A COGNITIVE LOAD THEORY PERSPECTIVE ON COOPERATIVE LEARNING AND STUDENT PERFORMANCE

Abstract

Cooperative learning is a key design element in modern business education. Cognitive Load Theory suggests that the additional related difficulty of managing the social fabric in a student group may interfere with intended positive outcomes of cooperative learning. This study first establishes how students' learning outcomes depend on how they perform in cooperative learning exercises and how much they participate in those exercises. Second, it uses Cognitive Load Theory to explain why these effects are different when the content students are expected to master becomes more difficult. It tests the resulting hypotheses on a dataset with 578 observations collected in the context of a six-module class.

INTRODUCTION

Cooperative learning is a key theme in literature on university education in management (Bacon, Stewart, & Silver, 1999), accounting (Usoff & Nixon, 1998), marketing (Bacon, Stewart, & Stewart-Belle, 1998), and finance (Chen & Yur-Austin, 2017) education journals. It is used widely in universities (Foldnes, 2016), and particularly in business schools around the world (Dahl, Peltier, & Schibrowski, 2018). Cooperative learning has been associated with improved learning outcomes for students (Foldnes, 2016), and the ability to learn and perform in teams is considered one of the key characteristics for successful careers (Loingon, Woehr, Thomas, Loughry, Ohland, & Ferguson, 2017). At the same time, literature suggests that a lack of teamwork skills is a key shortcoming of many business school graduates (Chen, Donahue, & Klimoski, 2004).

However, research on student learning in business schools is silent on how the success of cooperative learning is contingent on two important factors. First, it is unclear whether the positive learning outcomes from cooperative learning persist if task difficulty is high. Literature on teaching and learning in the natural sciences (e.g., Berger & Hänze, 2015) argues that task difficulty has a negative influence on the positive effect of cooperative learning on student performance. This is because students that are expected to solve difficult tasks are exposed to substantial cognitive load, which makes it close to impossible to both collaborate effectively and absorb new materials (Sweller, 1988; Sweller, Ayres, & Kalyuga, 2011). Second, it is unclear to which extent the degree to which students contribute to cooperative learning activities conditions the positive learning outcomes. Literature explaining the quality of cooperation among students (e.g., Leonardi, Jackson, & Diwan, 2009) argues that frequently incentive structures for students in business schools favors individual performance over group performance. Consequently, particularly high-performing students develop work practices that go against optimal learning in cooperative environments (for a distinction between cooperative and collaborative learning please see Matthews et al. (1995)). Peer evaluation is a key lever to encourage positive cooperation among students (Millis & Cottell, 1998), and aligns learning outcomes in business schools with demands from business practice. Moreover, empirical literature on student learning in business schools only very rarely considers variation in learning outcomes within students. Because outcomes are usually aggregated (e.g., for a class), variation in learning success for different topics covered is frequently hard to isolate from variation across students.

Cognitive Load Theory (CLT, Paas, Renkl, & Sweller, 2003) provides a theoretical basis for addressing these important omissions in literature. It suggests that more cognitively demanding tasks lead to more cognitive load, which reduces the availability of cognitive resources that can be dedicated to managing the social fabric and communicating for successful group learning. Cognitive load is argued to be contingent on four characteristics of the material that is to be understood: complexity, implicitness, level of abstraction, and openness (Edwards and Dall'Alba, 1981). Generally, the cognitive load is contingent on the number of interlinked conceptual elements that need to be understood in order to solve the task (Brünken, Seufert, & Paas, 2010). This load is a predictor of task difficulty (Schnotz & Kürschner, 2007). In cooperative learning, cognitive load may be further increased because inputs from materials, as well as the social fabrics in a group and communication need to be considered simultaneously. Because of this additional load, the benefit from cooperative learning could be reduced. This phenomenon is called the "split-attention effect" (Sweller, van Merrienboer, & Paas, 1998).

Students are sometimes discouraged from participating actively in cooperative learning activities (Leonardi, Jackson, & Diwan, 2009) because student performance is frequently based on an individual-level assessment (e.g., an exam). Peer evaluations are a key tool to making sure that students participate in cooperative learning activities (Chapman &

van Auken, 2001). Nevertheless, some students will not participate in cooperative learning activities. If this is the case, their peer ratings should reflect the lack of participation, and learning outcomes should be reduced. In combination, cognitive load theory and insights on cooperative learning suggest that if students manage to actively engage with difficult materials, their in-group role will become that of an “expert” student (Berger & Hänze, 2015). Those “expert” students participate more actively than other students in solving cooperative learning exercises, and will hence benefit more. From a CLT perspective, students with high capability for social engagement and communication have more mental capacity available for absorbing difficult content. Consequently, for these students participation in cooperative learning has a particularly pronounced positive effect on learning outcomes.

This paper combines a CLT perspective on cooperative learning with an investigation into the benefits of cooperative learning for differently engaged students. The study is conducted in the context of a small-group (20-30 students) class that was repeatedly offered over several semesters from 2017 to 2019. The class was offered for students at both the undergraduate (BSc) and graduate (MSc) levels. The resulting 578 data points from 101 unique students are complemented with independent assessments of task difficulty. This independent assessment comes from two additional instances where this class was offered to a different student audience at a second business school in a foreign country.

The paper contributes to literature on cooperative learning in three ways. First, it establishes the positive effect of cooperative learning on student performance on within-student variation. Second, it takes a Cognitive Load Theory perspective on cooperative learning in management education, a perspective that has so far received limited attention. Doing so, this study also contributes to a discussion on different kinds of intelligence. Third, it establishes students’ degree of participation in a cooperative learning environment as an important contingency on its positive learning outcomes.

RELATED LITERATURE

Cooperative learning has been established as a key mechanism to maximize learning outcomes in the classroom (Johnson et al., 1979). However, most of the literature on cooperative learning focusses on primary and secondary school education (Herrmann, 2013). More recently, literature established cooperative learning as a successful method in tertiary education (Foldnes, 2016). In cooperative learning environments, students work in small groups. Cooperation leads to better learning outcomes because of social interdependence (Johnson et al., 2007): Students are more motivated to engage with the material if they are challenged to solve a task jointly. Cooperative learning has been delineated from collaborative learning in terms of the extent of collaboration necessary (Matthews et al., 1995). In collaborative learning students explain materials to each other, while in cooperative learning they work together on solving a task.

Cognitive load theory (Sweller, 1988) argues that students have to engage in schema acquisition and automation of thought processes are the key mechanisms to learning (Sweller, 1994). Every activity in the classroom that does not directly relate to at least one of these two mechanisms may hinder the achievement of optimal learning outcomes. In addition, interactivity among tasks that relate to each of the two mechanisms makes it harder to efficiently acquire knowledge (Maybery et al., 1986). If elements are highly interactive, it will become harder to obtain a good knowledge of the combined effect, and learning about the elements separately will not help substantially to in understanding the big picture (Sweller & Chandler, 1994).

Students engaging in teaching activities vis-à-vis their peers is a central element in many collaborative learning activities (Berger & Hänze, 2015). Students that instruct their peers in a certain task are called “expert students” in cooperative learning literature (e.g., Sternberg, 1998). In a setting including “expert students”, cooperative learning takes the form of student-student instruction, rather than co-creation of knowledge (Moreno, 2009). In such settings, the interdependence among participating students is lower than in symmetric settings that have a co-construction focus (Slavin, 1996). As a consequence, learning outcomes may be lower unless a classroom design that introduces reciprocity into the student-student interaction (such as a jigsaw design) is introduced (Berger & Hänze, 2015).

THEORY AND HYPOTHESES

It has long been established in learning and education literature that cooperative learning is an important element in students' future career success. This is the case because (1) increasing task complexity in the business world leads to increased specialization, which requires more cooperation (Kolb, 1999), and (2) because recruiters actively seek "people skills" relating to managing teams when looking for adequate candidates (Messmer, 1999). Consequently, cooperative learning is a much-applied technique in courses in business schools. Its use has been associated with better intellectual and social learning (Hill & Hill, 1990). It has proven difficult, however, to isolate students' learning from cooperative environments from students' ex-ante intellectual and social capital (Carini, Kuh, & Klein, 2006). This is because student ability and their ability to learn in a cooperative environment are consequences of similar intellectual and social capacities (Shulman, 2002). In order to assess the relationship between participation in learning activities and learning outcomes, student performance on cooperative learning activities, as well as their performance in the activity that is practiced in cooperative learning, need to be analyzed separately. Ideally, this would be done while controlling for student ability. If this is done, literature suggests a positive effect of engagement in cooperative learning and exam performance (Johnson, Johnson, & Smith, 1998). This is the baseline hypothesis for this paper.

Hypothesis 1: The better a student's performance in a cooperative learning exercise, the better the student's exam performance.

Students that are offered opportunities to practice cooperative learning and participate in team-based tasks have better opportunities in the job market, because they practice teamwork (Erez, LePine, & Elms, 2002). However, incentive structures at universities are often detrimental to participation in such cooperative learning activities, because they favor individual-level exam performance over cooperative assessment (Leonardi, Jackson, & Diwan, 2009). A solution for this conundrum is the use of peer-evaluation (Meenakshi, 2012). Peer-evaluation forces students to assess each other's contribution to cooperative learning exercises. Moreover, if peer-evaluation is part of students' individual class score, it also aligns incentives between participation in cooperative learning and individual performance. Because participation in cooperative learning is associated with better learning outcomes, more active participation is associated with positive learning outcomes.

Hypothesis 2: The more a student engages in a cooperative learning exercise, the better the student's exam performance.

The two processes argued in hypotheses 1 and 2 are not independent. Cognitive Load Theory (CLT) as a theoretical framework allows integrating the lines of reasoning. Particularly, it argues that students' ability to absorb, process, and apply knowledge in classes is a function of how demanding the learning process is (Edwards and Dall'Alba, 1981). Particularly, the number of interrelated learning processes drives the difficulty at which students learn new concepts (Brünken, Seufert, & Paas, 2010). The less interrelated two concepts are, the more easily can students focus on them sequentially. This reduces cognitive load, and should increase learning outcomes (Schnotz & Kürschner, 2007). If students have to develop understanding of a concept in groups, at least two cognitive processes need to run simultaneously and interactively. First, students need to collect and internalize information. Second, students need to navigate the group's social fabric and communicate their opinions and findings to fellows, and vice-versa. The second element should be independent of a learning module’s difficulty. The first element, however, leads to higher cognitive load. As a consequence, learning outcomes should be reduced if a module is particularly difficult.

> **Hypothesis 3a**: The more difficult the materials covered in a cooperative learning exercise, the weaker the positive effect of cooperative learning on exam performance.

When students are confronted with difficult materials, their ability to work cooperatively will be diminished because cognitive load is higher. Consequently, students cluster into groups according to their intellectual and social abilities (Berger & Hänze, 2015). Some students take the role of “expert students”, who actively explain materials to their colleagues (Renkl, 1995). In the context of CLT, becoming an expert student is associated with the second element driving cognitive load mentioned above: communicating and navigating the social fabric. Some students have higher capacity for these tasks, which frees capacities for internalizing the materials discussed. Consequently, students with the ability to more easily manage the social component of cooperative learning have more capacity to absorb intellectual content, everything else being equal. Of course, this line of reasoning requires keeping students’ overall learning capacity constant. If this is the case, “expert students” are expected to benefit more strongly from a cooperative learning exercise. Students that participate actively in cooperative learning despite the difficulty of a module can be identified as such expert students. Those students that have particularly much capacity for social interaction will more easily absorb difficult materials in a cooperative setting because the cognitive load they feel from group learning is lower. This “social intelligence” helps them benefit from group learning despite high difficulty. The more difficult materials are, the more capacity for internalizing the materials is needed, and the more important is the ability to free those capacities.

Hypothesis 3b: The more difficult the materials covered in a cooperative learning exercise, the stronger the positive effect of engagement in cooperative learning on exam performance.

DATA AND SAMPLE

The data for this study are collected in five tranches. These tranches correspond to courses taught at a leading European Business School ("School A") between 2017 and 2019. Two of the tranches are MSc-level courses, and three are BSc-level courses. Each course consists of eight sessions, in six of which different topics are discussed. Session seven is a case-study session, where materials from the individual sessions are discussed in the context of a more complex case. Student performance on the case study is not relevant for this study, but included as a control variable. Session eight is a final exam. At the beginning of sessions two through seven, students are asked to answer theory questions and solve short computation exercises on materials covered in the session before. Students work on these exercises in groups of four to five, and can use all materials to answer the questions. The average time to solve these questions is 20 minutes. The final exam in session eight is structured according to the sessions. The final exam is done individually in a "closed book" format, without any aids beyond a simple calculator. The resulting data are for 101 unique students, who participated in 578 class sessions. 312 of those sessions were taken by MSc students, the remaining 266 by undergraduate students.

MEASURES

The dependent variable in this study is the exam score (in per cent) that students obtain for the questions that belong to the respective sessions. The key independent variables are the score (in per cent) that students obtained on the exercise sheets that they solved in the beginning of the session following the one when a module was discussed, and a peer-rating score (in per cent) that each student assesses all group members on. The moderating variable is the difficulty of a module's materials. This variable is created from independent classes discussing the same materials. These classes take place at a different leading European Business School ("School B"), and exam materials are created equivalently to the class that the dependent and independent variables are generated from. The task difficulty variable is the inverted average score (in per cent) over all students (54) at School B. Student participation in the class when materials are initially discussed, and in the session when the exercise sheet is solved, are controlled for. Moreover, scores on a case study report are controlled for. Unobserved student and class characteristics are captured through the hierarchical methodology described in the next section.

METHODOLOGY

Hypotheses are tested in a random intercept model structure (Alcácer, Chung, Hawk, & Pacheco-de-Almeida, 2018). This model structure avoids bias from unobserved student characteristics that influence the dependent variable, but are omitted from the estimation model. It also allows the analysis of variation in the effects of independent on dependent variables, which will be used to motivate the interaction effects hypothesized above empirically, in addition to the theoretical reasoning presented. This paper uses the lmer() command (De Boeck, Bakker, Zwitser, Nivard, Hofman, Tuerlinckx, & Partchev, 2011) in an R 3.5.1 distribution (R-Core-Team, 2017) for estimation. In analytical terms, the estimation equation models the exam score per module (*m*) by student (*i*):

$$exam\ score_{i,m} = \beta_0 + \boldsymbol{\beta_1} \cdot \boldsymbol{Controls_{i,m}} + \beta_2 \cdot exercise\ score_{i,m} + \beta_3 \cdot peer\ rating_i + c_i + \epsilon.$$

As suggested by hypotheses 3a and 3b, the coefficients β_2 and β_3 are decomposed to analyze variation across students, as well as variation for different values of module difficulty:

$$\beta_2 = \gamma_0 + \gamma_1 \cdot module\ difficulty_m.$$

$$\beta_3 = \delta_0 + \delta_1 \cdot module\ difficulty_m.$$

RESULTS

Summary statistics and pairwise correlations are presented in Table 1. Exam scores by module are on average 87 per cent, with quite substantial variation, as shown by the histogram presented in Figure 1. Report scores are on average 91 per cent, students generally participate in classes actively. This holds for both the respective session when materials are discussed, and the session when cooperative learning exercises are conducted. The maximum participation score per session is five points. Session difficulty, which represents inverse exam score per module at School B, is on average 0.3, which corresponds to an average exam score of 70 per cent in School B. The difference between this value and the dependent variable may be explained by the fact that cooperative learning exercises are not used in School B. Exercise scores are on average 84 per cent, which is again lower than exam scores. This points towards the fact that there is a positive learning effect from cooperative learning exercises. Average peer rating scores are 98 per cent, variation here mainly comes from students that do not participate, and who receive substantially lower scores from their peers.

[please place Table 1 and Figure 1 approximately here]

Inferential analyses are presented in Table 2. Model 1 is a baseline model. The results in model 1 support prior literature that shows student participation in a session to lead to better exam performance ($p<0.007$; e.g., Massingham & Herrington, 2006). It is interesting to see that the strong positive effect of learning in the session when materials are first introduced is statistically ($p<0.007$) and economically (0.13) larger than the coefficient of participation in the session when group learning exercises are conducted (0.007, $p<0.133$). Model 1 in Table 2 also shows that graduate students tend to perform better (everything else equal) than undergraduate students, as evidenced by the significant ($p<0.026$) and negative (-0.031) coefficient of the undergraduate dummy. The difficulty of materials discussed in a session negatively influences exam performance ($p<0.001$).

[please place Table 2 approximately here]

Model 2 introduces the first variable of interest into the model. As expected, it shows that the performance in a group learning activity positively influences student performance in the final exam ($p<0.009$). Hypothesis 1 receives empirical support from this finding (the effects are very similar in models 2, 3, and 4, which is the full model without interaction effects). In model 3, the peer-rating variable shows a positive influence on exam scores as well ($p<0.019$). Hypothesis 2 receives support from this finding as well. Model 4 is a combined model of the two findings, and the findings remain statistically equivalent if the respective other is controlled for ($p<0.007$, and $p<0.014$). Figure 2 shows partial effects for hypotheses 1 (left panel) and 2 (right panel).

[please place Figure 2 approximately here]

Before we move on to discussing interactions in models 5-7, an analysis of the variation in coefficients across students may shed some light onto the difference in effects that can be observed across sessions. Figure 3 shows the coefficients of exercise score and peer rating on exam performance for the respective modules. We see that there are six different coefficients, one for each module (as mentioned before, the class used for this analysis has six content modules). If we sort these coefficients by model difficulty (which is done in Figure 3), we see structural dependencies. In the left panel in Figure 3, we see that there is very little structural variation between the coefficients of exercise score on performance and module difficulty. The pairwise correlation between the two variables, as indicated by the dashed blue line, is very close to zero (-0.06). This provides first evidence against the mechanism hypothesized in hypothesis 3a. The right panel in Figure 3 shows the structural variation of the coefficient for the effect of peer rating on exam performance. If the coefficients are sorted by module difficulty, we see a strong positive correlation, as indicated by the dashed blue line. This indicates empirical support for hypothesis 3b.

[please place Figure 3 approximately here]

In order to obtain tests of hypotheses 3a and 3b controlling for the effects of other variables, as well as unobserved student characteristics, we investigate the coefficients β_2 and β_3, as explained above in the methodology section. Particularly, we are interested in how the effect of performance in group learning exercises (H3a) and participation in those exercises (H3b) on exam performance are influenced by the difficulty of the material covered. Models 5 to 7 in Table 2 indicate how the effects in H1 and H2 are moderated by module difficulty. Model 5 shows that there is no substantial moderation of H1 by module difficulty ($p<0.970$). Hypothesis 3a does not receive empirical support. Model 6 (as well as model 7), however, show that the effect of participation in the group learning exercises on exam performance is the stronger, the more difficult the materials covered ($p<0.003$). Hypothesis 3b receives empirical support from this model. Figure 4 shows effect plots of the difference in effect between high and low session difficulty. When sessions are one standard deviation more difficult than average, there is a strong positive relationship (left panel). When sessions are one standard deviation less difficult than average, there is no significant relationship between peer ratings and exam performance.

[please place Figure 4 approximately here]

DISCUSSION AND CONCLUSION

This paper suggests that Cognitive Load Theory can be used to explain how student learning from cooperative learning activities is contingent on several important factors. The empirical research design, moreover, uses variation on the within-student level, because every student has to complete a six learning modules, and then is tested individually in a final exam. This makes it possible to establish the positive effect of cooperative learning on exam performance beyond between-subject variation, and to isolate the effect of active cooperation from successful learning. Using hierarchical linear modelling techniques, this study also explores how differences in module difficulty condition the positive effects of cooperative learning performance and participation in those activities on exam performance.

The empirical analyses presents statistical support for three of the four hypotheses suggested based on CLT. Students indeed benefit from successfully solving cooperative learning exercises, even if student characteristics are held constant (hypothesis 1). Moreover, more active participation in cooperative learning exercises is beneficial for exam performance (hypothesis 2), beyond the performance in the cooperative learning exercise. Hypothesis 3a, however, is not supported by the empirical findings. The expected moderation of the positive effect of successful completion of cooperative learning exercises by module difficulty is not present in the empirical analyses. This may be the case because students are not ignorant of how difficult which module is, and respond by dedicating more effort to those modules outside of the cooperative learning environments. Consequently, they may make up for learning success they missed out upon during the time dedicated to cooperative learning. Finally, hypothesis 3b, which suggests that students with more capabilities to manage complex social environments benefit even more if the cognitive load is increased by task difficulty, is supported.

The paper contributes to literature on cooperative learning along three lines. First, it makes an important contribution to literature by moving beyond between-student variation in establishing the positive effect of cooperative learning on learning outcomes. Holding student characteristics constant, it shows that different learning outcomes from cooperative learning exercises leads to differences in exam performance. Second, it introduces a CLT perspective into literature on business education, which helps explain how participation in group learning is related to module difficulty and exam performance. Finally, it establishes the degree of participation in cooperative learning as a separate effect on exam performance. This is effect is shown to exist independently of the effect of success in cooperative learning on exam performance.

This paper also opens several avenues for future research. First, CLT may help understand management education better beyond cooperative learning. Other learning designs, such as inverted classrooms may exhibit similar effects because students also act as "expert students" if they are charged with explaining a concept to peers. In addition, digital learning designs, including blended learning approaches, may also contribute from a CLT perspective, because they add another layer to cooperative learning: the degree of digital capabilities. This may have similar moderating effects on the relationship between student learning and exam performance, both in cooperative and individual learning environments.

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Figure 1: Histogram of exam scores

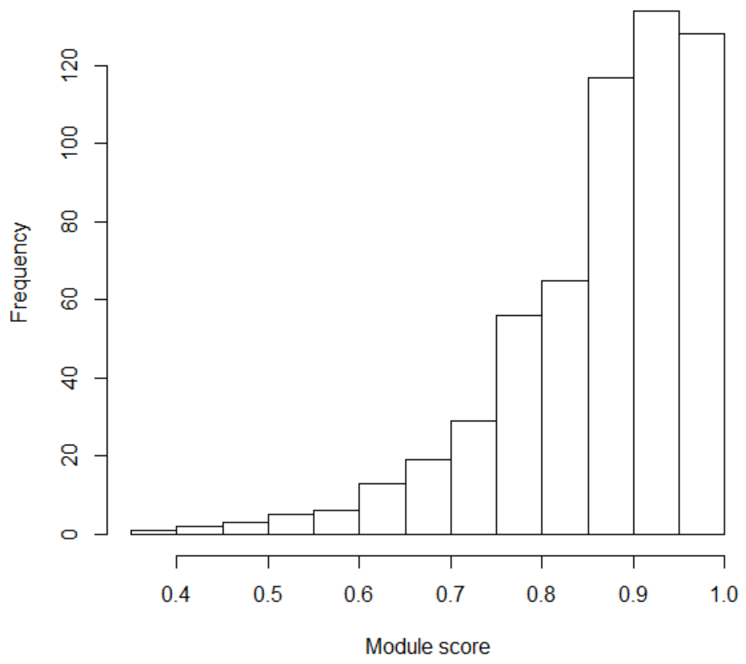

Figure 2: Effect plots for hypotheses 1 and 2

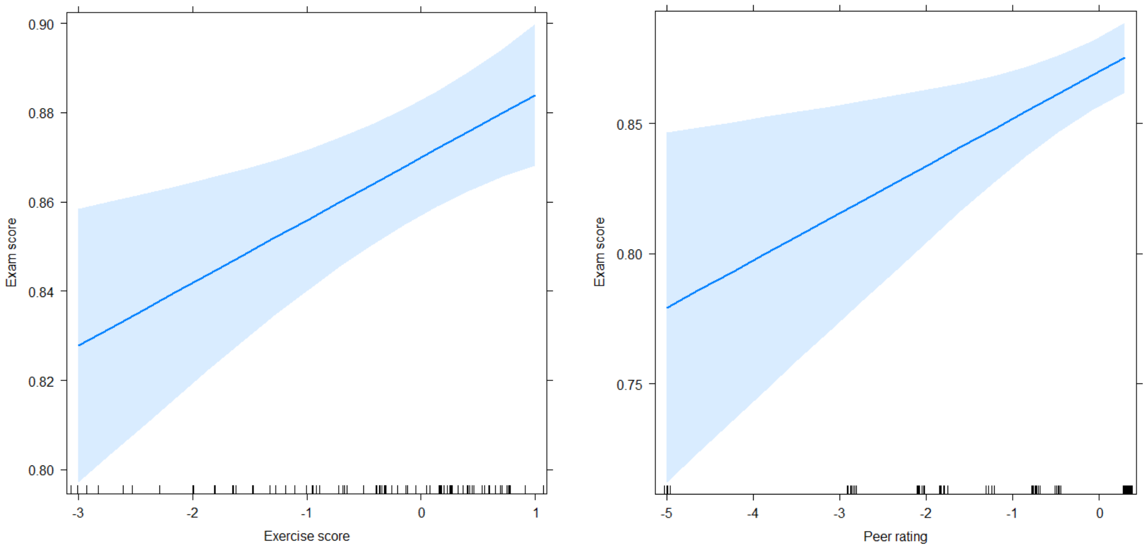

Figure 3: Coefficients by session against session difficulty

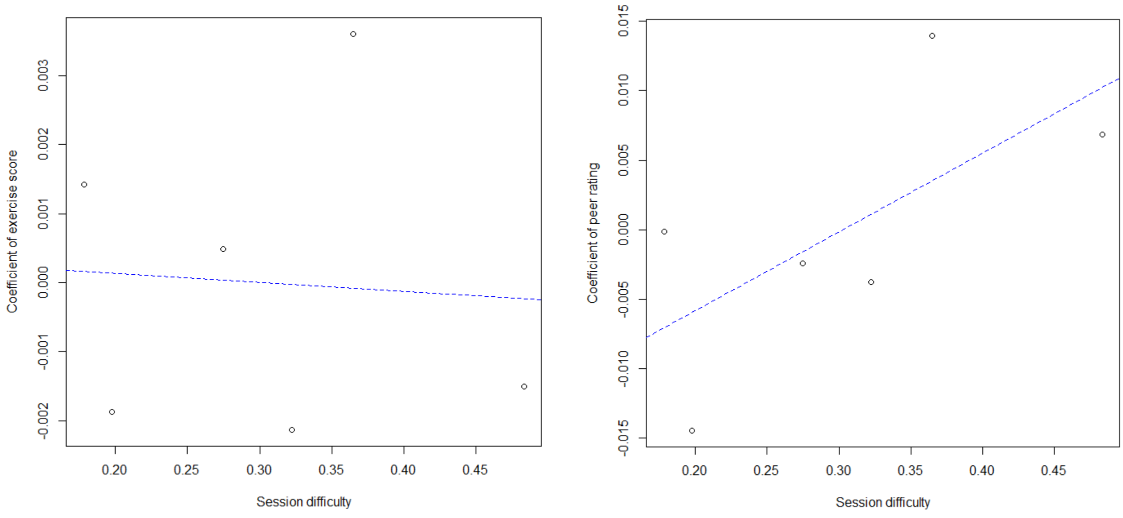

Figure 4: Partial effect of peer rating on exam score for high (left) and low (right) session difficulty

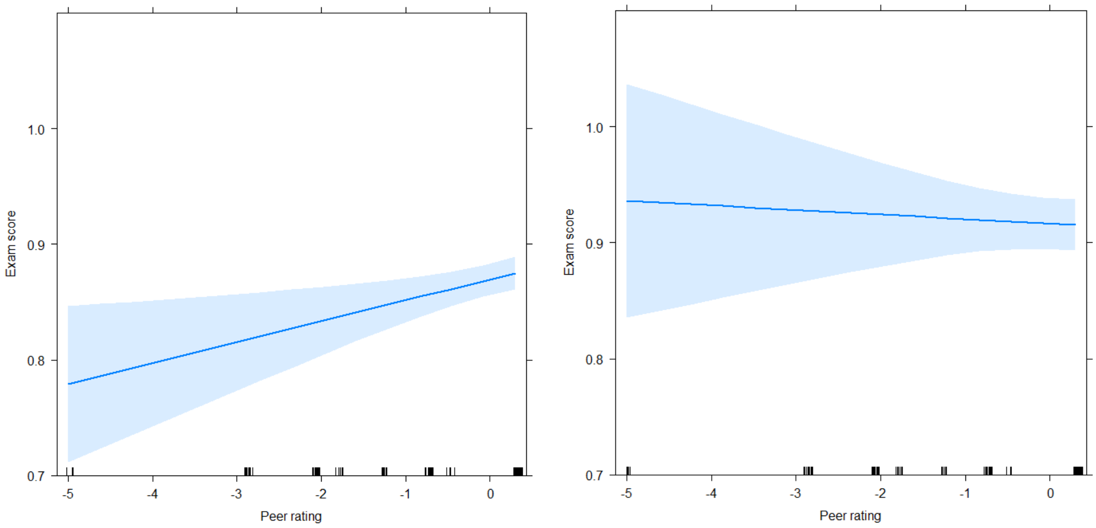

Table 1: Summary statistics and pairwise correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Exam score	1	0.007	0.171	0.034	-0.272	0.264	0.171
(2) Report score	0.007	1	0.051	0.039	0.004	0.015	0.237
(3) Participation content session	0.171	0.051	1	-0.061	-0.217	0.099	0.126
(4) Participation exercise session	0.034	0.039	-0.061	1	0.138	0.039	0.086
(5) Module difficulty	-0.272	0.004	-0.217	0.138	1	-0.412	0.001
(6) Exercise score	0.264	0.015	0.099	0.039	-0.412	1	0.012
(7) Peer rating	0.171	0.237	0.126	0.086	0.001	0.012	1
Mean	0.870	0.915	4.555	4.495	0.303	0.836	0.979
Standard deviation	0.112	0.063	0.915	0.929	0.106	0.133	0.063

Table 2: Inferential statistics on hierarchical linear modelling. Standard errors in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	0.874	0.861	0.925	0.913	0.913	0.912	0.912
	(0.106)	(0.104)	(0.106)	(0.104)	(0.104)	(0.104)	(0.104)
Report score	-0.052	-0.046	-0.104	-0.099	-0.099	-0.099	-0.099
	(0.109)	(0.108)	(0.109)	(0.107)	(0.107)	(0.107)	(0.107)
Participation content session	0.013	0.013	0.012	0.012	0.012	0.012	0.012
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Participation exercise session	0.007	0.006	0.006	0.006	0.006	0.006	0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Undergraduate dummy	-0.031	-0.026	-0.027	-0.021	-0.021	-0.021	-0.021
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Module difficulty	-0.029	-0.024	-0.029	-0.023	-0.023	-0.024	-0.024
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Exercise score		0.013		0.013	0.013	0.012	0.012
		(0.005)		(0.005)	(0.007)	(0.005)	(0.007)
Peer rating			0.016	0.017	0.017	0.006	0.006
			(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
Exercise score *Module difficulty					0.0002		-0.00003
					(0.004)		(0.004)
Peer rating * Module difficulty						0.011	0.011
						(0.004)	(0.004)
Observations	578	578	578	578	578	578	578
Akaike Inf. Crit.	-968.021	-964.003	-963.392	-959.782	-948.609	-957.318	-946.128