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IDENTIFYING LEARNER TYPES IN DISTANCE TRAINING BY USING STUDY TIMES

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Background

Distance learning research intensively investigates how to foster successful student learning (Rowe & Rafferty, 2013). One research focus is to explore the extent that learner characteristics and skills determine learning outcomes and to elaborate predictive models of performance (e.g., Akçapınar et al., 2015; Yukselturk & Bulut, 2007). Although these approaches often start with diagnostics of learner characteristics before learning (e.g., Yukselturk & Bulut, 2007), diagnostic methods applied while learning are becoming popular nowadays (e.g., Kinnebrew et al., 2013; Lile, 2011). Modern approaches use data mining and learning analytics to identify learners that have problems. These methods attempt to benefit from objective data that are provided by various types of log systems catching online traces (e.g., Akçapınar, 2015). Data mining methods might result in better online diagnostics and intervention methods when the mechanisms behind usage pattern are known. Hence, it is recommended to relate usage patterns to student characteristics to render them meaningful (Akçapınar, 2015).

The following study gained objective and subjective study time indicators and used them to identify groups of learners in a distance-training course. The groups were first compared in some characteristics that have already been shown to be empirically relevant for distance learning and that address motivational, affective, cognitive and skill aspects (i.e., domain-specific prior knowledge, intrinsic motivation, computer attitude, computer anxiety, and learning strategies). This step, which should show the extent that these correlates affect study time, could serve as a starting point for adequate interventions. Second, group differences in learning were explored to show the relevance of study time for learning. This step should show how study time is related to learning. Our investigation was conducted against the background of self-regulated learning (Rowe & Rafferty, 2013).

Self-regulated learning, learning strategies and motivation

"Self-regulation refers to self-generated thoughts, feelings, and actions that are planned and cyclically adapted to the attainment of personal goals" (Zimmerman, 2000; p.14). Bringing cognitive, metacognitive, motivational and behavioural skills into action and using them adequately are thought to be the core of competent learning (Wild & Schiefele, 1994). Accordingly, self-regulated learning is understood as a process that "involves students' intentional efforts to manage and direct complex learning activities toward the successful completion of academic goals" (Rowe & Rafferty, 2013; p.590). Self-regulated learning was found to be significantly related to (academic) performance (e.g., Agustiani et al., 2016; Song et al., 2016) and is particularly considered a key component of successful distance learning because of its high demands on self-regulation skills to succeed (Rowe & Rafferty, 2013). Management skills, especially managing time and organizing learning effectively, were significant predictors of learning success (e.g., Tsai & Tsai, 2003; Yukselturk & Bulut, 2007).

Related to self-regulated learning, Lee (2013) discussed deep and surface learning approaches, characterized by motives and strategies. These approaches refer to usage patterns of learning strategies that learners show while performing specific learning tasks. In her study, she reported that deep learning correlated with higher performance in distance learning, whereas surface learning correlated negatively. She further discussed that surface learning is more likely guided by extrinsic motives while exerting minimal effort to pass a course, whereas deep learning is more likely guided by intrinsic motives and the desire to comprehend the material. Similar patterns of correlations between motives and performance have been found. For example, deep motives were found to correlate positively with performance, surface motives negatively (e.g., Akçapınar, 2015; Yurdugül & Menzi Çetin, 2015; Lee, 2013).

Overall, motivation to learn has been the focal correlate of learning success. Intrinsic motivation refers to performing a task, because it is inherently interesting or enjoyable. Extrinsic motivation pertains to performing a task, because it leads to a separable outcome (Ryan & Deci, 2000). Intrinsic motivation is connected to high-quality learning and to successful distance learning (Ryan & Deci, 2000, Yukselturk & Bulut, 2007). A higher level of intrinsic motivation might make learners invest more resources in learning and particularly process information more deeply, thus contributing to successfully passing tests (Lee, 2013; Yurdugül & Menzi Çetin, 2015).

Prior knowledge, computer attitude, and computer anxiety

The level of prior knowledge is known to predict school and academic performance and especially influences learning in various instructional settings (e.g., Hailikari et al., 2008; van Gog et al., 2005). In general, possessing prior knowledge is considered a desirable condition for learning (e.g., Chi, 2006). Learning succeeds best when new information can be connected to available knowledge from long-term memory (van Gog et al., 2005). Prior knowledge was shown to affect performance in various educational contexts. The more students knew, the more they gained when studying. In the context of complex learning environments, including distance learning scenarios, domain-specific prior knowledge is known to positively influence performance (e.g., Knestrick et al., 2016; Song et al., 2016; Stiller, in press). A higher level of prior knowledge was also found to correlate with higher levels of self-regulation skills (e.g., Chi, 2006; Hailikari et al., 2008).

The influence of computer attitude and computer anxiety on self-regulated learning has been reported in the literature. Attitudes are often defined as beliefs that are organized in topics. Hence, the computer as a self-experienced instrument for working and learning might be of interest in distance learning (Richter et al., 2010). Computer anxiety is considered a trait, which comprises both cognitive and affective components such as feelings of anxiety and worrisome

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thoughts (Richter et al., 2010). Anxiety and attitude are assumed to have only a direct influence on self-efficacy, which then directly influences performance and course usage (e.g., Hauser et al., 2012). In this context, a negative attitude and a considerable level of computer anxiety might lead to a lower level of self-efficacy and thus to inadequate usage of learning strategies. Studies have indicated that adequate use of strategies correlate with positive attitudes and a lack of anxiety (e.g., Tsai & Tsai, 2003; Wong et al., 2012) and that negative attitudes correlate with worse performance (e.g., Stiller, in press).

Usage data of online learning environments, study time and learning

Usage data of an online or distance learning environment can inform educators about learning and in particular about performance (Akçapınar et al., 2015; Kinnebrew et al., 2013; Lile, 2011). For example, usage patterns gained by log file analyses could be related to level of performance and surface and deep learning approaches (Akçapınar, 2015; Akçapınar et al., 2015). A less intensive usage reflected by low numbers of events (logins, posts etc.) and short event times (e.g., total time spent in the online environment) correlated with surface learning and low performance, and an opposite pattern of intensive usage correlated with deep learning and high performance (Akçapınar, 2015; Akçapınar et al., 2015). Among the usage pattern variables, various time measures were indicative of learning approaches and level of performance (Akçapınar, 2015; Akçapınar et al., 2015), suggesting that time spent on the learning task is important for successful online learning apart from frequency of participation (e.g., Akçapınar, 2015).

Research objectives and expectations

Groups of students should be profiled based on their study periods in a distance training. Therefore, students were first clustered according to their module study times into fast and slow learners. First, the clusters were compared on the learner characteristics of learning strategy usage, domain-specific prior knowledge, computer attitude and computer anxiety, and in reference to their demographic characteristics. Second, they were compared in the experienced difficulties of content and learning, the invested effort and experienced pressure while learning, and performance. Clusters are expected to be meaningful entities that differ in relevant individual characteristics influencing distance learning, learning experience, and performance.

Method

Sample

The data of 159 (68% female; age: M = 37.42 years, SD = 8.98, range from 21 to 60 years) of the 318 in-service teachers who registered for a distance training about media education in the German Federal State of Bavaria were used for this study. They had completed at least one training module by taking the final module test. In-service teachers were recruited by promoting the training offline via flyers at all elementary schools, secondary schools, secondary modern schools, and high schools in Bavaria. Most teachers worked in secondary modern and high schools, followed by elementary and secondary schools, and other school types (see results section).

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Description of the distance training

The training was based on a modular design and instructional texts. Students could learn at their own pace and at any time, and they could freely decide how many of the modules to study and in which sequence. The starting point of the training was a Moodle course portal. It consisted of nine modules, an introductory module, and eight modules about media education (e.g., Generation SMS: The use of mobile phones by children and adolescents; How to find a good learning program: Evaluation criteria for educational software). The introductory module informed about content, technical requirements, course organization, and learning skills. Each module had a linear structure of six sections: (a) An overview of the content and the teaching objectives was presented in the module profile, followed by (b) a case example of a real-life problem. (c) A test of domain-specific prior knowledge was used for activating prior knowledge and giving feedback about its level. (d) The instructional part comprised an instructional text and optional supporting material. (e) A questionnaire about studying the module was provided. (f) A final performance test evaluated learning success and provided feedback. The workload for studying a module was estimated to take 60 to 90 minutes. Students were supported via email, chat, and phone.

Procedure and measurements

The first login directed a student to the introductory module, which could be studied optionally. Then, students completed the first questionnaire assessing demographic information and the student characteristics in focus. Then, the eight course modules were accessible. A prior-knowledge test was presented at the beginning of each module and a final module test at the end. Students were questioned about each module before completing it by taking the final module test. A student could provide up to eight data sets, one for each module.

The first questionnaire assessed intrinsic motivation (Interest/Enjoyment scale; Leone, 2011), attitude towards computers and computer anxiety ("Confidence in dealing with computers and computer applications" and "Personal experience/learning and working/autonomous entity" scales; Richter et al., 2010), skills in using meta-cognitive learning strategies, time management strategies, and strategies to arrange an adequate learning environment (Wild & Schiefele, 1994). Scale scores were calculated as means of items.

The module questionnaires measured the effort put into learning and the tension experienced while learning (Effort/Importance and Pressure/Tension scales; Leone, 2011), and the difficulty of contents and studying (one item each; de Jong, 2010). Per module, prior knowledge was assessed with a 5-item and performance with a 15-item multiple-choice test (including the pre-test items). Tests were considered appropriate for measuring learning success, because the training was intended to provide factual knowledge. Per module, the scores of the multiple-item scales were calculated as the mean of items, prior-knowledge and performance scores were calculated as percent correct. A high score expresses a higher level of the feature except for computer attitude, which indicates a low negative attitude. Finally, means were calculated across the number of completed tests.

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Results

A short and long study-time group were identified by considering the following three criteria. (a) The objectively measured period between completing the prior knowledge test and starting the final module test was calculated as an indicator of a module's study time. Periods are assumed to be reliable for detecting short study times. The criterion to classify study time as short was set to 20 minutes. A successful completion of any module was calculated with a workload of 60 to 90 minutes. (b) The objectively measured periods are not reliable when they are longer, because they might include periods not dedicated to learning (e.g., pauses or time between downloading and studying a script). Accordingly, the self-reported study time was used instead as an indicator of study time. The criterion to distinguish between short and long study periods was set to 25 minutes. (c) Finally, learners having studied at least one of the modules with a short study time were assigned to the short study-time group; otherwise, they were assigned to the long study-time group. This process resulted in 117 long study-time learners and 42 short study-time learners. Slightly more than half (57%) of the students in the short study-time group studied most of their modules quickly. No differences were found between the study-time groups for sex, age, type of school, and number of successfully completed modules (for analysis, the categories of 0 to 3 and 4 to 7 completed modules formed one group each; see Tables 1 and 2). The students mostly completed one (17%), two (12%) or all modules (43%), but less often three to seven modules (23%).

Table 1: The demographic characteristics of the registered in-service teachers and their successfully completed modules.

		No. (%) of studying students	No. (%) of short study-time students	No. (%) of long study-time students	λ^2	*df*	*p*
	Total	159 (100.00)	42 (26.42)	117 (73.58)			
Sex	Female	108 (67.92)	28 (66.67)	80 (68.38)	0.41	1	ns
	Male	51 (32.08)	14 (33.33)	37 (31.62)			
Type of school	Elementary school	20 (12.58)	7 (16.67)	13 (11.11)	3.77	4	ns
	Secondary school	14 (8.81)	4 (9.52)	10 (8.55)			
	Secondary modern school	69 (43.40)	16 (38.10)	53 (45.30)			
	High school	39 (24.53)	8 (19.05)	31 (26.50)			
	Other than listed	17 (10.69)	7 (16.67)	10 (8.55)			
Successfully completed modules	0-3	67 (42.14)	16 (38.09)	51 (43.59)	0.40	2	ns
	4-7	24 (15.09)	7 (16.67)	17 (14.53)			
	8	68 (42.77)	19 (45.24)	49 (41.88)			

The study-time groups were compared on the learner characteristics and the study ratings of interest (see Table 2). Significant differences were found only for prior knowledge, intrinsic motivation, and performance. Long study-time learners showed a higher level of motivation and performance but a lower level of prior knowledge. The ANOVA analysis with repeated measures of prior knowledge and performance revealed a large effect of time, $F(1,157) = 265.48$, $p < .001$, $\eta^2 = .63$, and a medium sized interaction effect, $F(1,157) = 10.41$, $p < .002$, $\eta^2 = .06$,

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showing that the long study-time students gained more knowledge than the short study-time students.

Table 2: Means and standard deviations of the student groups, results and effect sizes are shown. Rating scores range from 1 to 5, knowledge from 0 to 100% correct answers. One-sided Welch-tests and t-Tests were calculated.

	Short study-time group			Long study-time group						
	M	*SD*	*n*	*M*	*SD*	*N*	*t*	*df*	*p*	*d*
Age in years	37.55	9.26	42	37.38	8.92	117	.10	70.08	ns	.02
Intrinsic motivation	3.91	.52	42	4.07	.60	117	-1.70	83.91	.046	.28
Computer attitude	4.25	.73	42	4.21	.57	117	.36	59.98	ns	-.06
Computer anxiety	1.82	.78	42	1.81	.61	117	.09	59.85	ns	-.02
Metacognitive strategies	3.45	.58	42	3.52	.53	117	-.62	67.73	ns	.13
Time management	2.46	.91	42	2.53	.91	117	-.42	71.74	ns	.08
Learning environment	4.05	.69	42	4.08	.59	117	-.28	64.43	ns	.05
Prior knowledge	56.10	21.17	42	49.80	11.14	117	1.84	49.39	.036	-.44
Difficulty of contents	1.79	.77	40	1.63	.52	111	1.23	52.18	ns	-.27
Difficulty of studying	1.85	.74	40	1.66	.67	111	1.50	149	.068	-.28
Effort / Importance	3.26	.52	40	3.35	.55	111	-.94	149	ns	.17
Pressure / Tension	1.85	.78	40	1.79	.70	111	.49	149	ns	-.08
Performance	77.12	15.17	42	81.20	13.20	111	-1.65	157	.050	.30

Discussion

Two learner groups were formed according to study time per modules. One group completed most of their modules quickly, spending little time studying. Hence, these students likely missed important information that could not be organized and integrated to an adequate knowledge representation. Students of the second group spent reasonably long periods for studying, which allowed an adequate selection, organisation, and integration of important information. Evidence for this assumption was found only for performance (Akçapınar, 2015; Akçapınar et al., 2015). Groups also differed in motivation and prior knowledge. These findings are consistent with results on intrinsic motivation (e.g., Park & Choi, 2009). That is, learners spending more time with studying are more motivated. Overall, this pattern of results is not surprising given that intrinsic motivation is understood to be inherently linked to self-motivated learning (Ryan & Deci, 2000). The finding that a higher level of prior knowledge contributed to faster study periods could have occurred as a result of the method. A module was deemed successfully completed when a student correctly answered at least 50% of the items in given module test. Most students of the short study-time group had already met that criterion after the prior knowledge test. Consequently, they might have expected to perform equally well in the module post-test without spending much time studying a module. This procedure might have contributed to faster study times and worse performance.

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Overall, the results must be interpreted carefully. Although the sample size was adequate, the distance training modular design, the use of instructional downloadable pdf papers, and the special target group of teachers are all a matter of concern when generalizing conclusions, especially to whole distance study programmes. Nevertheless, the present study results are consistent with the theoretical approach and empirical evidence reported in literature.

Study time could be used as a predictor for how students study and thus for identifying students that should be guided to a deep learning approach (Akçapınar, 2015; Akçapınar et al., 2015). This might be especially important when log files cannot be used for calculating study times. For example, instructors cannot use them because of institution security policies, or the files do not contain this kind of information (e.g., for distance learning courses that provide offline instructional material). In general, when log files can be used, additional indicators are likely to exist that are related to learning approaches (Akçapınar, 2015; Akçapınar et al., 2015; Kinnebrew et al., 2013; Lile, 2011). The data used in this study were gained by a Moodle system protocolling the entry timestamp of course pages. Even self-reported study times seem useful.

A problem might arise by trainings that are free to everybody, for example, the training in this study. A wide range of motives could lead to course registration and to participation, making it difficult to assess which students are willing to study and complete the course and which students could be targets of interventions. One particular problem in the present training might have forced a gambling behaviour of students, because the hurdle to complete a module was set low by using multiple-choice items of low-medium level difficulty that tested for factual knowledge. Thus, students could try their luck in succeeding in subsequent module tests with little effort. More challenging tasks might have shifted learners to dropping out. Normally, such tasks cannot be solved by guessing solutions. Future research could aim to first identify user groups and analyse these groups separately to gain clearer insights about the factors that lead to dropout and learning success.

For practice and research, it seems promising to combine logfile analyses with an initial diagnostic of relevant learner characteristics and their framework conditions for studying. Logfile analyses could especially be used to support students in their learning behaviour and to lead them to higher performance, and it might also be used to identify and support students that drop out after having studied parts of a training (Akçapınar, 2015; Akçapınar et al., 2015; Kinnebrew et al., 2013; Lile, 2011). In complex educational environments like study programs, other possible correlates could be analysed such as academic background, grade-point average, or former distance learning experience and success (Lee & Choi, 2011).

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