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Identifying individual differences using log-file analysis: Distributed learning as mediator between conscientiousness and exam grades

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ABSTRACT

Online learning poses major challenges on students' self-regulated learning. This study investigated the role of learning strategies and individual differences in cognitive abilities, high school GPA and conscientiousness for successful online learning. We used longitudinal log-file data to examine learning strategies of a large cohort (N = 424) of university students taking an online class. Distributed learning, the use of self-tests and a better high school GPA was associated with better exam grades. The positive effect of conscientiousness on exam grades was mediated by distributed learning. Conscientious students distributed their studying over the course of the semester, which in turn, improved grades. The results provide insights into objective study behavior of online students and shed light on the question of how individual differences in cognitive and non-cognitive prerequisites shape the use of learning strategies and exam grades. Practical implications for online course designers and ideas for further research are discussed.

1. Introduction

Digitalization is on the rise, especially in higher education (Helsper & Eynon, 2010; Kirschner & De Bruyckere, 2017; Means, Toyama, Murphy, & Baki, 2013; OECD, 2016). Web-based instruction challenges students to organize their learning process in terms of making their own choices of where, what, and how long they study. This flexibility requires continual, autonomous planning and monitoring of one's own learning process, in short the competence to self-regulate study behavior (Schmitz & Wiese, 2006; Winne & Hadwin, 1998; Zimmerman, 2002). In the absence of weekly face-to-face lectures, it is even more important to distribute and monitor studying activities independently over time, in particular because distributed learning and self-monitoring (e.g., self-testing) have been shown to be highly beneficial for academic achievement (Dunlosky, Rawson, Marsh, Nathan, & Willingham, 2013; Dunn, Saville, Baker, & Marek, 2013; Nicol & Macfarlane-Dick, 2006; Rowland, 2014). So far, research in the field of online learning mainly investigated learning strategies in voluntary, informal online courses (e.g., massive open online courses) and focused on course dropout as a dependent variable (Hart, 2012; Lee & Choi, 2011). However, we have no clear picture how students deal with the challenges of obligatory online courses in formal educational settings, where dropout and course performance can have serious consequences. How do they organize their studying over the semester and how do learning strategies relate to exam grades? Further, it is unclear which individual learner characteristics contribute to successful online learning. Cognitive abilities and conscientiousness constitute powerful predictors of academic achievement in higher education (Poropat, 2011; Richardson, Abraham, & Bond, 2012; Schneider & Preckel, 2017), but how do these individual differences relate to successful online learning? Additionally, although conscientiousness is frequently mentioned as an important non-cognitive predictor of academic success, we do not know which mechanisms drive this effect. In what respect do conscientious students differ from less diligent students in their learning strategies and how do these differences ultimately affect performance?

Taken together, our goal is to analyze predictors for study success that are widely discussed in the literature (Schneider & Preckel, 2017) and to investigate their role in online learning. First, we test the effectiveness of two well-established learning strategies (distributed learning and the use of self-tests) with respect to exam grades in an ecologically valid, graded online course. By this means, we help establishing evidence-based learning strategies that can be used as interventional advice for students taking online courses. Moreover, we shed light on the role of individual differences in cognitive abilities, high school GPA and conscientiousness for exam grades. Specifically, we explore patterns of weekly time investment in a learning management system and examine whether the effect of conscientiousness on exam grades is mediated by distributed learning. Thereby, we deepen our understanding of the mechanisms underlying the effect of

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conscientiousness on exam grades.

2. Literature review

2.1. Distributed learning and self-testing as learning strategies

Learning strategies, also referred to as study behavior or study skills “can be broadly defined as behaviors serving to acquire, organize, synthesize, evaluate, remember, and use information”, including procedural (e.g., time management) and metacognitive (e.g., doing self-tests) strategies (Gurung, Weidert, & Jeske, 2010, p. 1). However, which learning strategies should students use to perform well in the next exam? Research from traditional face-to-face learning environments refers to the importance of distributed learning and self-tests, that have both been shown to be highly efficient learning strategies (Dunlosky et al., 2013; Dunn et al., 2013). Distributed learning implies that information is studied over multiple occasions that are spaced in time. This strategy yields greater long-term retention than cramming in one long session for an equivalent amount of time (Benjamin & Tullis, 2010; Bjork, Dunlosky, & Kornell, 2013). Hence, distributed learning is expressed in a continual study habit and can be understood as a time management strategy (Credé & Kuncel, 2008). Self-testing helps identifying knowledge gaps and at the same time constitutes a learning strategy that facilitates knowledge retrieval and transfer (Rowland, 2014). Therefore, self-testing can be viewed as a metacognitive learning strategy.

2.2. Measuring learning strategies

Research on the effectiveness of distributed learning and self-testing has been conducted predominantly in traditional face-to-face settings (Dunlosky et al., 2013). However, along with the increase of freely available online learning opportunities, for instance massive open online courses (MOOCs), new possibilities for the analysis of learning strategies emerged. Learning management systems (LMS) automatically record online log-file data, for instance the number of clicks or minutes students spent on a certain task. Those individual log-files provide objective information on the use of learning strategies that go beyond self-reports, which might be prone to memory distortion or social desirability (Roth, Ogrin, & Schmitz, 2016).

Research in the field of educational data mining used log-files to identify learning strategies and classify learners with respect to their strategy use (Bannert, Molenar, Azevedo, Järvelä, & Gašević, 2017; Papamitsiou & Economides, 2014). For instance, MOOC-users who successfully completed a course were more likely to follow the recommended learning path, which also entails that they distributed their studying activities throughout the course (Kizilcec, Piech, & Schneider, 2013; Maldonado-Mahauad, Pérez-Sanagustín, Kizilcec, Morales, & Munoz-Gama, 2018). Further, “binge watching” many videos in a row, an indication of massed study, was practiced more frequently by dropouters than course completers (Davis, Chen, Hauff, & Houben, 2016). In the same vein, MOOC-users who tested themselves were more likely to pass the course than users who did not complete self-tests (Kizilcec, Pérez-Sanagustín, & Maldonado, 2017; Maldonado-Mahauad et al., 2018; Papamitsiou & Economides, 2014).

Converging evidence form this line of research points to the importance of distributed learning and self-testing for successful online learning. However, voluntary MOOCS differ from formal educational setting at universities, where dropout can have negative consequences, i.e. having to repeat a course or receiving bad grades. Moreover, abovementioned studies focused on course completion as a main dependent variable, which cannot reveal qualitative differences in outcomes, for instance in grades.

2.3. Learning strategies and performance in higher education

In recent years, on-campus university teachers increasingly enrich their courses with online or blended learning elements and provide their learning materials partially or entirely via LMS (Means et al., 2013). Studies that investigated online learning strategies in formal educational settings showed that log-files recorded in the LMS can predict performance outcomes (Cheng, Paré, Collimore, & Joordens, 2011; Imhof & Spaeth-Hilbert, 2013; Imhof & Vollmeyer, 2009; Macfadyen & Dawson, 2010; Morris, Finnegan, & Wu, 2005). For instance, frequency measures, e.g. a higher number of clicks in a LMS, and duration measures, e.g. a higher total time spent in a LMS, were associated with better exam grades (Imhof & Vollmeyer, 2009; Morris et al., 2005). Further, engagement with discussion posts (Cheng et al., 2011; Macfadyen & Dawson, 2010; Morris et al., 2005) and the use of online self-tests (Imhof & Spaeth-Hilbert, 2013; Macfadyen & Dawson, 2010) have been found to benefit performance. However, in those studies, time spent online and the number of clicks were recorded only once, at the end of the course, which does not allow investigating the effects of distributed learning on performance.

To date, there are only few studies that linked online learning trajectories to performance (Goda et al., 2015; Jovanović, Gašević, Dawson, Pardo, & Mirriahi, 2017). Jovanović et al. (2017) analyzed students' online learning strategies in a blended learning course and classified students according to their strategy use. Clusters of students that regularly accessed the LMS and applied various learning strategies wrote better grades compared to student profiles that were characterized by a highly selective use of the LMS. Results speak for the importance of a more distributed study habit, but the clustering approach does not allow testing the effects of specific learning strategies on grades. Goda et al. (2015) categorized learners according to their learning progress over time, whereby the vast majority of students belonged to the group of procrastinators that started to work on the given exercises shortly before the deadline. The authors reported group differences in favor of those students with a more distributed learning habit compared to cramming. As previously indicated, a continuous measure of course engagement over time would further allow investigating how more or less distributed learning affects performance. The research gap is in the analysis of learning strategies and performance of individual learners across time. Besides that, the abovementioned studies did not account for learner characteristics, like cognitive abilities or conscientiousness. It is still unclear which individual prerequisites might drive differences in learning strategies that ultimately affect performance.

2.4. The role of cognitive abilities and conscientiousness for online learning

The assumption that students differ in their ability to cope with the increased self-regulatory demands of online lectures is reflected in their use of learning strategies and performance (Broadbent, 2017; Goda et al., 2015). Compared to students in face-to-face or blended learning courses, online learners need to monitor and regulate time and effort more extensively in order to achieve good grades (Broadbent, 2017; Broadbent & Poon, 2015). In the absence of weekly in-class lectures, there is no social pressure to at least prepare for class at a minimal level and students are not prompted by their teacher's assignments. Thus, students fail to engage with the learning material on a regular basis (Elvers, Polzella, & Graetz, 2003; Kizilcec et al., 2017). However, which student characteristics might be able to explain differences in the ability to cope with this self-regulatory challenge?

Foremost, cognitive abilities and previous academic achievement (high school GPA) have been shown to be two robust predictors of academic success in higher education (Gold & Souvignier, 2005; Richardson et al., 2012; Schneider & Preckel, 2017; Wedler, Troche, & Rammsayer, 2008). Intelligence is the most powerful predictor of academic performance (Furnham & Monsen, 2009; Roth et al., 2015), wherefore high school GPA is frequently used as a proxy for general cognitive abilities. In Germany, for instance, high school GPA entails grades from a wide range of subjects in the last two years of school, covering achievement in many different areas. Above that, high school GPA captures motivational variables, like self-efficacy and achievement motivation (Robbins, Lauver, Davis, Langley, & Carlstrom, 2004) and has been shown to be correlated with conscientiousness (Laidra, Pullmann, & Allik, 2007; Poropat, 2009, 2011).

Beyond this, conscientiousness is the personality trait that has most consistently been linked to academic success (O'Connor & Paunonen, 2007; Poropat, 2011; Richardson et al., 2012; Schneider & Preckel, 2017), especially in higher education (Poropat, 2009). Conscientious people are described as well-organized, hardworking and persistent (McCrae & Costa, 1987). Although research on the effects of individual differences on online learning performance is scarce (Lee & Choi, 2011; Morris et al., 2005), there is some evidence that conscientious students perform better academically (Arispe & Blake, 2012). One possible explanation is that conscientious students might be less prone to academic delay and more willing and able to distribute studying activities over time (Bidjerano & Dai, 2007). The continual engagement with the learning material in turn positively affects final course performance (Credé & Kuncel, 2008; Moon & Illingworth, 2005). This mediation hypothesis however has not been tested so far.

Taken together, research conducted in traditional educational settings point to the importance of individual differences in cognitive abilities, high school GPA and conscientiousness for overall study success. The question of how these cognitive and non-cognitive learner characteristics affect the use of learning strategies and performance in online courses needs further research.

2.5. Research questions and hypotheses

The focus of the study lies on two major research questions:

(1) Which learning strategies contribute to better exam grades in an online course?
(2) How do individual differences in conscientiousness, high school GPA and cognitive abilities affect the use of learning strategies and exam grades?

Regarding the first research question, we want to replicate and extend findings on effective learning strategies in online courses (Kizilcec et al., 2017; Maldonado-Mahauad et al., 2018; Morris et al., 2005). We go beyond previous research by testing the relative effectiveness of two well-established learning strategies, distributed learning and doing self-tests (Dunlosky et al., 2013), in an ecologically valid setting using a rich, longitudinal dataset of behavioral log-data. In this way, we are further able to disentangle the effect of overall time investment and distributed learning. We expect that it is not only the overall time investment that matters for performance, but rather how students use and distribute their study time over the course of the semester. According to previous literature on distributed learning and self-testing (Broadbent, 2017; Dunlosky et al., 2013; Imhof & Spaeth-Hilbert, 2013; Moon & Illingworth, 2005), we hypothesize that:

Hypothesis 1. Distributed learning and a higher number of self-tests predict better exam grades in an online course.

With respect to the second question, we contribute to research on the role of individual differences for successful online learning. Thereby, we aim to shed light on the question of how individual differences in cognitive and non-cognitive prerequisites shape the use of learning strategies and performance. We use three well-established predictors of study success (cognitive abilities, high school GPA and conscientiousness) and investigate their predictive power in addition to that of learning strategies. In line with previous literature (Richardson et al., 2012; Schneider & Preckel, 2017), we expect that:

Hypothesis 2. Individual differences predict exam grades in an online course.

Hypothesis 2a. Higher cognitive abilities predict better exam grades.

Hypothesis 2b. A better high school GPA predicts better exam grades.

Hypothesis 2c. Higher conscientiousness predicts better exam grades.

Since conscientiousness is related to better time and effort regulation (Bidjerano & Dai, 2007), we assume that highly conscientious students will engage in more distributed learning over the course of the semester compared to less conscientious students. More specifically, we expect the effects of conscientiousness on exam grades to be at least partly mediated by distributed learning (Credé & Kuncel, 2008; Farsides & Woodfield, 2003).

Hypothesis 3. Distributed learning mediates the relationship between conscientiousness and exam grades.

3. Method

3.1. Sample

A total of $N = 641$ ($n = 364$ female) initially enrolled in an introductory lecture to educational psychology for pre-service teachers. The lecture took place at a German campus university in the summer semester 2017. The lecture is a mandatory course in their first year of studies in a teacher training program. Halfway through the term, students could decide for themselves if they registered for the exam at the end of the semester (see Section 3.3.4). We excluded data from about 34% of students ($n = 217$, see Section 3.1.1), who did not take the final exam. Consequently, the final sample consists of $N = 424$ students ($n = 253$ female) from whom we gathered weekly log-files and exam grades at the end of the semester. Moreover, we have information on conscientiousness from a subsample of $n = 204$ students. We excluded one student, because he stated in the final control question that he did not answer the questionnaires faithfully. $N = 136$ students in the subsample further participated in a cognitive ability test and reported their high school GPA. We omitted data of four students, because they scored more than two standard deviations below average in the cognitive ability test. Visual inspection of the original paper-pencil tests yielded that these students had stopped working on the test after a few subtests. Students voluntarily decided whether they want to fill in the additional questionnaire and ability test (see Section 3.2). Hence, we do not have complete information on conscientiousness, high school GPA and cognitive abilities for the whole sample.

3.1.1. Dropout analysis

As mentioned above $n = 217$ students that initially enrolled for the course did not register for the final exam and hence were excluded from data analysis. Nevertheless, we had information on their weekly time investment in the LMS. Further, at the beginning of the semester, some of them also reported their high school GPA ($n = 59$), conscientiousness ($n = 60$) and participated in the cognitive ability test ($n = 43$). Therefore, we had the opportunity to check whether students who had dropped out of the course differed from those who registered for the final exam with respect to cognitive abilities, high school GPA, conscientiousness and learning strategies. There was no systematic difference in mean cognitive abilities (t (179) = 0.035, $p = .972$) or high school GPA (t (252) = 1.61, $p = .11$). However, a two sided t-test yielded a tentative trend for conscientiousness regarding course dropout (t (262) = 1.73, $p = .08$, Pearson's $r = 0.11$) in the sense that students who were lower in conscientiousness were more likely to drop the course and to not take the final test. Further, students who registered for the final exam spent more time in the LMS (see Section 3.3.1) (t (470.86) = 18.43, $p < .001$) and engaged in more distributed learning (see Section 3.3.2) (t (630.09) = 22.46, $p < .001$) compared to students who had decided not to take the final exam.

3.2. Design and procedure

In the first week of the online course, a kick-off meeting took place, where we informed students about the study procedure. The meeting was the only face-to-face session during the semester that was offered to provide information on the lecture content and procedure, and the regulations for the final exam. It was emphasized that any data would be processed anonymously. Students who did not attend this session received the information via e-mail. Furthermore, we asked students to fill in an additional questionnaire on personality and prior academic achievement either during the kick-off meeting or online via e-mail. Those students who were present at the kick-off meeting further completed a cognitive ability test. In return, students who filled in additional questionnaires could take part in a lottery and win cash prizes (1 × 200€, 1 × 100€, 10 × 50€). Students signed an informed consent, in which we assured that participation was voluntary and had no impact on their final grade. All procedures complied with APA ethical guidelines and were approved by the course coordinator and by the dean of the faculty.

3.2.1. Learning materials and course requirements

Learning materials were presented online in the web-based LMS *Ilias* (https://www.ilias.de/docu/goto_docu_root_1.html, see Section 3.2.2). The course contained six folders with learning materials for each of the six sections (introduction to educational psychology, developmental psychology, memory and learning, individual differences, learning disabilities, social psychology of learning and classroom management). For every section, the teacher offered podcasts including the lecture slides with additional audio recordings. Overall, students had access to 25 podcasts, which they could retrieve as often as they wanted. Students could listen to the podcasts exclusively online via the LMS. However, they had the possibility to download the corresponding lecture slides without audio recordings. Moreover, an additional video-clip and case studies were offered as supplementary learning materials. We attached a detailed description of the learning materials and lecture topics in Appendix A. In a separate folder, online self-tests (see Section 3.3.3) were provided for each lecture topic to support self-monitoring and familiarize students with the item format of the final exam. The single-choice questions were similar to those administered in the final exam that students had to pass for course credit (see Section 3.3.4). Further, to encourage continual, distributed learning, students had access to a document in the LMS containing an overview of learning suggestions for each week. These suggestions, however, were not compulsory, leaving students the opportunity to plan, organize, and monitor their learning behavior autonomously. Besides the online materials, students could use the recommended book that covered the topics of the lecture to prepare for the exam. Students were free to choose if they want to prepare for the exam using lecture slides only, lecture slides with audio recordings (podcasts) or the recommended book. There were no mid-term exams or otherwise mandatory tasks or deadlines. The final exam was the only obligatory, graded coursework that students had to pass.

3.2.2. Learning management system and log-files

As mentioned in the previous section, students could download lecture slides or work online using to the podcasts and online self-tests. Thereby, the LMS automatically recorded and continuously updated the total number of clicks and minutes a student spent online. This means that with every new login the system overwrote information from the last login. For this reason, we downloaded log-files on a weekly basis in order to be able to calculate weekly time investment in the LMS (see Section 3.3.1). Log-files only provided information on the overall time investment, but not on the sequence of learning activities, e.g. whether a student first listened to a podcast and then made a self-test. Likewise, we were not able to trace back how much time a student spent on a specific task in each week. However, it was possible to extract individual log-files for each student at the end of the course. By looking at every log-file individually, it was possible to get information on the overall number of self-tests accessed by each student and the percentage of correct answers in those tests (see Section 3.3.3).

3.3. Measures

We assessed weekly time investment in the LMS, distributed learning and the number of self-tests as well as performance in the final exam electronically via the LMS. Questionnaires were administered in paper-pencil format during the kick-off meeting or electronically via e-mail.

3.3.1. Weekly time investment and overall time investment

We measured the minutes students spent online in the LMS over the course of the summer semester 2017 running for 14 weeks from mid-April through mid-July. We omitted data from the first two weeks of the semester because some students registered for the course with delay. Further, until the third week, the vast majority of students (91%) had not yet logged-in to the online course. In the consecutive twelve weeks, we downloaded data every Monday afternoon. Since log-files were recorded automatically by the LMS, we collected a completely balanced panel dataset for each student measured at twelve time points during the semester, whereby the last data point represents the day of the final exam. Based on this information, we calculated the number of minutes spent online in each of the twelve weeks for every student (weekly time investment). Summing up weekly time investment gives us the overall time investment, i.e. the amount of minutes each student spent in the LMS over the whole course of the semester until the final exam.

3.3.2. Distributed learning

Additionally, we counted the number of weeks in which each student had accessed the LMS irrespective of the actual amount of time students spent online. We took this variable as an indicator of distributed learning. Higher values on this variable suggest a more distributed, continual engagement with the course content. If a student logged-in to the LMS even for a short period, we considered this as an indication that the student dealt with the learning materials to some extent. Since we gathered log-files over twelve weeks of the semester, values on this variable could possibly range from zero to twelve.

3.3.3. Self-tests

Sixteen self-tests were provided with varying amounts of items. Self-tests contained several single-choice questions with four options that covered different chapters of the lecture. At the end of each self-test, students received feedback and had the possibility to look up an explanation if an answer was wrong. Each student had permission to run every self-test twice. At the end of the semester, we counted the overall number of different self-tests for each student, which could range from 0 (none of the self-tests was made) up to 16 (all of the available self-tests were made). We used the number of different self-tests as an indicator of student's self-monitoring of learning. Further, information on the percentage of correct answers in the processed self-tests were available. However, since students could repeat each test twice, the distribution of test scores was heavily skewed with a median percentage of correct answers of 94% ($M = 0.76$, $SD = 0.43$). Further, test scores were highly correlated with the number of self-tests ($r = 0.73$, $p < .001$). Therefore, test scores were not used in subsequent data analysis.

3.3.4. Exam grades

The final exam at the end of the semester took place on campus in a PC pool under supervision of research assistants. Forty single-choice questions (4 options each) that covered the whole course content were

Table 1
Descriptive statistics and correlations between exam grades, learning strategies, conscientiousness, high school GPA, and cognitive abilities.

	M (*SD*)	[range]	1	2	3	4	5	6
1 Exam grade	2.61 (0.83)	[1.0; 5.0]						
2 Overall time investment (in minutes)	343.67 (351.54)	[0; 3255]	−.34***					
3 Distributed learning	5.60 (2.93)	[0; 12]	−.43***	.60***				
4 Number of self-tests	12.74 (5.57)	[0; 16]	−.43***	.32***	.31***			
5 Cognitive abilities	42.73 (9.63)	[23.75; 63.25]	−.19*	−0.14	−.18*	0.06		
6 High school GPA	2.31 (0.61)	[1.0; 3.6]	.54***	−.15*	−.24***	−.32***	−.21**	
7 Conscientiousness	4.05 (0.88)	[1.67; 5.83]	−0.08	0.12	.30***	0.05	−0.14	−0.09

Note. Learning strategies and exam grades (N = 424), cognitive abilities & high school GPA (n = 136), conscientiousness (n = 204). Smaller grades and high school GPA indicate better performance.
* $p < .05$.
** $p < .01$.
*** $p < .001$.

administered electronically via the LMS. Students had 45 min to work on the exam and earned one point for each correct answer yielding a maximum of 40 possible points. Exam grades could range from 1.0 ("very good") to 5.0 ("failed"). The exam was the only mandatory, graded task that students needed to complete in order to pass the course.

3.3.5. Conscientiousness

We used the German translation of the Big Five Inventory (BFI-2; Danner et al., 2016; https://doi.org/10.6102/zis247) to assess the personality dimension of conscientiousness with the respective facets orderliness (e.g., "*I keep things neat and tidy.*"), diligence (e.g., "*I am persistent, work until the task is finished.*") and reliability (e.g., "*I am dependable, steady.*"). Every test facet consists of four items on a six-point Likert scale ranging from "not true" to "true". Negatively coded items were reversed and a simple mean was computed. Overall, conscientiousness comprises the average of the three facets, whereby higher values indicate higher conscientiousness. Reliability analysis confirmed a good internal consistency of the scale (Cronbach's $\alpha = 0.77$).

3.3.6. Cognitive abilities

We measured cognitive abilities using the GkKT (Gießener kognitiver Kompetenztest; Ulfert, Ott, Bothe, & Kersting, 2017). The GkKT takes 30 min and the overall score has a range from 0 to 66 points. The test includes twelve time-limited subtests with a varying number of items. Six subtests (22 items) assess verbal abilities. The subtests encompass finding antonyms (4 items), analogies (5 items) and semantic relationships between words (3 items) as well as completing common German sayings (2 items), syllogisms (3 items) and word sequences (5 items). Three subtests (21 items) measure figural, non-verbal reasoning abilities. Those encompass entailing logical progressions for a series of figures (7 items), completing puzzles (7 items) and finding the way through a maze using mental rotation (7 items). Additional three subtests (23 items) measure numerical skills. Subtests include completing number sequences (9 items), solving mathematical word problems (6 items) and numerical matrices (8 items). Verbal and figural subtests consist of single-choice items with a varying number of distractors. Regarding the numerical subtests, short answers have to be provided in an open text field for each item. Results from the verbal, figural and numerical subtests are combined to an overall cognitive ability score. The overall score showed good internal consistency (Cronbach's $\alpha = 0.83$).

3.3.7. Previous academic achievement

Previous academic achievement was measured by self-reported high school GPA of the university entrance diploma (ranging from 1.0 = "very good" to 4.0 = "passed"). High school GPA includes grades in various subjects that were attained during the last two years of school. High school GPA is a widely used criterion for university applicant selection and shows a strong correlation with later university achievement (Richardson et al., 2012; Wedler et al., 2008).

3.4. Data analysis

We used SPSS 23 (IBM Corp., 2014) and Mplus 7.3 (Muthén & Muthén, 1998–2017) for data analysis. We set the critical alpha value at $\alpha = 0.05$ and controlled for Type I error accumulation within each regression analysis using the Benjamini-Hochberg correction (Benjamini & Hochberg, 1995). In a first step, observed p-values are sorted in ascending order, whereby k represents the rank of the ordered p-values ($k = 1, 2, 3, \ldots, m$) and m represents the overall number of tests. In a next step, thresholds for each p-value are adjusted by $(k * \alpha) / m$. For instance, the threshold for the smallest p-value is computed by dividing 0.05 by m, the threshold for the second highest p-value by dividing $(2 * 0.05) / m$, the third by dividing $(3 * 0.05) / m$ and so forth. This step-wise procedure controls for Type I error while being less conservative than the traditional Bonferoni approach. Furthermore, we controlled for collinearity in regression analysis. A pairwise correlation coefficient above 0.7, a variance inflation factor (VIF) above 10 and tolerance values below 0.1 indicate risk of collinearity (Dormann et al., 2013).

4. Results

4.1. Descriptive statistics and correlation analyses

Table 1 shows the descriptive statistics for the measures of learning strategies, exam grades, conscientiousness, high school GPA and cognitive abilities as well as the correlations among the variables.

4.1.1. Descriptive statistics and correlations among learning strategies

On average, students spent 343 min (about 7 h) online. The large standard deviation and range indicate that students used the LMS with varying intensity (see Table 1). They accessed the LMS in about six out of twelve weeks, which is reflected in the distributed learning variable. Some students distributed their studying activities across all twelve weeks, while others never accessed the LMS. Students used on average 13 out of 16 possible self-tests, whereby the majority of students (n = 266, 63%) accessed all tests and only a few students opened none of the self-tests (n = 36, 8%). Overall study time, distributed learning and the number of self-tests were significantly interrelated. Students, who spent more time online also distributed their studying activities over the semester and tested their knowledge more frequently. Taking together, descriptive statistics revealed a large heterogeneity in overall time investment and learning strategies between individuals.

Fig. 1. Average weekly time investment (in minutes) of high (blue, $n = 62$) and low (orange, $n = 60$) performing students. The grey line indicates average weekly time investment over the whole sample ($N = 424$). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

4.1.2. Descriptive statistics and correlation between learning strategies and exam grades

Exam grades ranged from 1.0 ("very good") to 5.0 ("failed") with a grand mean of 2.61 ($SD = 0.83$). Overall time investment, the number of self-tests and distributed learning were moderately correlated with subsequent exam grades (see Table 1). Students who used the LMS frequently (more minutes, more self-tests) and distributed studying activities across time achieved better grades. Fig. 1 illustrates this finding. Descriptively, those students, who earned very good grades in the final exam (blue line) used the LMS more frequently than low performing students (orange line) over the whole course of the semester. Students who performed poorly in the final exam confined their studying almost exclusively on the last three weeks of semester.

Regardless of the final grade, the overall trend (grey line) showed that all students increased their time investment over the course of the semester, which was also reflected in a positive linear time trend using a hierarchical linear regression ($b = 5.61$, $p < .001$).

4.1.3. Descriptive statistics and correlations between individual differences, learning strategies and exam grades

On average students earned 43 out of 66 points in the cognitive ability test. Cognitive abilities were significantly related to better exam grades, a better high school GPA and less distributed learning (see Table 1). Mean self-reported high school GPA was 2.3 ($SD = 0.61$). High school GPA showed a strong positive correlation with grades, whereby a better high school GPA was associated with better grades. Further, high school GPA was moderately related to overall time investment, distributed learning and self-tests. Students with a better high school GPA spent more time studying online, used more of the self-tests, and distributed their studying activities across the semester. The average self-reported conscientiousness was high ($M = 4.05$, $SD = 0.88$), but it was neither significantly correlated with grades, nor cognitive abilities nor high school GPA. However, higher conscientiousness was associated with more distributed learning across the twelve weeks of the semester.

4.2. Prediction of exam grades

To address 1, we performed a linear regression analysis of exam grades on behavioral measures of learning strategies, i.e., distributed learning and the number of self-tests (see Table 2). We used a step-wise procedure, in which we further controlled for overall time investment, since those students that used more self-tests and distributed their studying activities also invested a higher overall amount of time for studying (see Table 1). Collinearity indices were all within the proposed thresholds (correlation coefficients below 0.70, VIF: 1.2–1.8, Tolerance: 0.55–0.87).

In the first step, we found that students with a higher overall time investment received better grades, which explained about 11% of the variance in exam grades (see Model 1). Moreover, in line with H1, we found that distributed learning and a higher number of self-tests were associated with better exam grades (see Model 2 and Model 3). Altogether, the three predictors explained 26% of the variance in exam grades. However, after including distributed learning and the number of self-tests into the regression model, the effect of overall time investment turned non-significant.

Table 2
Regression models of exam grades on overall time investment and learning strategies.

Dependent variable: exam grades						
Predictors	β	p	R^2	ΔR^2	F	p
Model 1	**−0.336**	0.000	0.113	0.113	53.649	0.000
Overall time investment						
Model 2			0.172	0.059	43.745	0.000
Overall time investment	**−0.153**	0.006				
Distributed learning	**−0.305**	0.000				
Model 3			0.262	0.090	49.713	0.000
Overall time investment	−0.085	0.111				
Distributed learning	**−0.245**	0.000				
Number of self-tests	**−0.321**	0.000				

Note. $N = 424$. Exam grades: Smaller values indicate better exam grades. The bolded standardized regression weights were significant after applying Benjamini-Hochberg correction.

With respect to the second research question, we investigated whether individual differences in cognitive and non-cognitive prerequisites can explain variance in exam grades over and above the effects of learning strategies. To address 2, we included cognitive abilities, high school GPA and conscientiousness into a hierarchical linear regression model for the subsample of students that filled in the additional questionnaire and the cognitive ability test respectively. We used a step-wise procedure to investigate the unique effects of cognitive abilities, high school GPA and conscientiousness beyond that of learning strategies. We excluded overall time investment from the subsequent regression analyses, since it did not add to the prediction of exam grades beyond distributed learning and the use of self-tests (see Table 2).

In a first step, we included distributed learning, the number of self-tests and cognitive abilities into the regression model. Higher cognitive abilities significantly predicted better exam grades beyond learning strategies (see Table 3, Model 4). In a next step, students with a better high school GPA achieved better exam grades, which explained additional 14% of the variance in grades (see Table 3, Model 5). High school GPA showed the strongest beta weight followed by distributed learning and self-tests. However, the effect of cognitive abilities turned non-significant in Model 5. Finally, conscientiousness did not add to the prediction of exam grades beyond learning strategies and high school GPA (see Table 3, Model 6).

Table 3
Regression models of exam grades on learning strategies, conscientiousness, cognitive abilities and high school GPA.

Dependent variable: Exam grades						
Predictors	ß	*p*	R^2	ΔR^2	*F*	*p*
Model 4			0.256	0.256	15.175	0.000
Distributed learning	**−0.330**	0.000				
Number of self-tests	**−0.254**	0.002				
Cognitive abilities	**−0.215**	0.006				
Model 5			0.391	0.135	21.083	0.000
Distributed learning	**−0.229**	0.003				
Number of self-tests	**−0.152**	0.045				
Cognitive abilities	−0.118	0.105				
High school GPA	**0.411**	0.000				
Model 6			0.402	0.011	17.479	0.000
Distributed learning	**−0.257**	0.001				
Number of self-tests	**−0.154**	0.041				
Cognitive abilities	−0.105	0.150				
High school GPA	**0.418**	0.000				
Conscientiousness	0.110	0.126				

Note. $N = 136$. Exam grades and high school GPA: Smaller values indicate better exam grades. The bolded standardized regression weights were significant after applying Benjamini-Hochberg correction.

Altogether, the five predictors explained 40% of the variance in course grades. In line with H2b, high school GPA constituted a significant predictor of exam grades beyond distributed learning and the use of self-tests. In contrast to 2a and H2c, conscientiousness was not a significant predictor of exam grades and cognitive abilities only showed a significant effect before adding high school GPA to the regression model.

4.3. Mediation analysis

As stated in 3, we expected that the effect of conscientiousness on exam grades was mediated by distributed learning. For this purpose, we performed a path analysis using Mplus 7.3 software (Muthén & Muthén, 1998–2017). We used a bias corrected bootstrap method (5000 bootstrap samples) to calculate the confidence intervals of the model estimates. As predicted, we found a significant indirect effect of conscientiousness on exam grades ($\beta = -0.14$, 95% CI $[-0.22; -0.08]$), but no direct effect (see Fig. 2). The effect of conscientiousness on exam grades was fully mediated by distributed learning.

In order to obtain a better impression of how high and low conscientious students differ regarding their studying behavior, we plotted individual learning trajectories of weekly time investment over the course of the semester (see Fig. 3). We focused on the 10% of students with highest and 10% of students with lowest self-reported conscientiousness, for clarity of presentation.

Fig. 3 graphically underlines the association between conscientiousness and distributed learning (see also Table 1) for two extreme groups (students is the 10th and 90th percentile respectively). As had been shown in Fig. 1, students invested more time as they approached the exam date. Approximately, three weeks before the exam date, students sharply increase their time investment. While extremely low conscientious students confine their studying almost exclusively on the last few weeks before the exam, high conscientious students work more or less consistently throughout the semester.

5. Discussion

Although online lectures have become quite popular in institutions of higher education, we have no clear picture of how students deal with the inherent challenges, since this format puts a high demand on students' self-regulation competences. Assuming that individual differences play a role in how successfully students cope with the demands of online lectures, we investigated objective learning strategies and exam grades in an ecologically valid online lecture over the course of a whole semester. Distributed learning and the use of self-tests were associated with better exam grades. Beyond that, high school GPA explained differences in final exam grades while the effect of cognitive abilities vanished as soon as high school GPA was included in the regression model. Although there was no direct effect, we found a mediating effect of conscientiousness on grades via distributed learning. Less conscientious students postponed their studying until right before the final exam, which resulted in comparably low exam grades. Subsequently, we will discuss our findings with respect to the literature and suggest ideas for further research and practical implications.

5.1. Evidence-based learning strategies in online learning

In higher education, students are increasingly required to self-organize their learning. Online lectures constitute one extreme example, where self-regulatory demands are even higher because of the lack of weekly lecture appointments (Broadbent, 2017; Elvers et al., 2003). With our first research goal, we aimed to find out how students deal with this challenge and which learning strategies are associated with successful learning and better exam grades. Only by looking at individual overall time investment and two well-established learning strategies, we were able to explain a quarter of the variance in exam grades (see Table 2).

First, we investigated students learning trajectories. In line with previous research on massed study in online courses (Goda et al., 2015), we found a general increase in studying activity especially towards the end of the semester (see Fig. 1). Beyond that, we were able to show that students who distribute their studying activities over the semester achieved better grades compared to those who cram their learning time into just a few weeks (see Table 2). This is consistent with studies that showed that postponing study time is associated with lower performance (Kim & Seo, 2015; Moon & Illingworth, 2005; van Eerde, 2003).

Furthermore, we found that self-monitoring as indicated by the use of self-tests seems to be particularly important, which is in line with previous research (Imhof & Spaeth-Hilbert, 2013; Macfadyen & Dawson, 2010). The benefits of testing one's knowledge are twofold. On the one hand, testing helps identifying possible lacks of understanding. After receiving feedback, students have the possibility to look up those contents and amend their knowledge gaps (Nicol & Macfarlane-Dick, 2006). In addition, testing can be used not only for monitoring, but also as a learning strategy in its own right (Rowland, 2014). Testing thereby facilitates knowledge retrieval from long-term memory and promotes transfer to new domains (Dunlosky et al., 2013; Dunn et al., 2013). However, not every student seems to be aware of this effective learning strategy. About 40% of students did not make use of all possible self-tests and some tested themselves not even once.

Additionally, we found a strong correlation between distributed learning, the use of self-tests and overall time investment in the LMS (see Table 1). However, when including all three predictors into the regression model, only distributed learning and the number of self-tests

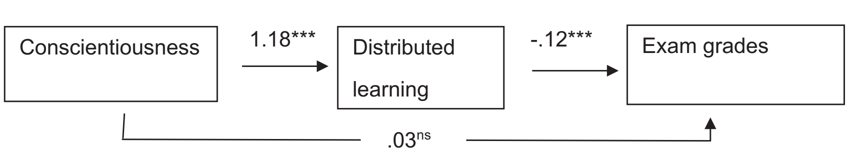

Fig. 2. Distributed learning as mediator of the effect of conscientiousness on performance.
Note. $N = 204$. Path weights are unstandardized. $^{***}p < .001$.

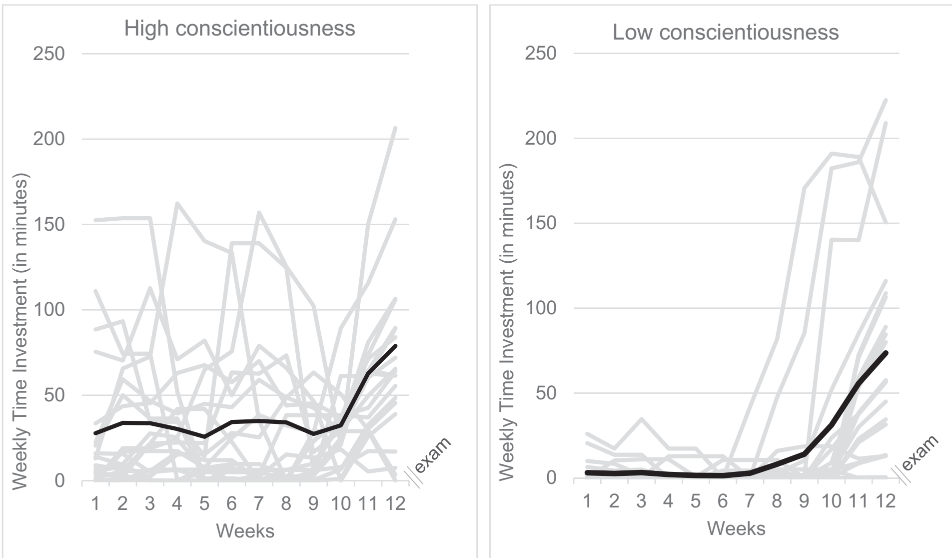

Fig. 3. Individual (grey) and average (black) weekly time investment in minutes for low ($n = 21$, 10th percentile) and high conscientious ($n = 21$, 90th percentile) students. *Note.* We computed moving averages of weekly time investment for every week t_w using the time investment in the respective preceding (t_{w-1}) and subsequent week (t_{w+1}).

constituted significant predictors of exam grades while overall time investment was not significant (see Table 2, Model 3). This result highlights the importance of distributed learning instead of cramming in one long session for an equivalent amount of time (Benjamin & Tullis, 2010; Bjork et al., 2013). It is not only the overall time investment that matters, but also the way students distribute and use their study time. In contrast to massed study, a continual and active engagement with the learning material fosters long term retrieval and transfer (Dunlosky et al., 2013; Dunn et al., 2013). Students who confine their studying to just a few weeks cannot catch up with those students who have consistently studied over the whole semester.

5.2. The effects of high school GPA and cognitive abilities on exam grades

Beyond behavioral log-data, we assessed cognitive abilities and high school GPA to explain individual differences in performance. In line with our hypothesis, we found that self-reported high school GPA predicted exam grades (see Table 3), an effect that has consistently been found in prior studies on academic performance in higher education (Gold & Souvignier, 2005; Richardson et al., 2012). High school GPA can be viewed as a proximate measure of general cognitive ability (Farsides & Woodfield, 2003; Wedler et al., 2008). Above cognitive capabilities, high school GPA also comprises achievement motivation and self-efficacy (Robbins et al., 2004). Thus, it is no surprise that high school GPA represents an important predictor of learning behavior and performance in higher education. Moreover, we gathered objective data on cognitive abilities. In line with our expectations, cognitive abilities positively predicted exam grades (see Table 3). However, when adding high school GPA, the effect vanished, which speaks for the assumption that high school GPA and intelligence share a considerable amount of variance (Furnham & Monsen, 2009; Roth et al., 2015). Nevertheless, it is important to differentiate between both constructs. For instance, in this study, cognitive abilities and high school GPA showed a positive, albeit small, correlation (see Table 1). Further, a better high school GPA was associated with more distributed learning, while higher cognitive abilities showed a negative correlation with distributed learning (see Table 1). Again, this result highlights that a better high school GPA is not only a matter of higher cognitive abilities but also the result of superior learning strategies (Robbins et al., 2004).

5.3. Conscientiousness, distributed learning and exam grades

Besides cognitive abilities, we investigated conscientiousness as a powerful non-cognitive predictor of academic performance (O'Connor & Paunonen, 2007; Poropat, 2011; Richardson et al., 2012). In contrast to the literature, we did not find a direct effect of conscientiousness on grades. This may be due to a selection bias in our final sample. Less conscientious students might have decided not to register for the final exam, because they had failed to study continually over the semester. Indeed, dropout analysis (see Section 3.1.1) yielded a tentative trend for conscientiousness regarding course dropout in the expected direction. Furthermore, less conscientious students may have failed to submit the additional questionnaires in the first place. However, mediation analysis showed that conscientiousness affects grades indirectly via distributed learning (see Figs. 2, 3). Students higher in conscientiousness engaged in more distributed learning compared to less conscientious students, which ultimately improved exam grades. This result is in line with research that showed that conscientiousness is associated with less academic procrastination and better studying habits (Bidjerano & Dai, 2007; Credé & Kuncel, 2008; Farsides & Woodfield, 2003; Schouwenburg & Lay, 1995; Watson, 2001). Students who are less organized and diligent are also more prone to delay their learning until the last minute, a learning behavior that is predominantly associated with worse performance (Kim & Seo, 2015; Moon & Illingworth, 2005; van Eerde, 2003).

5.4. Practical implications

The study results offer several possible applications for practitioners. Since the use of self-tests is beneficial for learning and performance, teachers should encourage students to monitor their own knowledge on a regular basis. Another possibility could be to integrate tests in the corresponding learning material and thereby force students to test themselves. Furthermore, our results underline the importance of time management strategies for successful online learning (Broadbent, 2017; Broadbent & Poon, 2015).

Results suggest that it would make sense for institutions of higher education to support students in the development of successful learning strategies. A high degree of autonomy and responsibility for dealing with the learning material and course requirements may be overwhelming for some freshmen. Therefore, it might be useful to offer learning strategy trainings alongside the online lecture to help students developing the necessary metacognitive skills to plan and distribute their studying activities appropriately (Bellhäuser, Lösch, Winter, & Schmitz, 2016). Especially less conscientious students struggle with the high self-regulatory demands of an online course. Interventions should therefore specifically target those students in order to help them dealing with the increased autonomy of an online course.

5.5. Study limitations and future research

Despite the important insights into online learning behavior of students, future studies should address some research limitations. First, although the course materials were presented online and there were no in-class lectures during the semester, we do not know how much time students spent studying offline, for instance by reading the recommended book. The time spent in the LMS only represents an approximate measure of the actual overall learning time students invested. Moreover, the course explicitly dealt with the topic of learning strategies (see Appendix A), which might affected students' behavior. Future studies could try to keep track of students learning outside the LMS by using for instance daily or weekly learning diaries in which students self-report their number of learning hours and learning strategies (Roth et al., 2016). However, those diaries might function as reminders and change the natural learning behavior (Schmitz & Wiese, 2006). In our study, we used weekly log-ins as an indicator of distributed learning. Weekly accesses in the LMS can be viewed as a measure of continual engagement with the lecture and learning material. Even though we were not able to capture the exact time investment, we demonstrated the importance of distributed learning over the course of the semester.

Another limitation is that, unfortunately, not all of the students filled in the additional questionnaire and ability test, which could have affected statistical power and, consequently, limits the generalizability of the results. Still, we gathered data from about half of our final pool of participants. Nonetheless, we have to keep in mind that the results are limited to one specific online lecture. Future studies should test the robustness of our findings in other online courses.

Furthermore, our results are based on correlational analysis, which does not allow drawing causal conclusions. However, one of our goals was to investigate the natural learning behavior of students taking an online course. Moreover, since the study was conducted in an ecologically valid, graded online lecture, it would have been unethical to experimentally manipulate the amount of invested learning time, for instance.

Finally, we focused on relatively stable trait variables: cognitive abilities and conscientiousness. State variables, like motivation, goal setting and effort management are very important for study success, too (Richardson et al., 2012), especially in online learning environments (Broadbent, 2017; Broadbent & Poon, 2015). Therefore, future research should investigate how motivation and self-regulation affect strategy use and learning behavior over time.

6. Conclusion

New technologies offer more flexibility and autonomy while learning. This study has shown that distributed learning and self-monitoring are crucial for successful online learning. However, especially weaker, less conscientious students are at risk to fail due to the increased self-regulatory demands. Hence, besides all the great advantages of digitalization, we must not forget to advice students how to utilize computer-supported learning environments for their own benefit. The digital natives' debate has shown that being surrounded by technology in everyday life even from an early age does not automatically imply that one knows how to use digital tools effectively (Helsper & Eynon, 2010; Kirschner & De Bruyckere, 2017). Therefore, online learning skills should be taught in formal educational settings to prepare future generations for the challenges that come along with the ongoing digitalization. Our results offer a good starting point for practitioners to equip students with effective learning strategies and specifically identify those students who have difficulties in dealing with the increased self-regulatory demands of an online course.

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Conflict of interest

None.

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Appendix A. Description of learning materials in learning management system

Podcasts	Additional materials and self-tests
Section 1: Introduction to educational psychology	
• Podcast 1: Introduction: Why do teachers need psychology?	• Case study • Self-test 1: Introduction to psychology
Section 2: Developmental psychology: theories, methods & findings	
• Podcast 2: Introduction to educational psychology and methods of educational psychology	• Book chapter and exercise (case study) from: Ormrod (2011): Educational Psychology.
• Podcast 3: Models of educational psychology, developmental tasks, the role of nature and nurture	• Self-test 2: Methods of educational psychology • Self-test 3: Models of educational psychology
• Podcast 4: Piaget's theory of cognitive development	• Self-test 4: Piaget's theory
• Podcast 5: Criticism of Piaget's theory	• Self-test 5: Criticism of Piaget's theory
Section 3: Memory and learning	
• Podcast 6: Introduction to chapter memory and learning	• Self-test 6: Experiments
• Podcast 7: What is an experiment?	• Self-test 7: Cognitive learning theories
• Podcast 8: Explicit & implicit memory, working memory, short-and long-term memory	• Self-test 8: Behavioral learning theory • Self-test 9: Observational learning
• Podcast 9: Cognitive learning theories, learning strategies: organization, elaboration, re-reading, retrieval practice	
• Podcast 10: Behavioral learning theory: classical conditioning	
• Podcast 11: Social-cognitive learning theories	
Section 4: Individual differences	

• Podcast 12: Introduction to chapter individual differences • Podcast 13: Role of individual differences on learning • Podcast 14: Theories on Intelligence • Podcast 15: Psychological tests: validity, reliability, objectivity • Podcast 16: Field studies • Podcast 17: Correlation • Podcast 18: Motivation: the role of goals • Podcast 19: Attribution theory	• Self-test 10: Intelligence • Self-test 11: Motivation • Self-test 12: Psychological tests and correlation
Section 5: Learning disability and problem behavior	
• Podcast 20: Introduction to learning disabilities and problem behavior • Podcast 21: Learning difficulties and possibilities to improve foster a favorable attributional style • Podcast 22: Attention deficit hyperactivity disorder: definition and interventions	• Self-test 13: Learning disabilities • Self-test 14: Problem behavior
Section 6: Social psychology and learning & classroom management	
• Podcast 23: Social psychology and learning • Podcast 24: Prejudice, Jigsaw classroom • Podcast 25: Classroom management	• Link to YouTube video: Visible learning (John Hattie) • Self-test 15: Social psychology and learning • Self-test 16: Classroom management

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