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

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A R T I C L E I N F O

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A B S T R A C T

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),