand the assignment.
ClearDifficult	Even if the assignment was clear, I found it difficult to complete the assignment.
PeerFeedback	The tutorials provided me with peer feedback that I could use to improve my work.
GroupImprove	Working with my group members helped me to improve my parts of the assignment.

We administered an on-line student questionnaire right after the history and ethics part were finished. Each questionnaire contained nine items about the assignment (see Table 1) measured on a five-point Likert scale. The *overall evaluation* was measured on a 10-point Likert scale, *enjoyment* and *relevance* on a 5 point Likert scale. Deep learning was measured by a selection of Approaches and Study Skills Inventory for Students (ASSIST) [8]. Motivation was measured with a selection of items from the 'Self-regulation questionnaire – Academics' [9]. It measured three types of motivation (intrinsic, internalized regulation and amotivation) reduced to two Likert-type items per scale.

5.2 Participants and Data Analysis

The response rates were 15.3% and 15.4% for 300 and 303 respondents out of 1962 for the open and structured approach respectively. The learning approach factors have Cronbach's alphas from .54 to .64, motivation had a Cronbach's alpha of .87.

For answering the research question 1, the standard questions at item level between the two versions were compared with t-tests. For answering research question 2, we performed stepwise regression analyses for the deep, surface and strategic learning factors in both the open and the structured approach. All analyses were performed using SPSS.

6 RESULTS

6.1 Differences open and structured approach

Results showed that the open approach led to significantly more surface learning and significantly less strategic learning compared to the structured approach. However none of the approaches led to deep learning significantly above the average of 3 at the 5 point Likert scale.

Table 2. Paired Samples Statistics “Open approach” and “Structured approach” (per component). Mean difference ΔM, (significance of difference) and Cohen’s d. Overall score on a 1-10 Likert scale, all others on a 1-5 Likert scale. Items indicated with “[i]”.

		Open approach		Structured approach			
	N	M	SD	M	SD	ΔM(sign)	d
Overall evaluation[i]	160	4.94	1.87	6.39	1.49	-1.45***	-0.86
Relevance[i]	160	2.50	1.09	2.85	1.02	-0.35***	-0.36
Enjoyment[i]	160	2.24	1.04	2.91	0.97	-0.67***	-0.66
Autonomous Mot	160	1.98	0.81	2.26	0.83	-0.28***	-0.41
Amotivation	160	2.87	1.17	2.54	1.16	0.33***	0.31
Deep Learning	158	2.95	0.69	3.03	0.75	-0.08	-
Strategic Learning	158	3.28	0.70	3.46	0.65	-0.18**	-0.26
Surface Learning	158	3.21	0.81	2.84	0.72	0.37***	0.47

The structured approach also realised higher overall student evaluation, relevance, autonomous motivation compared to the open approach. This answers RQ1 that a structured approach gives better results in terms of motivation, learning approaches, relevance and students’ overall evaluation.

6.2 Hierarchical Multiple Regression

For the open approach, the hierarchical multiple regression revealed that at stage one, *Lectures*, *Sources* and *Activities* contributed significantly to the regression model, $F(13,285) = 4.305$, $p < .001$) and accounted for 16.4% of the variation in deep learning. Introducing the motivation variables explained an additional 10.4% of variation in deep learning and this change in R^2 was significant, $F(14,284) = 7.440$, $p < .001$. When motivation was added in step 2 of the model, the predictors of step 1 were not significant anymore. For the structured approach, *Lectures*, *Sources* and *GroupImprove* contributed significantly to the regression model, $F(13,267) = 7.772$, $p < .001$ and accounted for 27.5% of the variation in deep learning. Introducing the motivation variables explained an additional 10.8% of variation in deep learning and this change in R^2 was significant, $F(14,266) = 11.793$, $p < .001$. When motivation was added in step 2 of the model, *Sources* was not significant anymore but *Lectures* and *GroupImprove* remained significant predictors.

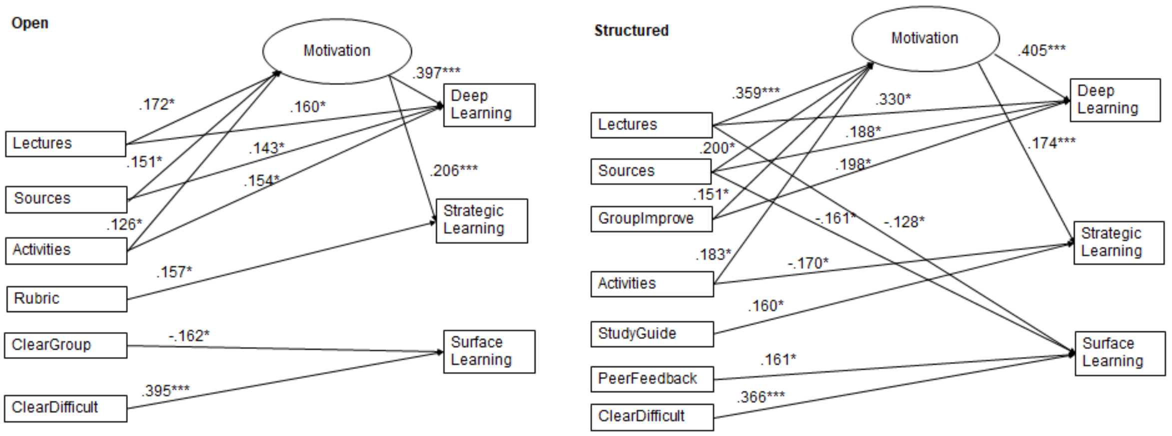

Fig. 1. Hierarchical Multiple Regression of deep-, strategic, and surface learning, with motivation as interim variable.

For strategic learning in the open approach, *Rubric* was the only significant predictor and contributed to the regression model F (13,285) = 1.718, p< .05 and accounted for 7.4% of the variation. Introducing the motivation variable explained an additional 2.8% of variation in strategic learning and this change in R^2 was significant, F (14,284) = 2.274, p < .001. In the structured approach, *StudyGuide* and *Activities* were significant predictors of strategic learning and contributed to the regression model F (13,267) = 3.379, p< .001) and accounted for 14.1% of the variation in strategic learning. Introducing the motivation variable explained an additional 2% of variation in strategic learning and this change in R^2 was significant, F (14,266) = 3.565, p < .001. The study guide and activities during tutorials remained significant predictors after the addition of motivation in step 2.

ClearGroup and *ClearDifficult* were predictors of surface learning, contributed to the regression model F (13,285) = 6.875, p< .001) and accounted for 23.9% of the variation in strategic learning for the open approach. Introducing the motivation variable did not contributed to the model as motivation was not predicting significantly surface learning. *ClearDifficult* and *PeerFeedback* were predictors of surface learning and contributed to the regression model F (13,267) = 8.874, p< .001) and accounted for 30.2% of the variation in surface learning for the structural approach. Introducing the motivation variable did not contributed to the model as motivation was not predicting significantly surface learning.

Deep, strategic, and surface learning play a similar role in predicting overall evaluation. Deep and Surface are most important predictors (see Table 4).

Table 3. Bètas of stepwise regression analysis for the open and structured approach on deep, strategic, and surface learning

	Item	Open β	Structured β
Overall evaluation	Deep	,32***	.33***
	Strategic	,16**	.17**
	Surface	-,27***	-.24***
	R^2	*.22*	*.26*
	F(3,296)	*28.99****	*33.72****

7 DISCUSSION

7.1 The structure dilemma

Our analysis showed that the open approach led to higher surface learning. The strong predictive power of *ClearDifficult* in both approaches indicates that students missed guidance and had the feeling they failed to make sense of the assignment. Items addressing group support as *ClearGroup* and *PeerFeedback* added to this lack of control. Providing more options for control and competence will decrease students' surface learning. Surprisingly, *Motivation* is not a significant (negative) predictor for surface learning. SDT predicts either a negative influence of motivation or a positive of amotivation. One possible explanation could be that students' motivation level did not matter when they faced difficulties making sense of the assignment and decided to approach it in a superficial way.

In the structured approach students felt more they could make sense of the assignment. Not surprisingly, course aspects that helped to focus on achieving higher grades are important predictors such as *Rubric* or *StudyGuide*. *Motivation* plays a role here by *Lectures*, *Sources*, and *Activities*. It must be noted, however, that the overall predictive power for strategic learning is low and interpretations should be taken with caution.

Deep learning was not really addressed in either of the two approaches. Providing structure seems indispensable, but at the same time appears to trap students. Students are not familiar with history and ethics methodologies, they cling to the structure they are offered and cannot free themselves from this structure. A possible way to avoid the dilemma might be to connect to students' need for structure and their intrinsic motivation before they really start the assignment. The strong predictive power of motivation for deep learning suggests that it is very important [6]. The assignment and accompanying tutorials should start from students' life worlds with real life but not too complex cases. It may be beneficial to involve students' 'own' departmental staff to convince students about the relevance. *Lectures* that provide clear input for the assignment are a strong help for deep learning. Although it seems rather peculiar that lectures for 250 students could add to deep learning, students might expect both a motivational setting and good guidance for the translation of the theory to a relevant case. Next to lectures, *Sources* and *Activities* can add to deep learning.

Deep learning is an important predictor for students' overall course evaluation. This must be seen as a very positive result and a confirmation of SDT. Students want to be motivated for a course. Evaluating the overall course, their perception of deep learning plays a major role. Let this be an encouraging message for all teachers that sometimes feel disappointed in their search for more motivational history, ethics or other non-engineering courses in engineering education.

7.2 Further research

Our research has some weaknesses. Our learning approach and motivation factors consisted of a limited number of items and could be enlarged to achieve stronger factors. We did not report on student differences because of the limited scope of this article. Other research shows that these are very important and also here, many differences can be expected between different students. Further research could tackle these weaknesses.

Both the predicting independent variables and their beta's in the regression analysis show remarkable similarities for the open and structural case. Our research set-up provided us a first confirmation of the replication of our analysis. However, it would be interesting to see whether this analysis shows different patterns in different contexts. It would also be interesting to see the proposed changes about lectures, cases and group work have an effect on motivation, deep learning and overall student evaluation.

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