# PREDICTING EASE OF STUDYING AND LEARNING SUCCESS FROM LEARNER CHARACTERISTICS IN A DISTANCE TRAINING FOR IN-SERVICE TEACHERS

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**ABSTRACT**
How to support students in successful learning is one of the persisting problems of distance and online learning. One research focus that can inform educators is to explore the extent that learners' characteristics and skills determine learning. Thus, this study explores the effects of domain-specific prior-knowledge, intrinsic motivation, computer attitude, computer anxiety, and learning management skills on learning in a training course about media pedagogy for teachers. The data were collected from 49 in-service teachers who answered various questionnaires and took knowledge tests. By using regression analyses, we investigated the extent that the selected learner characteristics account for ratings of content difficulty, studying difficulty, experienced pressure/tension, and effort/importance while learning and for performance. Content difficulty was best predicted by computer anxiety and studying difficulty by computer anxiety and intrinsic motivation. The experienced pressure/tension was best predicted by intrinsic motivation and time management skills. Effort/importance was best predicted by meta-cognitive skills and performance by meta-cognitive skills and prior knowledge.
**Keywords:** Distance training, teacher training, higher education, self-regulated learning, computer attitude, computer anxiety, Cognitive Load Theory.

## INTRODUCTION
Distance learning methods are well established in the areas of continuing and higher education (e.g., Allen & Seaman, 2016). Although 30 years of ample empirical studies have provided sound theoretical and practical knowledge, we still need more insights on how to foster successful student learning (Jo, Park, Yoon, & Sang, 2016). One empirical approach is to explore the extent that learners' characteristics and skills determine learning outcomes and to use critical characteristics as starting points for interventions. The following study explores the predictive power of in-service teachers' motivational, affective, cognitive, and skill aspects on cognitive load and performance against the background of the Cognitive Load Theory (Paas & Sweller, 2014) by using a script-based distance training about media pedagogy. Based on the empirical literature, the authors had focused on domain-specific prior knowledge, intrinsic motivation, computer attitude, computer anxiety, and learning strategies.

## COGNITIVE LOAD THEORY
The Cognitive Load Theory sets working memory in the center of learning and problem solving (Paas & Sweller, 2014). Particularly, the capacity of working memory and its processing limits (e.g., in time) are emphasized and how the capacity is occupied by cognitive processes (Paas & Sweller, 2014). The load imposed on working memory by information being processed is then called cognitive load (Paas & Sweller, 2014). A distinction is made between intrinsic, germane, and extraneous load. Intrinsic load has often been described as the basic amount of processing required for understanding the presented information (Sweller, 2010). Intrinsic load relates to the number of relevant information elements to be learned and their interactivity. Interactivity is reflected in the concurrent processing of information elements in working memory that must be performed to understand the subject matter. A higher level of elemental interactivity is usually associated with the learning content being rated as more difficult and, in consequence, also with studying being rated as more difficult. Germane load builds upon intrinsic load and relates to creating schemas from relevant information elements and storing them in long-term memory (Sweller, 2010). Extraneous load relates to the processing of irrelevant information elements in working memory, which can impede knowledge acquisition. The presentation manner

of the material resulting from inappropriate instructional designs are considered a main source of extraneous load (Paas & Sweller, 2014; Sweller, 2010). Learning is often difficult because of working memory limitations. A cognitive overload of working memory capacity mostly occurs when intrinsic load or extraneous load is high. Successful learning occurs when working memory capacity is not overburdened by overall cognitive load and when as much capacity as is available can be allocated to germane load.

## STUDENT CHARACTERISTICS

### Domain-specific prior knowledge

Simonsmeier et al. (2018) showed in their current meta-analysis that prior knowledge has a medium to strong causal effect on knowledge after learning. They reported that the correlation between domain-specific prior knowledge and knowledge at posttest was high overall with $r > .50$. They also investigated knowledge gains over time – with less statistical power due to the number of studies – and found a significant compensatory effect (negative correlation) for instructions with low cognitive demands and a non-significant but descriptively observable Matthew effect (positive correlation) for instructions with high cognitive demands. The compensatory effect is suggestive of the expertise reversal effect described and empirically investigated against the background of Cognitive Load Theory. The expertise reversal effect refers to "the reversal in the effectiveness of instructional formats or procedures as levels of learner expertise in a domain change when relatively more guided instruction is beneficial for novices, but is disadvantageous for more expert learners" (Kalyuga, 2014, p. 593). Expertise reversal effects were found in a variety of instructional designs that were less complex with relatively short learning situations (Kalyuga, 2014). Expertise reversal effects are not strongly expected to occur in distance-training courses, which typically allow self-paced and self-sequenced learning with varying degrees of freedom and thus allowing experienced learners to regulate their learning more adequately (Kalyuga, 2014). In correspondence with the meta-analyses of Simonsmeier et al. (2018), research on complex learning environments that included distance learning scenarios has also mainly focused on overall correlations between prior knowledge and post-learning test performance. These studies have found a positive impact on a variety of performance measures (e.g. Amadieu, Tricot, & Mariné, 2009; McDonald & Stevenson, 1998; Stiller & Bachmaier, 2018; Stiller, 2003, 2009, 2019). However, the results included no statements about the existence of expertise reversal effects.

In reference to the Cognitive Load Theory, prior knowledge should influence the experienced intrinsic and overall cognitive load while learning. As prior knowledge reduces the complexity of the content, a higher level of prior knowledge should be related to a lower level of intrinsic load and vice versa. It might be suggested that typically, a lower level of intrinsic load is related to a lower level of germane load because the number of new information elements and their interactivity is less for advanced learners. Consequently, advanced learners might experience a lower level of overall working memory load. Studies reporting corresponding results are sparse and inconsistent. For example, Stiller and Köster (2017) found weak evidence for the assumed relationship between prior knowledge and intrinsic and various overall load measures (reported in the supplementary file), whereas Stiller and Bachmaier (2018) reported no evidence for the relationship.

### Intrinsic motivation

Overall, motivational factors of students are assumed to explain and predict successful learning in general and distance/online learning in particular (Jones & Issroff, 2007; Stiller & Bachmaier, 2018). One focus of research has been on intrinsic motivation, which refers to performing an activity that is inherently enjoyable or interesting, and its relation to high-quality learning (Ryan & Deci, 2000; Schunk, Pintrich, & Meece, 2008). Overall, positive correlations between intrinsic motivation and performance/achievement is evidence for this supposed relation (Ali & Franklin, 2001; Aragon, Johnson, & Shaik, 2001; Artino, 2008; Delialioglu, 2005; Fredericksen, Pickett, Shea, Pelz, & Swan, 2000; Cerasoli, Nicklin, & Ford, 2014; Orhan Özen, 2017; Richardson, Abraham, & Bond, 2012; Sankaran & Bui, 2001; Stiller & Bachmaier, 2018; Waschull, 2005; Yukselturk & Bulut, 2007). Meta-analyses reviews have revealed intrinsic motivation as a medium to strong predictor of performance and achievement (Cerasoli et al., 2014; Orhan Özen, 2017; Richardson et al., 2012; Schneider & Preckel, 2017). Students who are more intrinsically motivated might put more effort into learning and especially processing information more deeply, which is assumed to lead to higher performance and achievement.

According to the Cognitive Load Theory, (intrinsic) motivation is assumed to influence how students prepare for learning, the levels of intrinsic, germane and extraneous load they will experience, and how they regulate cognitive loads while learning (Ismail, Kuldas, & Hamzah, 2013; Moreno & Mayer, 2007; Schnotz et al., 2009; Stiller & Bachmaier, 2018; van Merriënboer & Ayres, 2005; Vollmeyer & Rheinberg, 2006). (Intrinsic) motivation could affect all types of load during learning (Schnotz et al., 2009; Ismail et al., 2013; Stiller & Bachmaier, 2018). Intrinsic motivation may even be more important for regulating load when it is high. The

Cognitive Load Theory perspective mainly relates a higher level of intrinsic motivation to a higher level of germane load (which could be interpreted as high-quality learning). In a distance-training context, Stiller and Bachmaier (2018) found evidence for these assumptions. Small positive relations were revealed between intrinsic motivation and learning skills (i.e., the usage of meta-cognitive learning strategies and strategies for arranging an adequate learning environment), invested effort, and performance.

**Learning strategies**

A successful distance/online student is assumed to be a good self-regulated student (Barnard, Lan, To, Paton, & Lai, 2009) who adequately uses cognitive learning strategies, metacognitive learning strategies, and resource management strategies (Pintrich, 1999). For distance learning, metacognitive strategies for planning, monitoring and regulation of cognitive processes and resource management strategies for managing and controlling the study environment are considered to be among the most important strategies (Lee, Choi, & Kim, 2013). In particular, time management strategies and strategies for arranging the study environment are focused among resource management strategies. From a Cognitive Load Theory perspective, a higher level of strategic abilities of students might affect cognitive load while learning. For example, when students study without disturbances and distractions and focus cognitive resources on information processing more efficiently, extraneous load should decrease, and germane load should increase. Higher strategical student abilities might avoid overload, which in turn should result in more successful learning and consequently test performance. In contrast, lower levels of strategic abilities might lead to less learning success. In addition, Stiller and Bachmaier (2018) proposed that having sufficient time to process the content might result in experiencing lower levels of intrinsic load (i.e., managing the same amount of element interactivities in shorter periods might also increase the task difficulty). In distance learning, the empirical evidence corresponds to this rationale. Management skills have been found to be significant predictors of learning achievement (e.g., Yukselturk & Bulut, 2007) and dropout (e.g., Hart, 2012; Lee & Choi, 2011). Stiller and Bachmaier (2018) showed a predicting power of strategy usage on ratings of content difficulty (intrinsic load) and invested effort but not performance. The latter result could be explained by task difficulty and study time. Even students with lower levels of strategic abilities might have been able to master the learning task because it was relatively easy (they were only required to acquire factual knowledge), and they could spend as much time as they needed. In other words, a simple spend-more-time-on-studying strategy would have been a successful strategy for distance students (i.e., trainee teachers).

**Computer attitude**

Blignaut, Burger, McDonald and Tolmie (2005) defined computer attitude as “a complex mental state that affects a human’s choice of action or behavior toward computers and computer-related tasks” (p. 500). Computer attitude includes affective, conative, and cognitive components (Richter, Naumann, & Horz, 2010). Attitudes are often defined as beliefs that are organized in topics (Tourangeau, 1992; Tourangau, Rasinski, & D’Andrade, 1991), which reflects a cognitive perspective. Richter, Naumann and Groeben (2000; cf. Richter et al., 2010), for example, focused on the topic “computers as an object of personal experience” and furthermore on the subtopic “computers as a self-experienced instrument for working and learning.” In addition, attitudes are assumed to reflect a bipolar structure. Thus, a person might concurrently hold negative and positive beliefs about computers (Pratkanis, 1989). Richter et al. (2000, 2010) termed their positive attitude component as a “beneficial tool” dimension and the negative component as an “autonomous entity” dimension of computer use. For example, students might concurrently believe that computers are helpful tools that make learning and working easier and also that computers are uncontrollable and mysterious machines. Only a few studies have investigated the effects of computer attitude on distance and online learning, particularly assessing course usage, dropout and performance. Negative attitudes affected course usage, persistence, and performance negatively (e.g., Stiller, 2009, 2019), whereas positive attitudes (including attitudes toward e-learning, internet use, information technology, or technology use) had positive effects (e.g., Bernard et al., 2004; Sam, Othman, & Nordin, 2005; Stiller & Köster, 2016).

From a Cognitive Load Theory perspective, attitude towards computers is a feature of a student that might affect working memory load while learning. Discussing attitude towards computers for learning must address the positive and the negative attitude components. Having a high level of the positive attitude component (e.g., as a beneficial tool; Richter et al., 2010) might advantageously work like intrinsic motivation by stimulating students to put more effort into learning and especially into processing information more deeply, which is assumed to lead to higher performance and achievement. Believing to use a helpful tool for learning and working might be a (powerful) motivator for practicing learning and working. Low levels of beneficial-tool beliefs are less likely to induce effort. Conversely, the presence of a negative attitude component might create extraneous load that stems from processing disturbing thoughts about the functioning of the computer in use (e.g., the computer malfunctioning or even crashing). Cognitive processes that do not contribute to schema acquisition and automation are per definition extraneous load. Learners without a negative attitude component should have fewer disturbing thoughts and thus a lower level of extra working-memory load. Correspondingly, they should be able to use the memory resources more adequately for intrinsic and germane processing load.

**Computer anxiety**

Blignaut et al. (2005) defined computer anxiety as “a diffuse, unpleasant, and vague sense of discomfort and apprehension when confronted by computer technology or people who talk about computers” (p. 500). They added that computer anxiety comprises “an array of emotional reactions, including fear, apprehension, uneasiness, and distrust of computer technology in general” (p. 495). Correspondingly, Igbaria and Parasuraman (1989) earlier described computer anxiety as “the tendency of an individual to be uneasy, apprehensive, or fearful about the current or future use of computers in general” (p. 375). Most studies about distance learning have investigated the influence of computer anxiety on learning, based on the assumption that anxiety directly influences self-efficacy, which influences computer usage and performance (Desai, 2001; Hauser, Paul, & Bradley, 2012; Saadé & Kira, 2009; Sam et al., 2005). These studies have found that computer anxiety is related to higher dropout (Stiller & Köster, 2016, but also see Long et al., 2009; Stiller & Bachmaier, 2017, 2018), lower levels of perceived ease of use of learning environments (Abdullah & Ward, 2016; Baki, Birgoren, & Aktepe, 2018), and lower performance levels (Desai, 2001; Hauser et al., 2012; Saadé & Kira, 2009; Sam et al., 2005; Stiller & Bachmaier, 2018).

Blignaut et al. (2005) summarized that computer anxiety was often conceptualized in the early research on computer anxiety as a component of attitude and that the concepts of computer anxiety and negative attitude toward computers were used interchangeably. As stated above, for example, Richter et al. (2010) distinguished between positive and negative computer attitudes that co-exist concurrently. Furthermore, they also separated computer anxiety from computer attitudes in their Computer Literacy Inventory (Richter et al., 2010). Blignaut et al. (2005) also stated that computer anxiety might not be solely responsible for a negative attitude and that a positive computer attitude, a negative computer attitude, and computer anxiety may be independent of each other. For example, a negative attitude towards computers might not concurrently mean the presence of computer anxiety. Nevertheless, empirical studies have revealed high correlations between negative attitude and computer anxiety when investigating distance learners. For example, Stiller and Köster (2017) and Stiller and Bachmaier (2018) reported correlations of .57 and .83 between the level of computer anxiety and the level of a negative computer attitude for their sample of employees and trainee teachers.

Richter et al. (2010) considered computer anxiety a trait comprising cognitive and affective components (e.g., worrisome thoughts and feelings of anxiety). From a Cognitive Load Theory perspective, when using a computer for learning, students with a higher level of computer anxiety might experience more disturbing thoughts and emotional reactions that contribute to a higher level of extraneous load. Furthermore, extraneous load should additionally rise when students try to cope with negative thoughts and emotions because coping processes do not contribute to schema acquisition and automation. In contrast, learners with low levels of computer anxiety are less likely to experience an extra extraneous load. Thus, they might adequately construct schemas and automate them. Research about computer anxiety based on Cognitive Load Theory is rare.

## RESEARCH QUESTION AND EXPECTATIONS

The research question guiding this study was: To what extent is the experienced cognitive load while studying a distance-training course and learning success explainable by motivational, affective, cognitive, and learning skill characteristics of students? To answer this question, we analyzed the data of in-service teachers who had participated in a continuing education distance-training course on media education by using regression analyses. We investigated whether domain-specific prior knowledge, intrinsic motivation, computer attitude, computer anxiety, and learning strategy usage could be used to model five cognitive load assessments, which are ratings of content difficulty, learning ease, experienced pressure/tension, and effort/importance while learning, and test performance.

**Domain-specific prior knowledge.** We assumed that the learning material and thus studying is easier for learners having a higher level of domain-specific knowledge because they already know a part of the material to be learned. When studying is easier, learners should also feel less pressure and tension while studying and invest less effort. Thus, the level of prior knowledge is expected to correlate negatively with the experienced difficulty of the learning task (i.e., intrinsic load), the experienced difficulty of learning (i.e., overall cognitive load while studying), the effort put into studying, and the pressure and tension felt while studying but positively with test performance.

**Intrinsic motivation.** We assumed that learners invest more effort into learning and feel less pressured when they are more intrinsically motivated. This might also correspond to an experience of ease of content and learning. Thus, the level of motivation is assumed to correlate positively with the effort put into studying but negatively with the experienced difficulty of the learning task (i.e., intrinsic load), the experienced difficulty of learning (i.e., overall cognitive load while studying), and the pressure and tension felt while studying. Consequently, being more motivated might also result in higher test performance.

**Learning strategy usage.** We assumed that planning and controlling learning, managing study time, and arranging a learning environment adequately reduces extraneous load for learners (e.g., they will be less interrupted by unexpected disturbances and have all necessary working material at hand), and lets them experience learning as easier and less tense. In addition, learners can direct more effort into studying. Thus, the level of strategy usage is expected to correlate negatively with the experienced difficulty of the learning task (i.e., intrinsic load), the experienced difficulty of learning (i.e., overall cognitive load while studying), and the pressure and tension felt while studying but positively with the effort put into studying. Consequently, a higher level of strategy usage might also result in higher test performance.

**Computer attitude and computer anxiety.** A negative computer attitude and computer anxiety should be accompanied by, for example, task irrelevant thoughts and regulation of negative emotions triggered when using a computer. This load by task irrelevant processes should impair learning. Thus, the level of computer anxiety and a negative computer attitude are assumed to correlate positively with the experienced difficulty of learning (i.e., overall cognitive load while studying), the pressure and tension felt while studying, and the experienced difficulty of the learning task (i.e., intrinsic load) but negatively with the effort put into studying. Consequently, a higher level of computer anxiety and a negative computer attitude might result in worse test performance.

## METHOD

### Sample

The data for analyses were taken from a subset of 318 in-service teachers who had voluntarily enrolled in a continuing vocational distance-training course on media education in the German Federal State of Bavaria. The course was advertised by flyers at all primary, secondary general, intermediate, and grammar schools in Bavaria. The subset comprised 49 teachers (15.4%) who had studied all eight modules of the training course. Not considered for analysis were the data of 250 teachers who had completed less than eight modules and the data of 19 teachers who had completed all modules but at least one of them very fast. By eliminating these data sets from the analyses, we intended to reduce or control the influence of factors that could be confounded with the number of completed modules and study time. For example, the number of completed modules and study time of modules could be confounded with motivation. Thus, we excluded all learners from analyses who were assumed to have not invested enough time for seriously studying the content. We set the criterion for minimum invested study time per module to 25 min, given an estimated 60–90 min workload per module.

Table 1 shows the descriptive data of the enrolled teachers and the subset. More female than male in-service teachers enrolled in the training and studied all modules of the training. The mean age of all enrolled teachers was about 40 years (n = 317), and the mean age of the subset was slightly less with 37 years. Most enrolled teachers and subset teachers worked in intermediate and grammar schools, followed by primary and secondary general schools.

**Table 1:** Demographic characteristics of the enrolled teachers and its subset.

| | Enrolled teachers | Subset of teachers |
|---|---|---|
| *N* | 318 | 49 |
| *M* of age in years (*SD*) | 39.61 (9.69) | 37.16 (8.57) |
| Range of age in years | 21-70 | 26-59 |
| Female (%) | 179 (56.3%) | 36 (73.5%) |
| Male (%) | 139 (43.7%) | 13 (26.5% |
| Primary school | 32 (10.1%) | 6 (12.2%) |
| Secondary general school | 33 (10.4%) | 1 (2.0%) |
| Intermediate school | 130 (40.9%) | 24 (49.0% |
| Grammar school | 72 (22.6%) | 14 (28.6%) |
| Other than listed | 51 (16.0%) | 4 (8.2%) |

### Description of the distance-training course

The distance-training course was developed using Moodle. After the first course login, the introductory module providing information about content, technical requirements, course organization, and self-management for successful distance learning was displayed. The student teachers could freely decide whether to study the introductory module. The main content of the Moodle course comprised eight modules on media education. The student teachers could freely decide how many modules to study, the sequence in which to study the chosen modules, and how long to study the modules.

Each module was linearly structured by six screen pages. The first page, named *module profile*, presented the overview of the module content and the teaching objectives. The second page provided a case example featuring a real life problem that was designed to emphasize the relevance of the content and to trigger the students' curiosity. The third page requires the students to take a domain-specific prior-knowledge test without a time limit. The test was designed to activate students' prior knowledge and to give feedback about its level. The fourth page gave access to the obligatory instructional text and optional material for further elaboration (e.g., links to videos, audios, webpages, and literature). The fifth page was the module questionnaire about studying the module. The sixth page forced the students to take the final module test; the test evaluated the students' learning success and provided feedback.

The workload for each module was estimated between 60 and 90 min, totaling 8 to 12 hours of work to complete the training. When learners needed support, they could ask for help by email, chat, or phone. Consulting by chat and phone was offered within office hours announced at least four weeks in advance, and emails were answered within a few hours.

**Procedure and measurements**

***Procedure.*** The training was provided during a regular German school year. First, interested teachers registered online. After registration, the teachers could login to the Moodle course. The first login directly placed the teachers into the introductory module. This was designed to stimulate a self-preparation for distance learning, but studying the module was not obligatory. Leaving the introductory module directed the teachers to the first online questionnaire, which gathered demographic information and assessed various learner characteristics. After completion of the questionnaire, the teachers could choose the order in which to study any of the eight course modules. Each module gathered data about teachers' prior knowledge (see section "description of the distance-training course"; Module Page 3), how they experienced studying the module (module questionnaire on Module Page 5), and their test performance after studying a module (Module Page 6). A teacher could provide up to eight data sets, depending on the number of completed modules. Tables A to C of the appendix list the items of the measurement scales.

***First questionnaire.*** The questionnaire was composed of scales for assessing (1) the motivation to participate in the training, (2) attitude towards computers, (3) computer anxiety, (4) the use of meta-cognitive learning strategies, (5) the use of time management strategies, and (6) the use of strategies for arranging an adequate learning environment. Participation motivation was assessed with the Interest/Enjoyment scale of the Intrinsic Motivation Inventory (IMI; Ryan et al., 1982). The attitude towards computers was assessed with the scale "Personal experience/learning and working/autonomous entity" of the Questionnaire for the Content-Specific Measurement of Attitudes toward the Computer (QCAAC; Richter et al., 2010). This scale measures the negative attitude component described as the presence of regarding computers being uncontrollable machines based on personal experience with using computers as a means for learning and working. Cognitive and affective components of computer anxiety was assessed with the scale "Confidence in dealing with computers and computer applications" of the QCAAC. Finally, learning competence was operationalized by the use of three exemplary persistent strategies of self-regulated learning. The use of meta-cognitive learning strategies (comprising planning, monitoring, and regulating), time management and learning environment were assessed by the corresponding scales of the Questionnaire for Measuring Learning Strategies of Students (Wild & Schiefele, 1994).

***Module questionnaires.*** Four subjective rating instruments assessed the experienced cognitive load while learning. Two 5-items scales of the IMI were used: The Effort/Importance scale (an indirect measure of cognitive load) and the Pressure/Tension scale (a direct measure). Additionally, two direct measures of intrinsic and overall load were applied: A one-item rating of content difficulty assessed intrinsic load and a one-item rating of difficulty of studying assessed overall load.

***Tests of prior knowledge and performance.*** The training was intended at providing factual knowledge. Hence, multiple choice tests were considered appropriate for assessing corresponding prior knowledge and learning success. Each module provided a prior knowledge test at the beginning and a performance test at the end of a module. Each prior knowledge test comprised five multiple-choice items, and each performance test 15 items. The five items of the prior knowledge test were also included in the performance test. Each item provided four answers, and at least one of them was correct.

**Annotation to measurements**

Table 2 presents the scale features, based on the data of the total sample (n = 318). The teachers' individual scores were calculated as follows.

***First questionnaire.*** Means of item ratings were calculated for all scales used in the first online questionnaire measuring participation motivation, computer attitude, computer anxiety, and usage of three selected learning strategies. All items were rated on a 5-point Likert-scale coded from 1 to 5. Higher scores reflect higher feature levels of teachers except for computer attitude. Higher computer attitude scores reflect a low negative attitude, which could be vaguely interpreted of as a "positive" attitude.

***Module questionnaires.*** First, means of item ratings were calculated for the Effort/Importance and Pressure/Tension scales for each module. The one-item rating of intrinsic and overall load were taken as given. Then, means were calculated over the eight module scores. High scores reflect high loads.

***Tests of prior knowledge and performance.*** First, test scores for domain-specific prior knowledge and performance were calculated as percent correct answers for each module. Then, means were calculated over the eight module scores.

**Table 2**: Means and standard deviations as well as the potential score range of the used measurements are shown.

| | #I(1) | #A(2) | Range | M | SD | n | α(3) | #A(2) | M | SD | n |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Participation motivation | 7 | 1 | 1-5 | 4.00 | .62 | 318 | .84 | 1 | 4.23 | .49 | 49 |
| Computer attitude | 9 | 1 | 1-5 | 4.23 | .59 | 318 | .80 | 1 | 4.19 | .54 | 49 |
| Computer anxiety | 8 | 1 | 1-5 | 1.77 | .63 | 318 | .82 | 1 | 1.81 | .63 | 49 |
| Meta-cognitive strategies | 11 | 1 | 1-5 | 3.43 | .61 | 318 | .81 | 1 | 3.56 | .57 | 49 |
| Time management | 4 | 1 | 1-5 | 2.47 | .90 | 318 | .83 | 1 | 2.45 | .87 | 49 |
| Learning environment | 6 | 1 | 1-5 | 3.99 | .68 | 318 | .80 | 1 | 4.02 | .66 | 49 |
| Prior knowledge | 5 | 1-8 | 0-100 | 48.71 | 16.34 | 255 | .45(4) | 8 | 48.68 | 10.80 | 49 |
| Intrinsic load | 1 | 1-8 | 1-5 | 1.67 | .63 | 159 | | 8 | 1.69 | .51 | 48 |
| Overall load | 1 | 1-8 | 1-5 | 1.70 | .70 | 159 | | 8 | 1.66 | .56 | 48 |
| Effort/Importance | 5 | 1-8 | 1-5 | 3.33 | .54 | 159 | .59(4) | 8 | 3.45 | .44 | 48 |
| Pressure/Tension | 5 | 1-8 | 1-5 | 1.80 | .72 | 159 | .87(4) | 8 | 1.91 | .73 | 48 |
| Performance | 15 | 1-8 | 0-100 | 80.12 | 13.82 | 159 | .56(4) | 8 | 86.86 | 6.57 | 49 |

(1) Number of items used for assessment. (2) Number of assessments an individual score is based on. (3) Cronbach's alpha. (4) Mean Cronbach's alpha.

## RESULTS

**Correlations between variables**

Table 3 provides an overview over the 66 correlations calculated between the variables under focus. We did not control for cumulative alpha error (e.g., applying the Bonferroni-Holm correction results in four significant correlations, i.e., all absolute values r ≥ .58) because considering only the largest correlations would not be helpful with interpreting the results of the subsequent regression analyses. Thus, we reported all significant correlations using non-corrected Alpha levels.

**Table 3:** Correlation matrix of variables.

| | | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | n |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Intrinsic motivation | .15 | -.18 | -.03 | .13 | .12 | .07 | $-.25^{+}$ | $-.34^{*}$ | -.23 | .10 | .01 | 49 |
| 2 | Computer attitude | | $-.75^{***}$ | .14 | .10 | .04 | .04 | $-.26^{+}$ | $-.34^{*}$ | -.09 | -.03 | .20 | 49 |
| 3 | Computer anxiety | | | -.08 | .03 | .09 | -.12 | $.38^{**}$ | $.44^{**}$ | $.28^{+}$ | .10 | -.06 | 49 |
| 4 | Prior knowledge | | | | .00 | -.01 | .01 | -.14 | -.15 | .05 | -.08 | $.37^{**}$ | 49 |
| 5 | Metacognition | | | | | $.58^{***}$ | $.31^{*}$ | .00 | .07 | .12 | $.34^{*}$ | $.27^{+}$ | 49 |
| 6 | Time management | | | | | | $.42^{**}$ | .14 | .10 | $.25^{+}$ | .13 | .04 | 49 |
| 7 | Learning environment | | | | | | | -.17 | -.14 | -.07 | .07 | .12 | 49 |
| 8 | Intrinsic load | | | | | | | | $.71^{***}$ | $.45^{***}$ | $-.31^{*}$ | -.17 | 48 |
| 9 | Overall load | | | | | | | | | $.72^{***}$ | -.20 | $-.26^{+}$ | 48 |
| 10 | Pressure/Tension | | | | | | | | | | .03 | -.18 | 48 |
| 11 | Effort/Importance | | | | | | | | | | | .06 | 48 |
| 12 | Learning performance | | | | | | | | | | | | 49 |

*Note.* $^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$.

The pattern of correlations between the learner characteristics is very clear. The matrix shows four essential correlations among 21 calculated correlations. Computer anxiety highly correlated with computer attitude. Students with lower levels of computer anxiety reported more positive attitudes towards computers (i.e., the absence of negative computer attitudes). Furthermore, medium to large sized positive correlations were found between the reported usages of the three focused learning strategies. No other relevant correlations could be observed.

Large-sized, positive correlations were found between intrinsic load, overall cognitive load, and pressure/tension, which all are subjective direct assessments of cognitive load. The higher that learners rated their intrinsic load, the higher was their experience of overall cognitive load and their experienced pressure and tension. In other words, the higher learners rated the content difficulty, the higher the difficulty of studying was rated, and their experienced pressure and tension. Effort/importance did only correlate significantly with intrinsic load. The more effort was reported, the less intrinsic load was experienced. For performance, some minor negative correlations with direct load assessments were found, but not with effort/importance. The higher the experienced load, the lower the score on the performance tests.

Medium-sized correlations were mostly found between the learner characteristics, intrinsic load, and overall load. Intrinsic motivation, computer attitude, and computer anxiety correlated significantly with these load ratings. Being more motivated and having a more positive computer attitude were related to experiencing less intrinsic and overall cognitive load. In contrast, being more anxious about computers was related to experiencing more load. That is, content and studying difficulty were rated higher. Pressure/tension as an overall load measure showed the same pattern of correlations as intrinsic and extraneous load, but correlations were weaker and negligible for computer attitude. In addition, time management correlated positively with the experienced pressure and tension. That is, reporting a higher level of time management was connected to a higher level of experienced pressure and tension. Prior knowledge and metacognitive strategy usage had a positive impact on performance. The more the students knew about the content before learning and the more they reported using metacognitive strategies, the higher their score in the final module tests. The indirect measure of overall cognitive load (i.e., the experience of effort/importance) only showed one significant correlation with metacognitive learning strategy usage. The more they reported using the strategy, the higher the experience of effort and importance.

**Regression Analyses**

All cognitive load measures could be modeled by multiple linear regressions on the learner characteristics in focus (see Table 4 and 5). Backward elimination models consistently resulted in a multiple correlation of between .34 and .52 and an explained variance between .12 and .27.

**Table 4:** Summary of models.

| | *R* | *R²* | *Adjusted R²* | *SE* | *DW* | *F* | $df_1$ | $df_2$ | *p* |
|---|---|---|---|---|---|---|---|---|---|
| Intrinsic load | .38 | .14 | .12 | .48 | 1.71 | 7.56 | 1 | 46 | .008 |
| Overall load | .52 | .27 | .23 | .49 | 1.94 | 8.11 | 2 | 45 | .001 |
| Pressure/tension | .36 | .13 | .09 | .70 | 1.85 | 3.36 | 2 | 45 | .044 |
| Effort/importance | .34 | .12 | .10 | .41 | 2.25 | 6.04 | 1 | 46 | .018 |
| Performance | .46 | .21 | .18 | 5.95 | 2.03 | 6.25 | 2 | 46 | .004 |

**Table 5:** Results of the multiple linear regression analyses (backward elimination).

| | | *B* | *SE* | *ß* | *t* | *df* | *p* | *tolerance* |
|---|---|---|---|---|---|---|---|---|
| Intrinsic load | (Constant) | 1.13 | .21 | - | 5.32 | 46 | .001 | |
| | Computer anxiety | .30 | .11 | .38 | 2.75 | 46 | .008 | 1.00 |
| Overall load | (Constant) | 2.29 | .70 | - | 3.29 | 45 | .002 | |
| | Intrinsic motivation | -.30 | .15 | -.27 | -2.05 | 45 | .046 | .97 |
| | Computer anxiety | .35 | .12 | .40 | 3.06 | 45 | .004 | .97 |
| Pressure/Tension | (Constant) | 2.97 | .89 | - | 3.33 | 45 | .002 | |
| | Intrinsic motivation | -.39 | .21 | -.26 | -1.88 | 45 | .067 | .99 |
| | Time management | .23 | .12 | .28 | 2.00 | 45 | .052 | .99 |
| Effort/Importance | (Constant) | 2.52 | .38 | - | 6.60 | 46 | .001 | |
| | Metacognition | .26 | .11 | .34 | 2.46 | 46 | .018 | 1.00 |
| Performance | (Constant) | 64.49 | 6.72 | - | 9.60 | 46 | .001 | |
| | Metacognition | 3.17 | 1.52 | .27 | 2.09 | 46 | .042 | 1.00 |
| | Prior knowledge | .23 | .08 | .37 | 2.86 | 46 | .006 | 1.00 |

Intrinsic load could be modeled by computer anxiety only. The higher that students reported computer anxiety, the higher their intrinsic load. Similarly, overall load could be modeled by computer anxiety and intrinsic motivation. Computer anxiety showed a higher predictive power on overall load than intrinsic motivation. The higher that computer anxiety was experienced, the higher the overall load. In contrast, a higher intrinsic motivation reduced the experience of overall load.

Pressure/Tension could be modeled by intrinsic motivation and time management. Both variables showed about equal predictive impact. The higher the time management scores, the higher that pressure and tension were rated by the learners. Conversely, a higher intrinsic motivation reduced the experienced pressure and tension.

The resulting model of Effort/Importance only contained the usage of metacognitive strategies. The higher that metacognitive strategy usage was reported, the higher the experienced effort and importance. No other variable remained significant in the model. Similarly, metacognitive strategies were also positively related to performance, but performance could also be modeled by prior knowledge. Prior knowledge appeared to be a stronger predictor of performance than metacognitive strategy usage. Students reporting higher prior knowledge and strategy usage performed better on the final module tests.

**Self-correlation, homoscedasticity, and non-collinearity**

The self-correlation of residuals per regression model was tested with the Durbin-Watson test. Values in the interval of 1.5 to 2.5 indicate the non-existence of self-correlations. For all of the resulting regression models, the values lie in the mentioned interval. Hence, the absence of self-correlation of residuals is assumed for all models (see Table 4).

Homoscedasticity was tested by the Koenker test (Koenker, 1981). Homoscedasticity was marginally violated for intrinsic load ($\lambda^2$ = 3.99, $df$ = 1, $p$ = .05) and overall load ($\lambda^2$ = 5.22, $df$ = 2, $p$ = .07), but not for Pressure/Tension ($\lambda^2$ = 1.82, $df$ = 2, $p$ = .40), Effort/Importance ($\lambda^2$ =.23, $df$ = 1, $p$ = .64), and performance ($\lambda^2$ = 1.63, $df$ = 2, $p$ = .44).

Non-collinearity focuses on the correlations between predictors and could be controlled by the statistic of tolerance. Values less than .10 are indicative of collinearity of predictors, whereas values near 1 are unproblematic. The tolerance indices of all regression models suggest non-collinearity of predictors.

## DISCUSSION

One approach towards designing high-quality distance courses that meet the needs of students is to focus on identifying crucial learner characteristics of successful learners (Yukselturk & Bulut, 2007). Adopting this approach, we investigated how a set of motivational, affective, cognitive, and skill aspects of in-service teachers could explain their learning success when studying a script-based distance course about media education. In this section, we also discuss how the identified student characteristics assessed in this study should be considered when designing distance-learning courses.

Before the results are discussed, one point about computer anxiety and attitude should be noted. Although positive and negative computer attitude and computer anxiety are assumed to be independent constructs (Blignaut et al., 2005; Richter et al., 2010), research in distance learning has revealed high correlations between negative computer attitudes and computer anxiety (e.g., Stiller & Köster, 2017; Stiller & Bachmaier, 2018), including the current study. Hence, results of negative computer attitudes are not strictly separable from computer anxiety. This fact can be attributed to the special sample groups used in studies that have investigated distance learning. Distance and online learners could have a stronger correspondence between computer attitude and anxiety than learners in non-computer-based learning environments.

The analyses in the current study showed that domain-specific prior knowledge and metacognitive strategies had a significant predictive value for the level of performance, with prior knowledge showing the highest impact. This result reflects previous research findings about prior knowledge (Amadieu et al., 2009; McDonald & Stevenson, 1998; Simonsmeier et al., 2018; Stiller, 2003, 2009, 2017; Stiller & Bachmaier, 2018) and self-regulated learning strategies as represented by metacognitive strategies (Hart, 2012; Lee & Choi, 2011; Yukselturk & Bulut, 2007). The corresponding explanations are that prior knowledge makes it easier to assimilate new information and learning strategy usage makes it easier to build or to elaborate schemas, which leads to better test performance. Furthermore, self-regulation skills, represented by the usage of time management and metacognitive strategies in the current study, significantly correlated positively with experienced pressure/tension while learning and invested effort. These skills also remained as significant predictors in the backward regression models. Overall, these results indicate that self-regulation skills are important when arranging and organizing for learning and thus contribute to successful learning.

Intrinsic motivation has been proposed to play a significant role for successful distance learning, but it had no impact on performance in the current study. This result contradicts previous research at the first glance (Ali & Franklin, 2001; Aragon et al., 2001; Artino, 2008; Delialioglu, 2005; Fredericksen et al., 2000; Sankaran & Bui, 2001; Stiller & Bachmaier, 2018; Waschull, 2005; Yukselturk & Bulut, 2007). Thus, higher levels of intrinsic motivation appear to not influence students' studying and learning efforts and the resulting test performance. But intrinsic motivation had a significant predictive power for the experienced overall load and pressure/tension. Intrinsic motivation correlated negatively with overall load and experienced pressure. Students with a higher motivation reported a lower level of studying difficulty and pressure and tension while learning. These results indicate that intrinsic motivation contributes to learning success by managing cognitive load while learning, which is consistent with the literature on learning success.

Computer attitude and computer anxiety have also been proposed to play a significant role for successful distance learning, but they had no impact on performance, invested effort, and experienced pressure while learning. This result contradicts previous research on performance (Desai, 2001; Hauser et al., 2012; Saadé & Kira, 2009; Sam et al., 2005; Stiller, 2009, 2019; Stiller & Bachmaier, 2018). Thus, lower levels of computer anxiety and more positive levels of computer attitude appear to not influence students' studying efforts and their experience of pressure and tension and test performance. However, computer anxiety significantly predicted intrinsic and overall load, and computer anxiety correlated positively with intrinsic and overall load. Overall, these results indicate that computer anxiety only contributes to the experience of learning as being more difficult, as indicated by the subjective one-item ratings of content and studying difficulty, but not to more learning success.

**Limitations**

There are some limitations of the study that must be considered. First, the sampling method was inherently biased because only the best student teachers, who finished all training modules successfully, were selected. Thus, the results point to learner characteristics that predict knowledge acquisition among the best. These characteristics might not be the most important ones for students that had intended to work only on a few selected modules or students that had decided to drop out from training after completion of a view modules. Consequently, optimizing a course design according to the significant learner characteristics in this study might only foster learning in already successful learners.

Second, the distance-training course used in this study is one among many. It sets specific demands on learners that might differ from other investigated courses. The mixture of online introduction, offline learning, and online testing might not allow to easily generalize results to other distance courses, particularly when they use, for example, more interactive and dynamic media (e.g., simulations and videos) and group work. Learners confronted with other trainings with a defined set of demands might need other abilities to be successful learners. A better approach when investigating distance and online courses could be to first analyze the learning task and then identify abilities that a successful learner should have. Nevertheless, some learner characteristics and abilities might be important for any type of distance course such as motivation or learning strategies. When a learning task is easy and not very time consuming, however, students might still acquire knowledge when they are low in motivation and have low abilities in organizing their learning, for example, in rote learning.

Third, the analytical design also bears problems. As dependent measures, we used mean scores calculated over all eight modules for analyses. This procedure might result in underestimations of effects because learner characteristics, such as intrinsic motivation, computer anxiety, and computer attitude, might change when learners are studying over a longer time period. For example, distance and online courses might act as interventions that change computer anxiety and computer attitude (Dupin-Bryant, 2002; Woszczynski, Lazar, & Walker, 2004). Moreover, the student level of motivation is suggested to underlie fluctuations or might decrease when studying is not as satisfying as expected. Thus, when computer anxiety and motivation decrease and computer attitude becomes more positive, existing effects might be reduced because the scores might be less influenced by the changed learner characteristics. Finally, this was a nonexperimental field study, which would benefit from a replication study under more controlled conditions.

**Conclusion**

Overall, our results are consistent with former research when focusing on both objective performance and subjective cognitive load measures. From the perspective of learning strategies, we conclude that students should be supported in their self-regulation because a higher level of strategy usage is connected to a higher level of invested effort and performance and to a lower level of experienced pressure and tension while learning (e.g., Yukselturk & Bulut, 2007). Prior knowledge should also be considered when designing a training for reaching high performance levels. That is, training should be more tailored to student's prior knowledge. The overall experience of content difficulty and studying difficulty was linked to motivation and computer anxiety. Thus, a distance training should also be designed in a way to reduce computer anxiety (and to positively influence computer attitude) and to make learning an interesting event (Yukselturk & Bulut, 2007).

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**APPENDIX**

The following tables list the translated German items of the questionnaires used for assessments.

**Table A:** Items assessing intrinsic motivation, computer attitude, and computer anxiety were rated on 5-point Likert scales from "do not agree" to "agree".

| | |
|---|---|
| Intrinsic motivation (scale "Interest/Enjoyment" by Ryan et al., 1982; authors' translation based on Leone, 2011) | |
| 1 | I think I will enjoy studying the modules very much. |
| 2 | I think studying the modules will be fun to do. |
| 3 | I think studying the modules will be a boring activity. |
| 4 | I think studying the modules will not hold my attention at all. |
| 5 | I think studying the modules will be very interesting. |
| 6 | I think this activity will be quite enjoyable. |
| 7 | I think I will not enjoy studying the modules. |
| Computer attitude (scale "Personal experience/learning and working/autonomous entity" by Richter et al., 2000, 2010) | |
| 1 | To me, the computer seems too unreliable to use as a learning tool. |
| 2 | I am often frustrated by the fact that the computer simply does not make sense to ordinary people. |
| 3 | When I use the computer for work, I constantly worry that it might break down. |
| 4 | Working with the computer is often frustrating because I do not understand the machine. |
| 5 | Sometimes my computer does things I do not understand. |
| 6 | The computer programs that I use for learning and working are sometimes hard to understand. |
| 7 | When I work with a computer, I feel that the computer does what it wants. |
| 8 | If I have computer problems while I am working, I feel helpless. |
| 9 | I wish I had to work less with computers. |
| Computer anxiety (scale "Confidence in dealing with computers and computer applications" by Richter et al., 2000, 2010) | |
| 1 | I feel confident in using the computer. |
| 2 | I panic when my computer crashes. |
| 3 | In working with the computer, I am easily frustrated when problems occur. |
| 4 | Working with the computer makes me uneasy. |
| 5 | When working with the computer, I am often worried that I might break something. |
| 6 | I feel that I cannot really control my computer. |
| 7 | If possible, I avoid working with the computer. |
| 8 | In the case of occurring computer problems, I stay calm. |

**Table B:** Items assessing learning skills were rated on 5-point Likert scales from "very rarely" to "very often".

| | |
|---|---|
| Meta-cognitive strategies (Griese et al., 2015); (p) = planning, (m) = monitoring, (r) = regulating | |
| 1 | I try to consider beforehand which areas of certain topics I have to study and which I do not have to study.(p) |
| 2 | Confronted with a difficult subject matter I adapt my learning strategy accordingly.(r) |
| 3 | If I do not understand everything I am reading, I will try to make a note of the gap in my knowledge and sift through the material again.(r) |
| 4 | I decide in advance how much subject matter I would like to work through in this session.(p) |
| 5 | Before starting on an area of expertise, I reflect upon how to work most efficiently.(p) |
| 6 | I plan in advance in which order I want to work through the subject matter.(p) |
| 7 | I ask myself questions on the subject matter in order to make sure that I have understood everything correctly.(m) |
| 8 | In order to find gaps in my knowledge I sum up the most important contents without using my notes.(m) |
| 9 | I work on additional tasks in order to determine if I have truly understood the subject matter.(m) |
| 10 | In order to check my own understanding I explain certain parts of the subject matter to a fellow student.(m) |
| 11 | When an aspect seems confusing or unclear, I examine it again thoroughly.(r) |
| Time management (Griese et al., 2015) | |
| 1 | I work according to a schedule. |
| 2 | I decide on the times for my learning. |
| 3 | I fix the hours I spend daily on learning in a schedule. |
| 4 | Before each study period I appoint the duration of my work. |
| Learning environment (Griese et al., 2015) | |
| 1 | I work in a place that makes it easy to concentrate. |

| | |
|---|---|
| 2 | I design my work environment in a way that I am distracted as little as possible. |
| 3 | When learning I always sit at the same place. |
| 4 | When studying I make sure that I can work uninterrupted. |
| 5 | My workplace is designed in a way that makes it easy to find everything. |
| 6 | At my desk I have the most important papers within reach. |

**Table C:** Items assessing cognitive load were rated on 5-point Likert scales from “do not agree” to “agree”.

| | |
|---|---|
| Intrinsic and overall load ratings (by authors; authors’ translation) | |
| 1 | The content of the module was well comprehensible. (intrinsic load) |
| 2 | Studying the module was very difficult for me. (overall load) |
| Indirect measure of overall load (scale “Effort/Importance” by Ryan et al., 1982; authors’ translation based on Leone, 2011) | |
| 1 | I put a lot of effort into processing this module. |
| 2 | I didn’t try very hard to do well at processing this module. |
| 3 | I tried very hard on processing this module. |
| 4 | It was important to me to do well at processing this module. |
| 5 | I didn’t put much energy into processing this module. |
| Direct measure of overall load (scale “Pressure/Tension” by Ryan et al., 1982; authors’ translation based on Leone, 2011) | |
| 1 | I did not feel nervous at all while working through this module. |
| 2 | I felt pressured while working through this module. |
| 3 | I was very relaxed in working through this module. |
| 4 | I was anxious while working through this module. |
| 5 | I felt very tense while working through this module. |

  