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Deadlines don't prevent cramming: Course instruction and individual differences predict learning strategy use and exam performance

Maria Theobald [a,*], Henrik Bellhäuser [b], Margarete Imhof [b]

[a] DIPF | Leibniz Institute for Research and Information in Education, 60323 Frankfurt am Main, Germany
[b] Psychological Department, Johannes Gutenberg-University Mainz, 55122 Mainz, Germany

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ABSTRACT

The goal of the present study was to investigate how course instruction and individual differences in general academic competences and conscientiousness relate to students' learning strategy use and exam performance. The sample comprised two cohorts of university students who attended a lecture on the same topic, but with varying course instruction: In the blended course ($N = 238$), the teacher applied deadlines for self-testing and offered regular in-class meetings to encourage distributed practice over the semester. In the online course, students studied independently without regular meetings, nor deadlines ($N = 200$). Learning strategies were measured objectively using behavioral log-file data. Students in the blended course used fewer self-tests than online students which was associated with poor exam performance. Academic competences (high school GPA) positively predicted exam performance via more distributed practice and self-testing. Conscientiousness was related to more distributed practice which was associated with better exam performance. Results revealed that (voluntary) in-class meeting and deadlines did not prevent cramming. Especially less conscientious students with lower general academic competences need further support in applying efficient learning strategies.

1. Introduction

Universities undergo a digital transformation (OECD, 2016). The amount of courses using online instruction is increasing in order to deal with a growing number of students entering the university with heterogeneous previous knowledge and educational background (Lingenau & Ahel, 2019). Online courses offer students a high degree of autonomy since they can make their own choices about where, what, and for how long they want to study. However, this autonomy challenges students to self-regulate their studying (Broadbent & Poon, 2015). For instance, online learners frequently fail to distribute their study time over the semester (Goda et al., 2015) which is associated with lower academic performance (Moon & Illingworth, 2005). Especially less conscientious students with lower academic competences struggle with the increased self-regulatory demands of online instruction (Credé & Kuncel, 2008; Hart, 2012). This raises the question of how online courses should be designed to support students with different individual prerequisites while studying online.

2. Literature review

An adapted version of Biggs' model of study process (Biggs & Tang, 2007; Jones, 2002) builds the theoretical foundation of this study in which we focus on the variables presented in Fig. 1. The model suggests that teaching context and student characteristics predict students' engagement which, in turn, affects the outcomes they achieve from studying. Hence, this model offers an integrative framework to test the role of teaching context, student characteristics (and their interaction) for learning strategy use and learning outcomes. In this study, the online course refers to a fully asynchronous online instruction where students self-pace their study activities (see Section 3.2.1). In the blended scenario, learning materials are also accessible online. However, the teacher offers regular, optional in-class meetings and limits the access to self-tests to encourage distributed practice (see Section 3.2.2). Student engagement subsumes behavioral (e.g., time investment), emotional (e.g., interest), and cognitive (e.g., learning strategies) engagement (Fredricks & Mccolskey, 2012). Learning strategies comprise behaviors serving to acquire and organize information (Gurung et al., 2010). In this study, we focus on procedural (e.g., distributed practice over a longer period of time) and metacognitive (e.g., doing self-tests to

* Corresponding author.
E-mail address: theobald@dipf.de (M. Theobald).

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monitor understanding) strategies.

2.1. Course instruction predicts learning strategy use and achievement

In fully asynchronous online courses students self-pace their study activities without regular meetings with a teacher (neither face-to-face, nor online). However, this flexibility requires continual, autonomous planning and monitoring of the learning process. In comparison, blended instruction mixes online and classroom instruction and typcially includes regular meetings with a teacher. This is why asynchronous online instruction is more challenging regarding self-regulation compared to blended instruction (cf. Broadbent, 2017).

Previous research showed that blended instruction benefits students' academic achievement compared to fully online or classroom instruction (e.g., Bernard et al., 2014; Means et al., 2013), which is mainly attributed to differences in teaching methods (Graham et al., 2014). For instance, regular meetings with a teacher as well as deadlines to prepare for the meetings in a blended learning course (in contrast to an online course without meetings, nor deadlines) could serve as learning reminders and encourage a continual engagement with the learning materials (Fulton et al., 2013; He et al., 2016). However, this hypothesis has not been tested so far since previous research mainly focused on investigating differences in learning outcomes (i.e., products, see Fig. 1) between online, blended, and classroom instruction. Prior studies that compared online, blended, and classroom instruction did not systematically investigate how specific teaching methods relate to differences in students' use of learning strategies (i.e., processes, see Fig. 1). This study aims to fill this gap by investigating how teaching methods (regular meetings with a teacher and deadlines) predict exam performance and the use of learning strategies.

2.2. Academic competences and conscientiousness predict learning strategy use and achievement

Besides teaching context, individual differences in students' general academic competences and conscientiousness are related to the use of learning strategies and academic achievement. First, high school GPA is frequently used as a proximate measure for general academic competences. High school GPA has consistently been found to predict better learning strategies (Credé & Kuncel, 2008) and better academic achievement (Richardson et al., 2012). Second, conscientiousness has been shown to predict better academic achievement in higher education (Arispe & Blake, 2012; Poropat, 2011). In comparison to other personality traits, such as extraversion or openness to experience, conscientiousness is most strongly related to metacognitive learning strategies, e.g., time management (Bidjerano & Dai, 2007), and has been found to predict more distributed learning (Theobald et al., 2018).

Taken together, high school GPA and conscientiousness could predict academic achievement indirectly via better learning strategy use. However, most research has been conducted in traditional educational settings (i.e., face-to-face lectures), while empirical evidence on the role of student characteristics for online and blended learning is scarce. Further, most studies only investigated the effects of student characteristics on learning outcomes (i.e., products, see Fig. 1) while neglecting how they relate to the application of learning strategies (i.e., processes, see Fig. 1). Thus, this study goes beyond previous research by investigating learning strategies as mediator between student characteristics and learning outcomes.

2.3. Interaction between student characteristics and teaching context

Moreover, it is unclear whether students differentially benefit from online or blended instruction depending on their individual prerequisites. Building on the research tradition on aptitude-by-treatment interactions (Cronbach & Snow, 1977), it has been suggested that teaching context and student characteristics interactively predict learning processes and outcomes. For instance, it has been shown that trainees with higher cognitive abilities benefit more from guided exploration compared to highly structured proceduralized instruction (Bell & Kozlowski, 2008). In the context of blended and online learning, it has been suggested that less able learners (i.e., learners with lower cognitive abilities or prior knowledge) should receive more guidance when studying online (see Brown et al., 2016 for an overview). In line with this, a recent study revealed that students with a better high school GPA (i.e., higher general academic competences) especially benefitted from blended instruction while students with lower high school GPA benefitted from traditional classroom instruction (Asarta & Schmidt, 2017). One explanation is that students with a better high school GPA use superior learning strategies and can more easily cope with the higher self-regulatory demands of online or blended instruction.

Likewise, students' conscientiousness and teaching context could interactively predict learning processes and outcomes. However, previous interactionist research provided inconclusive results. One study tested whether learners higher in conscientiousness benefitted from high (vs. low) learner control in a video-based e-learning program (Orvis et al., 2010). In the high learner control condition participants had more control over the instructional features that influence the pace, content, and structure of the training. Results revealed that, unexpectedly, there was no interaction between the level of learner control and learners' conscientiousness. The authors suggested that the duration of the training might was too short to unveil the advantages of high conscientiousness. High conscientiousness may be especially needed in

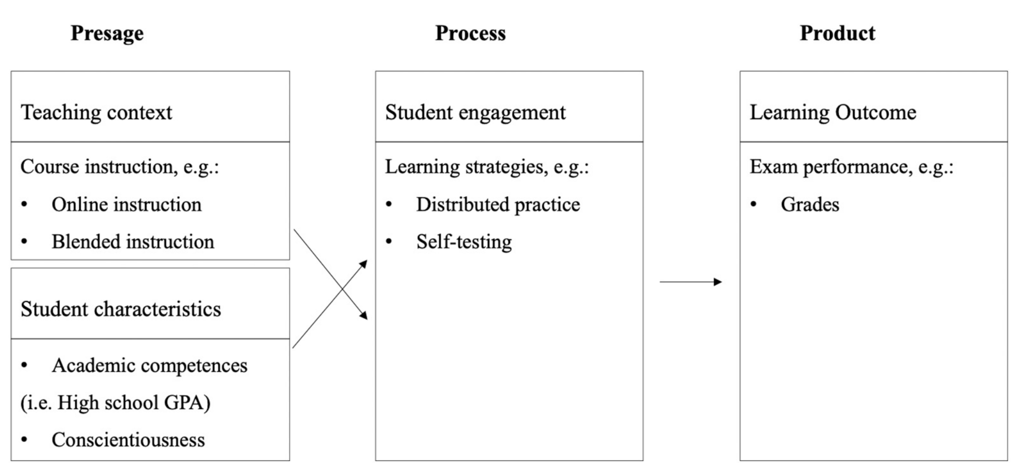

Fig. 1. Adapted model of study process (Jones, 2002).
Crossed arrows indicate and expected interaction between teaching context and student characteristics.

situations that require careful, long-term planning. For instance, one study tested the role of students' conscientiousness for distributed learning in an online course that lasted several weeks (Theobald et al., 2018). Results revealed that more conscientious students distributed their learning more equally over the semester which benefitted exam performance. On the downside, less conscientious students struggled with the high self-regulatory demands of online instruction. Applied to the current study, less conscientious students may benefit from more teacher support in a blended course.

Taken together, previous research suggested that learners may differentially benefit from online and blended learning depending on their individual prerequisites. However, research on the role of learners' academic competences (i.e., high school GPA) and consciousness mainly comes from training studies that were not conducted in a university setting. Further, none of the abovementioned studies compared the role of high school GPA and conscientiousness in an online and blended learning course. This study aims to fill this gap by examining whether students' high school GPA and conscientiousness differentially predict learning strategy use and learning outcomes in an online and blended course.

2.4. The present study

The present study builds on results of a previous study (Theobald et al., 2018). In this study, students struggled with the high self-regulatory demands of online learning and frequently failed to distribute their study time over the semester. At the same time, distributed practice and self-testing constituted highly effective learning strategies which were strongly related to better exam performance. We proposed that teachers should encourage students to distribute their study time and to monitor their own knowledge regularly. In the current study, we, thus, test whether regular meetings and deadlines (in a blended course) promote more distributed practice and self-testing compared to an online course without regular meetings, nor deadlines. More distributed practice and self-testing should, in turn, predict better exam performance (see Fig. 1). Hence, we expect that:

H1. Offering regular meetings and deadlines (in the blended course) is associated with better exam performance compared to online instruction without regular meeting, nor deadlines.

H2. Offering regular meetings and deadlines (in the blended course) predicts more distributed practice and a higher number of self-tests compared to online instruction which is, in turn, associated with better exam performance.

In addition, we showed that conscientious students distributed their studying more equally across the semester which was associated with better exam performance. Moreover, students with higher academic competences (better high school GPA) achieved better exam grades. However, we did not test whether students with higher academic competences applied superior learning strategies which may explain better exam grades. Hence, we aim to replicate and extend our previous findings and test whether individual differences predict better exam performance via learning strategy use:

H3. Higher academic competences and higher conscientiousness predict better exam performance regardless of course instruction.

H4. Individual differences in academic competences and conscientiousness predict better exam performance via more distributed practice and a higher number of self-tests regardless of course instruction.

Lastly, we go beyond our previous findings by testing whether the relative importance of academic competences and conscientiousness differs between course instructions (interactions between student characteristics and course instruction). Hence, we will compare the proposed process models (H3, H4) between online and blended instruction.

3. Method

3.1. Sample

Data was collected from two cohorts of pre-service teachers that enrolled in an introductory lecture to educational psychology at a German university in summer semester 2017 and summer semester 2018 respectively. The lecture is a mandatory course for undergraduate students in educational sciences, which is offered each semester. A total of $N = 641$ enrolled for the lecture in summer 2017 (online course) and $N = 587$ enrolled for the lecture in summer 2018 (blended course). Of those, $N = 258$ subjects in 2017 (40%) and $N = 303$ (52%) in 2018 volunteered and filled in additional questionnaires (see Section 3.3.1). The remaining students either decided not to answer the additional questionnaires or missed the kick-off meeting, where data collection took place. Further, $n = 57$ students in the online course and $n = 63$ in the blended course dropped out of the study, because they did not register for the final exam. Dropout rates were comparable between courses ($X^2(1) = 0.13$, $p = .720$). We compared all students who dropped out with students from both courses who decided to take the final exam. There were no systematic differences in age, gender, nor conscientiousness (all p-values $> .05$). However, students who dropped out reported a significantly worse high school GPA compared to students who attended the final exam ($t(558) = -3.07$, $p = .002$). Moreover, we excluded students, who stated in the final control question that they did not answer the questionnaires faithfully (online: $n = 1$, blended: $n = 2$). Hence the final sample comprised $N = 200$ students ($n = 131$ female, age: $M = 20.43$, $SD = 1.93$) in the online course and $N = 238$ ($n = 156$ female, age: $M = 20.45$, $SD = 1.92$) in the blended course. Groups were comparable with respect to gender, age, high school GPA, and conscientiousness (see Table 1). Students signed an informed consent, in which

Table 1
Means, standard deviation and pairwise comparisons between student characteristics, learning strategies and exam performance in online (N = 200) and blended course (N = 238).

		M	*SD*	*t*	*p*	Cohen's *d*
High school GPA	Online	2.69	0.61	1.35	0.177	0.13
	Blended	2.61	0.64			
Conscientiousness	Online	4.07	0.88	0.06	0.954	0.01
	Blended	4.07	0.80			
Online time investment[a]	Online	371.38	380.72	4.19	<0.001	0.40
	Blended	226.13	343.28			
Distributed practice	Online	5.61	2.67	−0.05	0.961	−0.01
	Blended	5.62	2.75			
Self-tests	Online	13.19	5.20	19.34	<0.001	1.85
	Blended	3.86	4.88			
Exam performance	Online	29.97	4.38	2.95	0.003	0.28
	Blended	28.68	4.67			

[a] One outlier in the blended course has been excluded from analysis due to an error in data recording.

we assured that participation was voluntary and had no impact on their final grade. All procedures were in accordance with the APA ethical guidelines and the ethical standards of the institutional review board. The study was approved by the course coordinator and by the dean of the faculty. An additional approval of the institutional review board was not needed because the changes in course design were covered by the freedom of teaching.

The present study included healthy adult participants who had no problems to understand the scientific background, the nature of the study, and the study protocol. Students were informed that participation was voluntary and had no impact on their course grade. In accordance with the APA ethical guidelines, all participants gave written informed consent after the nature of the study was explained to them. The study was approved by the course coordinator and by the dean of the faculty. We did not obtain an additional approval of the local ethical committee. The local ethical committee did not require formal approvement of our study because (1) students were not deceived about the purpose of the study, (2) students did not have to fill in an extensive amount of questionnaires (e.g., ambulatory assessment) and no invasive methods were used (e.g., blood sampling), (3) the procedure or duration of the study was not potentially burdensome as it was part of a regular university course, (4) the change in course design was covered by the academic freedom of teaching. The freedom of teaching allows teachers to change the course design and to evaluate the course design without prior consent from local ethical committee. Because of these four reasons, our classroom-based research was exempt from the purview of the local ethical committee.

3.2. Design and procedure

We used a quasi-experimental design to compare the use of learning strategies and exam performance between an online course and a blended course. In the blended course, the teacher offered regular in-class meetings and imposed deadlines for taking self-tests (see Section 3.2.2). The online course was offered in the summer semester 2017 while the blended course was offered in the subsequent summer semester 2018. Both semesters ran from mid-April until the end of June. Teacher, online learning materials and syllabus were identical in both semesters (see Section 3.2.1 and Appendix A for a complete overview on the lecture topics). The online course was offered for the first time, while the blended course had already been offered once before conducting the study (in the winter term 2017). Before that, the teacher had taught the course for several years using classroom instruction. In the first week of the semester, a kick-off meeting took place in both courses to familiarize students with the course content and procedure. In this meeting, students were invited to complete an additional questionnaire on high school GPA and conscientiousness (see Section 3.3.1). At the end of both semesters, students in both courses completed a computer-assisted multiple-choice exam on-campus. The exam constituted the only mandatory and graded task students needed to complete in order to pass the course.

3.2.1. Description of the online course and learning management system

In the online course, there was no further in-class meeting apart from the kick-off meeting in the first week of semester. All materials relevant for the exam were provided in the learning management system (LMS) Ilias. The Ilias course comprised six topics: introduction to educational psychology, developmental psychology, memory and learning, individual differences, learning disabilities, social psychology of learning and classroom management. For each topic, the teacher provided podcasts including the lecture slides with additional audio recordings (overall 25 podcasts, which took on average 10 min, see Appendix A). Students could listen to the podcast online via the LMS as often as they wanted and at any time throughout the semester. Further, students had the possibility to download the corresponding lecture slides but without audio recordings. Moreover, online self-tests (see Section 3.3.2) were provided for each topic to familiarize students with the item format of the final exam and support self-monitoring. Students could decide whether they wanted to use the podcasts, lecture slides, or the recommended chapter readings to prepare for the final exam. None of the online materials or self-tests were compulsory. Every student had the opportunity to organize and allocate study time autonomously.

3.2.2. Description of the blended course with weekly optional meetings and deadlines

Students in the blended course had access to the identical learning materials in the LMS as students in the online course. However, in contrast to the online course, the teacher offered weekly voluntary in-class meetings. In this study, blended instruction used a flipped classroom approach (Mazur, 2009). Students studied theoretical concepts individually at home while in-class meetings were used for active learning. Before each in-class meeting, students were asked to prepare the course topic by listening to the corresponding podcast and work on a self-test. In-class meetings were 90 min in length. No formal lecture was provided and the content from the podcasts was not repeated in class. During class, students were asked to work on various exercises that were meant to deepen the understanding of the lecture topics and to apply theoretical knowledge to practice. The exercise sheets included, for instance, short video clips, case studies, additional literature, or quizzes (see Appendix A). Students discussed the correct solutions with the teacher during class. Classroom activities intended to foster deeper learning beyond the learning content relevant to pass the final exam. There was no attendance policy, which means that students were free to choose whether to attend the weekly in-class meetings without risk of penalty for absences. Hence, students could decide to attend none of the in-class meeting thereby creating an online course for themselves. At the end of the semester, students self-reported how often they had attended the in-class sessions approximately (see Section 3.3.2).

Moreover, contrary to the online course, the teacher shared the learning materials successively, which means that the beginning of the semester, only the first section had been online. Afterwards, learning materials (podcasts and self-tests) were made accessible one-by-one to prepare for the corresponding in-class meetings. Podcasts remained online until the end of the semester, while self-tests were available for three weeks and afterwards closed again. This procedure intended to encourage students to distribute their studying over the semester and avoid "binge-testing" at the end of the semester.

3.3. Measures

Self-report measures were administered during the kick-off meeting in the first week of the respective semester. Measures of learning strategies and exam performance were assessed electronically via the LMS.

3.3.1. Student characteristics

3.3.1.1. High school GPA. Students self-reported their high school GPA of the university entrance diploma on a continuous scale that could range between 1.0 (i.e., "very good") and 4.0 (i.e., "passed"). High school GA was used as a measure of general academic competences, and was recoded such that higher values indicate a better GPA.

3.3.1.2. Conscientiousness. We used the German translation of the Big Five Inventory (BFI-2, Danner et al., 2016) to assess conscientiousness. The BFI-2 includes 12 items to assess conscientiousness using a six-point Likert scale that ranged from "not true" to "true". The items measured three facets of conscientiousness: orderliness (4 items, e.g., "I keep things neat and tidy.", $\omega = 0.88$), diligence (4 items, e.g., "I am persistent, work until the task is finished.", $\omega = 0.78$), and reliability (4 items, e.g., "I am dependable, steady.", $\omega = 0.63$). The 4 items per facet were aggregated to obtain measures of average orderliness, diligence, and reliability. The mean of the three scales provided a measure of overall conscientiousness. Reliability analysis confirmed a good internal consistency of the overall scale (ω = 0.87).

3.3.2. Learning strategies and exam performance

3.3.2.1. Online time investment. We measured online time investment, i.e., the number of minutes students spent in the LMS each week. Summing up weekly time investment yielded the overall online time investment over the course of the semester starting at the day of the kick-off meeting until the morning before the final exam took place. The time window was comparable in summer semester 2017 and 2018, which were both running 11 weeks from mid-April until the end of June.

3.3.2.2. Distributed practice. Hit Consistency (Asarta & Schmidt, 2017) was used as a measure of distributed practice. For each of the 11 weeks of the semester, students were assigned a "1", if they accessed the LMS at least once during the respective week (otherwise a "0" was assigned). At the end of the semester, we summed up the number of weeks in which a student accessed the LMS, which could range from zero (never accessed the LMS) to 11 (accessed the LMS every week). Higher values on this variable suggest a more distributed, continual engagement with the course content.

3.3.2.3. Self-testing. Students could work on 16 online self-tests containing a varying number of single-choice questions (four options each) that covered different chapters of the course. Self-tests were similar to those administered in the final exam that students had to pass for course credit. After each self-test, outcome feedback was provided and students had the possibility to look up an explanation if an answer was wrong. At the end of the semester, the sum of different self-tests completed by a student was used as an indicator of self-testing. Students in the online course could access all self-tests throughout the whole semester. In the blended course, self-tests were scheduled according to the corresponding in-class meeting and remained online for three weeks.

3.3.2.4. Exam performance. At the end of the semester, students in both courses attended a computer-based multiple-choice exam in a PC pool under supervision of research assistants. The exam was the only graded task necessary to pass the course. The exam encompassed questions that tested basic knowledge but also more advanced questions that required students to apply this theoretical knowledge. Reliability analysis revealed a good internal consistency of the exam (ω = 0.79). The exam covered the main topics of the lecture to assure high content validity. Moreover, exam performance substantially correlated with high school GPA ($r = 0.49$, $p < .001$). distributed practice ($r = 0.26$, $p < .001$) and self-testing ($r = 0.37$, $p < .001$), which speaks in favor of its construct validity. Students had 45 min to work on 40 single-choice questions (4 options each), whereby each correct answer yielded one point. Hence, students could earn between 0 and 40 points while higher values indicate better exam performance. A passing grade was awarded if students achieved at least 20 points (50%). Exams were comparable across courses in terms of format and coverage across course topics.

3.3.2.5. Class attendance. After taking the final exam, students in the blended course were asked via questionnaire to report retrospectively how many of the 11 in-class meetings they had attended approximately (4 options: 0 = "never", 1 = "once or twice", 2 = "between three and five times", 3 = "between six and nine times").

3.4. Data analysis

We used Stata 15.1 (StataCorp, 2017) and Mplus 7.3 (Muthén & Muthén, 2017) for data analysis and set the alpha value at 0.05. MPlus was used for the path analyses while the remaining analyses were conducted using Stata.

To test the direct and indirect effects proposed in the process model (see Fig. 1), we conducted path analyses in Mplus using a bias corrected bootstrap procedure (5000 bootstrap samples). The structural equation approach to mediation analysis allows to estimate indirect effects using multiple (latent or observed) independent variables and mediator variables within the same model (Hayes, 2009). Therefore, structural equation modeling has more statistical power and reduces estimation bias, which can occur when two mediator variables are correlated. As our data did not fulfill the assumption of multivariate normal distribution, we used the mean- and variance-adjusted LR test statistic (i.e., MLMV). The MLMV estimator yields the best combination of accurate standard errors and Type I errors even with nonnormal data (Maydeu-Olivares, 2017).

We used multiple group analysis to explore potential differences in the proposed process model between course instructions (online and blended). That is, we estimated correlations among variables separately for both groups. Afterwards, post-hoc Wald chi-squared tests indicated possible differences in correlations among variables between groups. Doing so, we tested whether the proposed processes and associations (see Fig. 1) were comparable in the online and blended course.

4. Results

4.1. Does course instruction predict exam performance via learning strategy use?

To test H1 and H2, we first investigated whether students in the blended instruction differ from students in the online instruction regarding exam performance and learning strategy use. After applying Bonferroni-Holm correction, three significant mean differences between groups emerged (see Table 1[1]). Students in the online course completed on average more self-tests, spent more time studying online, and performed better in the exam compared to students in the blended course. Distributed practice did not differ between groups (see Fig. 2).

In a next step, we tested whether learning strategies mediated the link between course instruction and exam performance. Results revealed that students in the blended course used fewer self-tests which predicted poor exam performance (see Fig. 3). The strong negative indirect path of course instruction on exam performance via less self-testing superimposed the positive direct relationship between blended instruction and exam performance. Overall, the model explained 21% of the variance in exam performance.

Taken together, in contrast to our hypothesis, offering regular in-class meeting and imposing deadlines on self-tests (in the blended course) did not encourage distributed practice. Complementary evidence comes from the analysis of class attendance in the blended course: Only 50% of students reported that they attended between six and nine of the eleven in-class meetings. One third (33%) of students reported that they went to the in-class meetings three to five times, 15% went to the meetings once or twice, and 2% never attended the in-class meetings. That is, most students in the blended course did not fully comply with the blended instruction. Moreover, in contrast to our expectations, students in the blended course used fewer self-tests, which was associated with poorer exam performance compared to students in the online course.

4.2. Do individual differences predict exam performance via learning strategy use?

To answer H3 and H4, we tested distributed practice and self-testing

[1] As all variables in Table 1 violated the assumption of normal distribution, we performed non-parametric Wilkoxon tests to compare the two groups. The results were comparable and led to the same conclusions.

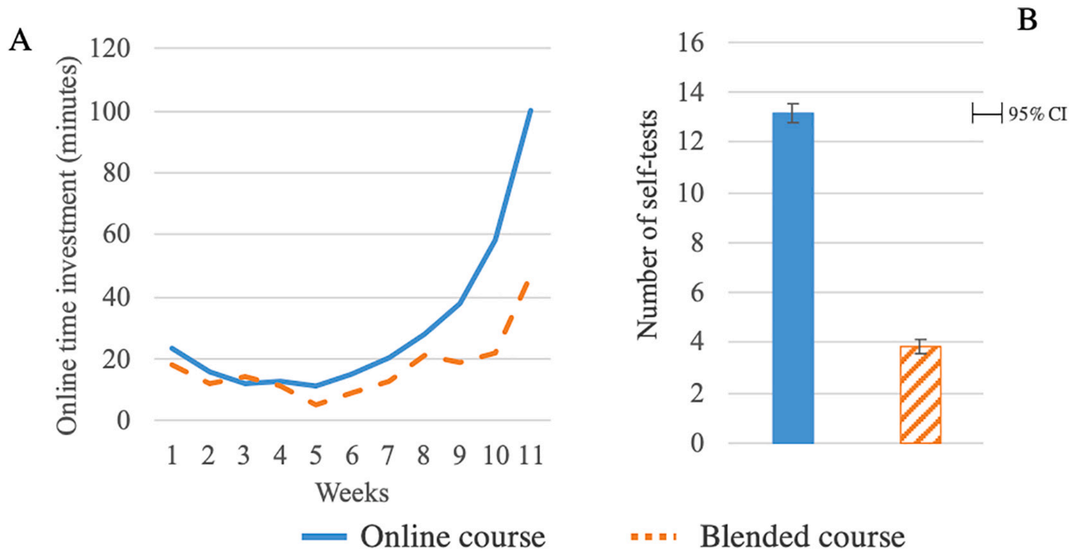

Fig. 2. (A) Average weekly online time invesment and (B) number of self-test in the online (solid) and blended course (dashed).

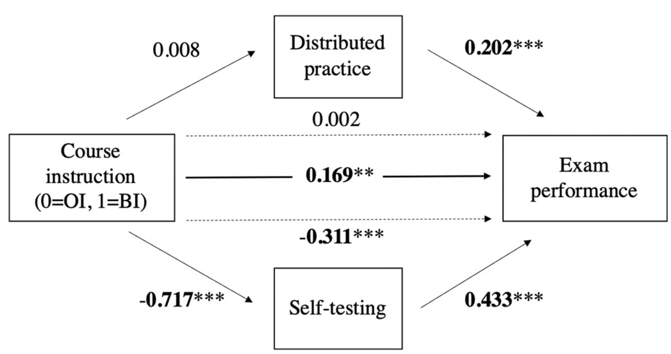

Fig. 3. Results of path analysis regressing exam performance on course instruction (OI = online, BI = blended) via distributed practice and self testing. Dotted lines indicate indirect effects. Default MPlus link funtions were used. Path weights are standardized.
N = 438.**p < .005, *** p < .0.001.

as mediators between individual differences and exam performance. Fig. 4 summarizes the results of the multiple group path analysis. Path weights were estimated separately for the online course (upper part), the blended course (middle part), and for the overall model (blended and online course together, lower part). The multigroup model provided an adequate model fit (RMSEA = 0.08; CFI = 0.96; SRMR = 0.06). We first describe the results for the overall model. Differences between the two courses are describes in the subsequent section (see Section 4.3).

According to H3, we expected that better academic competences (i.e., a better high school GPA) and higher conscientiousness would predict better exam performance. However, only high school GPA was associated with better exam performance while conscientiousness did not predict exam performance.

Next, we tested whether individual differences predicted exam performance via more distributed practice and a higher number of self-tests (H4). In line with H4, students with better high school GPA distributed their studying more equally across the semester and used more self-tests which was associated with better exam performance. Further, conscientiousness predicted better exam performance via more distributed practice, despite the insignificant direct path. However, in contrast to H4, conscientiousness was not associated with self-testing in the overall model. Accordingly, the indirect path from conscientiousness to exam performance via self-testing was not significant. The proposed model explained 40% of the variance in exam performance.

Taken together, results were partially in line with our hypotheses and the proposed process model. High school GPA predicted exam performance directly and indirectly via self-testing as well as distributed practice. Conscientiousness constituted, in part, an indirect predictor of exam performance.

4.3. Does the process model differ between course instructions?

In a last step, we explored whether the path weights regressing exam performance on individual difference variables via learning strategies differed between course formats. First, the more complex multiple group estimation provides a better model fit compared to an overall model, where equal path weights are assigned for both groups (X^2 (21) = 85.23, $p < .001$; unconstrained model: X^2 (42) = 759.01, $p < .001$; constrained model: X^2 (21) = 673.78, $p < .001$). Further, some discrepancies emerged: Distributed practice was a strong, positive predictor of exam performance in the online course, but not in the blended course. Relatedly, the indirect paths from conscientiousness and high school GPA to exam performance via distributed practice were only significant in the online course, but not in the blended course. In the blended course, only high school GPA predicted exam performance via more self-testing. Post-hoc Wald chi-squared tests revealed that the remaining paths weights, although varying in absolute size, did not differ significantly between models. Hence, the associations between individual differences, learning strategy use, and performance were largely comparable across course instructions.

5. Discussion

Building on the theoretical model of study process (see Fig. 1), we tested the role of course instruction and learner characteristics for students' learning strategy use and exam performance. Results showed that students in the blended course used significantly fewer self-tests than students in the online course which was associated with poorer exam performance. Further, students in both courses mainly studied during the last weeks of the semester. Hence, voluntary meetings and deadlines in the blended course did not encourage more distributed practice over the semester. Irrespective of course instruction, more conscientious students with better academic competences applied superior learning strategies which predicted better exam performance. Subsequently, we discuss findings in light of the theoretical model and previous empirical finding as well as suggest ideas for further research and practice.

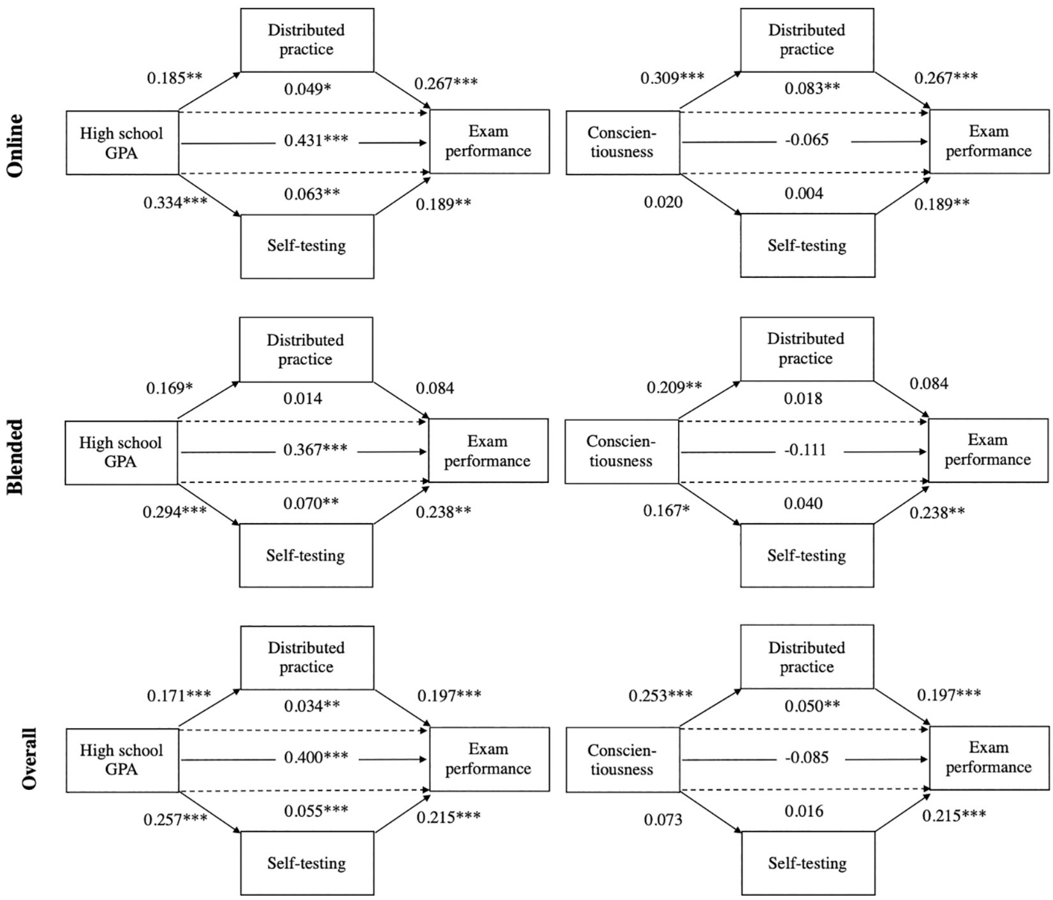

Fig. 4. Results of multigroup path analysis for online (upper part), blended (middle part), and combine course (lower part). Note that the two path models for high school GPA and conscientiousness were taested within the same analysis.
$N = 438$. $^*p < .05$, $^{**}p < .005$, $^{***}p < .001$. Path weights are standardized. Bold lines indicate direct effects,dotted lines represent indirect effects.

5.1. Course instruction predicts the use of learning strategies and exam performance

In this study, we investigated whether weekly deadlines and regular in-class meetings (applied in the blended course but not in the online course) encouraged distributed practice and self-testing over the semester. Contrary to the hypothesis, regular in-class meetings and deadlines were not associated with more distributed practice. Further, students in the blended course even used fewer self-tests than students in the online course which was, in turn, associated with poor exam performance.

One explanation for these unexpected results is that neither class attendance nor the use of self-tests were compulsory in the blended course. Hence, students decided themselves whether they wanted to go to the in-class meetings and whether they wanted to prepare for class using online self-tests. Some students never attended the in-class meetings, thereby creating an online course for themselves. Others might have decided to distribute their study time by attending the lecture regularly. This may explain why students in the blended course spent significantly less time in the LMS and did not distribute their study time more than students in the online course. However, without preparing study materials beforehand, students failed to fully benefit from attending the in-class sessions. For instance, the exercise sheets built on the core knowledge from the online materials, which were needed to answer the exercise sheets properly. Further, students in the blended course likely missed the deadlines for self-testing, especially because most students started studying only a few weeks before the exam. Indeed, students in the blended course answered on average 4 self-tests, which comes close to the number of self-tests that were still available in the last two weeks before the exam. Hence, deadlines did not prevent cramming and even backfired in the blended course since students missed the opportunity to use self-testing as a learning strategy.

This leads to the question on the optimal balance between learner autonomy and external teacher regulation. Sorgenfrei and Smolnik (2016, p. 163) argued that while "control over navigation and design, tend to increase learning outcomes [...], the effects of control over content and task selection are ambiguous." Similarly, it has been suggested that learners should be given control over surface-level features of the instruction, e.g. preferred examples, but not over deep level features of the instruction, e.g., pedagogical design (Brown et al., 2016). With respect to the design of the blended course, working on self-tests constituted a central task which helped students preparing for the exam. Hence, students should not decide by themselves whether they want to work on self-tests and receive feedback on their answers. Teachers could, for instance, send students self-regulation prompts to remind them on the importance of testing their own knowledge (Sitzmann & Ely, 2010). Teachers could further increase the incentives to work on self-tests. In a study by Fulton et al. (2013) students could earn bonus points if they submitted the tasks in time and lost bonus points if they missed the deadline, which constituted a strong penalty. In this study, frequent deadlines encouraged distributed practice. Hence, incentives might also enhance the effectiveness of deadlines.

Taken together, results underline the importance of considering the effects of specific teaching methods on learning strategy use and performance. In the same vein, a simplified distinction between online or blended instruction does not suffice to unveil potential reasons for their effectiveness. In other words, the effectiveness of online or blended instruction hinges on the specific teaching methods that are applied. This view is in line with results from a meta-analysis that showed that web-based instruction and classroom instruction are equally effective for teaching declarative knowledge when the same instructional methods are used (Sitzman et al., 2006). That is, the instructional methods determine students' learning and not the delivery mode per se (web-based vs. classroom instruction). Applied to the present study, the restriction of access to self-tests likely accounted for the differences in exam performance between groups to a large degree. This finding, however, does not allow the general conclusion that blended instruction is less effective than online instruction. In line with previous research (Graham et al., 2014), we rather argue for more systematic research on the core pedagogical features that make online or blended instruction most effective.

5.2. High school GPA and conscientiousness predict learning strategies and exam performance

Students with a better high school GPA used more effective learning strategies, i.e., they distributed their studying more equally across the semester and used more self-tests to monitor their understanding of the learning materials. In turn, superior learning strategies were associated with better exam performance. This result underlines that high school GPA can be viewed as a proxy for better general academic competences. High school GPA is not only correlated with cognitive abilities (Farsides & Woodfield, 2003; Theobald et al., 2018) but is also related to higher achievement motivation and self-efficacy (Robbins et al., 2004). Thus, it seems likely that students with a better high school GPA can cope more easily with the higher learner control of online or blended instruction. In support of this claim, students with better high school GPA were also less likely to drop out of the course.

Moreover, results revealed that conscientious students distributed their studying more equally over the semester which indirectly predicted better exam performance. Hence, in line with previous studies, conscientious students were able to deal with the increased self-regulatory demands of online and blended learning (Arispe & Blake, 2012; Theobald et al., 2018). Further, conscientiousness predicted a higher use of self-tests in the blended course, but not in the online course. This result can be explained by the limited access to self-tests in the blended course. In the blended course, less conscientious students who failed to distribute their study time missed the deadlines. In the online course, however, self-tests were available throughout the whole semester. Thus, even less conscientious students, who started studying only a few weeks before the exam, could access all of the self-tests. This result underlines that less conscientious students struggle to distribute their study time over the semester. Further, to the detriment of less conscientious students, the effectiveness of optional deadlines hinges on the students' ability to distribute their studying and testing over the semester. In other words, more conscientious students used the self-tests in the blended course before they were restricted, which explains the correlation between self-testing and conscientiousness in the blended course.

Notably, we did not find interactions between student characteristics and course instruction. In other words, the role of high school GPA and conscientiousness for learning strategy use and exam performance was similar for the online and blended course. One explanation is that both course instructions offered learners a similar amount of control over instructional features. For instance, students decided themselves in which order or pace they want to access the learning materials. Even students in the blended condition had a high level of learner control as they could decide themselves whether they want to attend additional in-class meetings. Hence, both course instructions required students to self-organize their studying. Future research could more systematically manipulate the amount of learner control between course formats (see e.g., Bell & Kozlowski, 2008; Brown et al., 2016 for training studies that tested the effects of learner control).

Taken together, results point to the importance of considering individual differences in online and blended learning. Irrespective of the course design, more conscientious students with better academic competences apply better learning strategies which benefits academic performance. On the other hand, especially less conscientious students with lower general academic competences struggle with the increased self-regulatory demands.

5.3. Study limitations and future research

Although the present study offered important insights on how course instruction and student characteristics shape learning strategies and performance of students, future studies should address some research limitations.

This study was designed to test how optional in-class meetings and deadlines relate to students' learning strategy use and exam performance. Therefore, we used a quasi-experimental design to compare learning strategy use and exam performance in a blended course (with in-class meetings and deadlines) and an online course (without in-class meetings, nor deadlines). We minimized cohort effects by conducting the study in two consecutive summer semesters which were comparable in terms of length and semester schedule. Further, self-selection is unlikely since students did not know ahead of time what kind of course instruction (online or blended) they were getting into. Moreover, we found that students did not differ with respect to high school GPA, nor conscientiousness, and dropout rates were comparable in both courses. Nonetheless, future studies could randomly assign students to either online or blended instruction during the same semester. In addition, as in-class meetings and deadlines for self-testing have been introduced at the same time, we cannot disentangle their effects on study behavior and performance. Further, course instruction might have caused differences in students' goal orientation. For instance, in contrast to online students, blended students, who attended the in-class meetings, had the opportunity to receive feedback on their learning progress from the teacher and their peers. This may have led some students to adopt performance-avoidance goals (cf. Dweck & Yeager, 2019), which can impair academic performance and motivation (Shim & Ryan, 2005). Taken together, future studies should further investigate how specific teaching methods can increase students' learning and motivation in blended and online courses.

Second, attendance in the blended course was not compulsory. Thus, we do not know if blended instruction (or more specifically class attendance) would have predicted distributed practice if all students had actually complied with the flipped instruction as intended. On the other hand, a liberal attendance policy is common, at least in Germany (Horneber & Penz, 2014). Hence, the general set-up of the study mirrors the typical conditions in regular university courses, where attendance is not mandatory. Future studies should test whether our results hold for other samples as well. Further, although students estimated their approximate class attendance at the end of the semester, future studies could record attendance weekly in order to avoid retrospective memory biases. Future studies should further test whether the results are replicable in other samples.

A third limitation arises from the fact that we do not know how much time students spent studying offline. Although podcasts were only available online, students could instead download the lecture slides only or read the recommended textbook to prepare for the exam. Hence, the overall time students spent in the LMS constitutes a rough measure of the actual time they invested for studying. Nonetheless, we believe that our measure of distributed practice, i.e., the number of weekly accesses in the LMS, constitutes a good proximate measure of the continual engagement with the learning material. Although we do not know the exact time investment, we could show the importance of distributed practice over the course of the semester. Future studies could triangulate the measurement of students' time investment and learning strategy use, e.g., using log-files and self-reports.

Fourth, this study tested the role of stable student characteristics, such as conscientiousness, for learning strategy use and exam performance. However, future research could examine how more variable factors, such as goal setting, predict learning. For instance, it has been shown that goal framing and content (e.g., learning goal vs. performance goal orientation) and goal proximity (e.g., proximal vs. distal goals) predict metacognitive activity (Kozlowski & Bell, 2006). Moreover, goals – and more specifically a discrepancy between goals and actual performance – can motivate subsequent regulation (Howardson et al., 2017; Theobald et sl., 2021). In online and blended learning, students are frequently required to self-regulate and evaluate their goal progress. Hence, examining how students' goals affect learning opens up a more dynamic perspective on learning processes that could inspire future research in online and blended learning.

Lastly, we concluded that deadlines did not prevent cramming as students in the online and blended course distributed their learning to a similar degree. However, one needs to be cautious when interpreting null results because a lack of a statistically significant effect does not imply that the null hypothesis is true. In this study, the average distributed practice score was almost identical across groups. Further, an equivalence test (see Lakens, 2017) indicated that the observed effect size ($d = -0.01$) was within the equivalent bounds of $d = -0.20$ and $d = 0.20$ ($t(427.01) = 2.05$, $p = .021$), meaning that we can reject an effect more extreme than these predetermined bounds. In other words, we can reject effects larger than 0.54 and lower than -0.54 scale values, which corresponds to a group difference of about half a week. These results suggest that the effect of course instruction on distributed practice is negligible. Nonetheless, future studies should test under which circumstances deadlines might prevent cramming.

5.4. Practical implications and conclusions

First, results of the present study revealed that teachers should not restrict the access to important study materials (e.g., self-tests) because deadlines do not necessarily prevent cramming. On the downside, a restricted access to study materials can even impede students' learning. Results, thus, stress the importance of careful course design on students' strategy use and performance thereby offering several possible applications for practitioners.

The success of blended instruction, especially the flipped classroom, crucially depends on students' compliance with the course instruction. In the flipped classroom approach (Mazur, 2009), teaching of basic concepts is moved out of class and in-class time is used for active and social learning. Students study the new learning materials online at home before each of the weekly in-class meetings. If students choose not to attend the in-class meetings, they miss the opportunity to fully benefit from in-depth discussions guided by the teacher. Likewise, even if students regularly attend the in-class meetings, they might benefit less if they fail to prepare the course materials beforehand. Therefore, teachers should take care that students use the available resources that are offered online.

Teachers could, for instance, integrate self-tests in the corresponding learning material and thereby encourage students to test themselves. Another possibility would be to send self-regulation prompts (e.g., Sitzmann & Ely, 2010) or to offer learning strategy trainings (Bellhäuser et al., 2016) alongside the course. Self-regulation interventions may help students developing the necessary metacognitive strategies to plan and monitor their studying appropriately. Interventions should especially target less conscientious students and students with lower high school GPA, because those students might face difficulties dealing with the increased leaner autonomy in online and blended courses.

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Declaration of competing interest

None.

Appendix A. Description of learning materials in learning management system

Podcasts & lecture slides	Learning materials & self-tests	Exercises in blended course
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 **Podcast 3**: Models of educational psychology, developmental tasks, the role of nature and nurture **Podcast 4**: Piaget's theory of cognitive development **Podcast 5**: Criticism of Piaget's theory	• Book chapter and exercise (case study) from: Ormrod (2011): Educational Psychology. • Self-test 2: Methods of educational psychology • Self-test 3: Models of educational psychology • Self-test 4: Piaget's theory • Self-test 5: Criticism of Piaget's theory	Exercise sheet on observational methods: • Students watch a video clip and observe a teaching situation • Students discuss pros and cons of observational methods and possible alternative methods Exercise sheet on Piaget: • Students watch video clips with short experiments testing children's stages of cognitive development • Students sort video clips based on Piaget's stages of cognitive development • Students discuss ways how teachers can support accommodation
Section 3: Memory and Learning		
Podcast 6: Introduction to chapter memory and learning **Podcast 7**: What is an experiment? **Podcast 8**: Explicit & implicit memory, working memory, short-and long-term memory **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	• Self-test 6: Experiments • Self-test 7: Cognitive learning theories • Self-test 8: Behavioral learning theory • Self-test 9: Observational learning	Exercise sheet on memory and learning • Students create a mind-map with important terms from research on memory • Students read a study on differential effects of mind-maps (Malycha & Maier, 2012) and are asked to describe key aspects of the study, e.g., what are the (in)dependent variables? • Case study on reading strategies: Students are asked to find out which strategies the child in the case study already know and should suggest ways to foster reading strategies Questionnaire on learning strategies

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Podcasts & lecture slides	Learning materials & self-tests	Exercises in blended course
		• Students are asked to fill in a learning strategy questionnaire and reflect on their answers (Wild & Schiefele, 1994) Exercise sheet on conditioning • Students are provided with exemplary situations and are asked to describe situations using terms from classical or operant conditioning • Students read a case study and suggest how they would modify the child's behavior using methods from operant conditioning
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	Exercise sheet and questionnaire on intelligence and mindset • Students are asked to fill in a questionnaire on intelligence and mindset and to reflect on their attitude (based on C.S. Dweck, 1999) • Students sort definitions of intelligence according to different intelligence theories Exercise sheet on interpretation of correlation • Students see various correlation figures and should interpret results • Students should discuss why correlation does not imply causality
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	Exercise sheet on motivation and learning disabilities, e.g.: • Students are asked about ways to improve motivation of children (with learning disabilities) • Students should report pros and cons of individual, social, and criterial frames of reference (especially for children with learning disabilities)
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	Exercise sheet on social psychology and learning • Students should think of possible situations in school when conformity and group pressure could play a role • Students were asked to read a paper about gender stereotypes and selfies (Döring et al., 2016), and were asked to analyze the paper (research question, methods, results, conclusions) • Students read a case study and were asked about ways to design effective group work

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