Does Context Matter? Investigating Factors Related to Students' Academic Achievement in Classroom and Online Courses

by

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Abstract

The aim of this thesis is to broaden the understanding of the relationships between target psychological constructs (i.e., self-regulation, motivation, self-theory of intelligence) and grades in a classroom setting as well as whether those target constructs are predictive of online course grades. We do so by collecting information from a large sample of undergraduate university students enrolled in either a traditional classroom or an online course and by analyzing the data using hierarchical regression analysis. In the present thesis, we demonstrate the strength of self-regulation and motivational constructs to positively influence classroom grades and present evidence that the constructs accounting for a significant amount of variance in classroom course grades are not applicable for explaining variance in online course grades. We discuss the implication of our findings as well as study limitations and point out potential direction for future work.

Table of Contents

List of Tables

List of Figures

List of Appendices

Chapter 1: Introduction

Students' learning outcome in traditional classroom settings is influenced by various psychological variables. For instance, self-regulation has a positive influence on students' academic achievement and is strongly correlated with learning outcomes (Garcia & Pintrich, 1996; Pintrich & De Groot, 1990; Pintrich, Smith, Garcia, & McKeachie, 1991). As a second example, research has shown that motivational constructs are positively related to students' learning outcome in traditional classroom settings (Pintrich & De Groot, 1990) and that students with high self-efficacy beliefs and students who approached their classes with an intrinsic goal for learning were more likely to receive higher grades (Garcia & Pintrich, 1996; Pintrich, Smith, Garcia, & McKeachie, 1993). Yet a third example is students' beliefs about intelligence, which are correlated with final grade (e.g., Chen & Pajares, 2010). In general, research has established these constructs and related variables as important predictors of students' classroom grades (e.g., Blackwell, Trzesniewski, & Dweck, 2007; De Castella & Byrne, 2015; Grant & Dweck, 2003; Hong, Chiu, Dweck, Lin, & Wan, 1999; Meece & Holt, 1993; Paunesku et al., 2015; Tempelaar, Rienties, Giesbers, & Gijselaers, 2015).

In contrast to classroom studies, research exploring the influence of psychological constructs in the context of online learning is limited, with a few noticeable exceptions (e.g., Puzziferro, 2008; Wang, Shannon, & Ross, 2013; Yeager et al., 2016). While some results from research in classroom contexts may transfer to an online context, this is not a given since the online context does afford some unique features (e.g., the asynchronous nature of online courses or the autonomy students experience in online learning environments). However, online courses have become a popular alternative or supplement to traditional classroom learning (Martel, Dupont, & Bédard, 2015; Seaman, Allen, & Seaman, 2018). Because online courses can deliver educational material to people and communities all around the world, interdisciplinary research at the intersection of the learning sciences and human-computer interaction (HCI) is essential for understanding the factors influencing success in online learning environments. This understanding can set the foundations needed to derive design guidelines on how to best support students enrolled in online courses.

1.1 Thesis goals

The goals of the present thesis are twofold:

(1) To broaden the understanding of the relationships between the target psychological constructs (i.e., self-regulated learning, motivation, self-theory of intelligence) and students' grades in a classroom setting, using a hierarchical regression analysis. Prior research suggests that these constructs do influence academic achievement (e.g., Bandalos, Finney, & Geske, 2003; Garcia & Pintrich, 1996; Gonida, Kiosseoglou, & Leondari, 2006; Jones, Wilkins, Long, & Wang, 2012; Kim, Park, & Cozart, 2014; Lin, Zhang, & Zheng, 2017; Niiya, Crocker, & Bartmess, 2004). However, a hierarchical regression model including all the afore mentioned psychological constructs has never been tested before.

(2) To extend the understanding of which of the target constructs are predictive of final course grades in online learning environments, using a hierarchical regression analysis.

Chapter 2: Related work

This review of the related work is divided into two sections. The first section describes the psychological constructs investigated in the present thesis as well as a representative sample of previous research. The second section briefly describes additional established variables influencing students' grades in classroom and online courses.

2.1 Psychological constructs influencing outcomes in academic classes

In the following section we review the relationship between key psychological constructs and academic achievement in traditional classroom and online learning environments.

2.1.1 Self-regulated learning

Pintrich and De Groot (1990) defined self-regulated learning as a process consisting of three elements that affect academic performance: (1) cognitive and metacognitive strategies, (2) resource management strategies, and (3) motivation. The first two elements are described in detail below, the third element will be described in the next section.

Cognitive strategies are the behaviors and thoughts that students engage in while studying. Examples of cognitive strategies include rehearsal, elaboration, and organization (Pintrich et al., 1991). Metacognitive strategies refer to strategies students use to plan, monitor and regulate their cognition, such as setting a goal to study, self-testing through questions about a text and rereading of the text (Pintrich, 1999). In addition to cognitive and metacognitive strategies, another aspect of self-regulated learning corresponds to resource management strategies, which enable students to control additional resources besides their cognition, e.g., manage their time and study environment, monitor and regulate their effort, collaborate with peers and seek help from peers or instructors (Pintrich et al., 1991, 1993).

Research in traditional classroom settings has shown that self-regulated learning strategies are beneficial for learning and that students who are achieving high grades are more likely to report the use of those strategies compared to low-achieving students (Bae, 2014; Chen, 2002; Garcia & Pintrich, 1996; Pintrich & De Groot, 1990). For instance, a multiple regression analysis performed by Chen (2002) showed that effort regulation (a resource management strategy) predicted test grades of college students enrolled in a face-to-face information systems class.

The use of self-regulated learning strategies is also associated with students' success in online courses. Puzziferro (2008) used an analysis of variance to test for differences in self-regulated learning based on grade. She found that college students who received higher grades in their online course reported higher use of self-regulating learning strategies than students who received lower grades. Broadbent and Poon (2015) conducted a meta-analysis on empirical studies of learning in online contexts published between 2004 and 2014. Their results showed that self-regulated learning strategies were significantly and positively associated with academic achievement.

2.1.2 Motivation

In general, motivation is conceptualized as directing individuals toward certain goals (Dweck & Elliott, 1983), as well as promoting initiation of certain activities and persistence in those activities (Stipek, 1993). According to Pintrich and De Groot (1990), motivation is considered a key factor influencing students’ ability to successfully self-regulate learning behaviors that affect academic performance. Pintrich and De Groot (1990) described three components that characterize student motivation: (1) a value component, (2) an expectancy component, and (3) an affective component.

The value component of motivation focuses on the reasons *why* students engage in a learning task. One reason refers to the value that students assign to the task. Specifically, the more meaningful, important and interesting a task appears to them and the more it is aligned with their goals, the higher is the assigned value. Another reason is the type of goals that students set to achieve with respect to some task or outcome. Pintrich and De Groot (1990) conceptualized these goals as either extrinsic or intrinsic, whereby both goal orientations are associated with different learning patterns.

Extrinsic goal orientation concerns the degree to which students participate in a task for reasons such as grades, rewards, or approval from others. The orientation towards extrinsic goals has also been described by other researchers as a performance-goal orientation (Dweck, 1986; Dweck & Leggett, 1988; Elliott & Dweck, 1988; Harackiewicz, Barron, Carter, Lehto, & Elliot, 1997; Middleton & Midgley, 1997). There are two main types of performance goals, performance avoid and performance approach. When oriented towards performance avoid goals, students' purpose in achievement settings is to avoid the demonstration of incompetence (Midgley et al., 2000). These students fall into a maladaptive pattern that hinder their self-regulation, task engagement, and performance (e.g., Elliot & Church, 1997; Elliot, McGregor, & Gable, 1999; Middleton & Midgley, 1997). In contrast to performance avoid goals, students oriented towards performance approach goals want to demonstrate their competence. The findings on the effect of these goals are more positive, with some researchers finding positive relationships with grades (Elliot & Church, 1997; Harackiewicz et al., 1997; Harackiewicz, Barron, Tauer, Carter, & Elliot, 2000).

In contrast to extrinsic goals, an intrinsic goal orientation concerns the degree to which students participate in a learning task for reasons such as challenge, curiosity, or mastery. The orientation towards intrinsic goals has also been described by other researchers as a mastery-goal orientation (e.g., Elliott & Dweck, 1988; Midgley et al., 1998, 2000). In a classroom study with fifth-grade students, Elliott and Dweck (1988) found that students with an orientation towards mastery goals aim to develop their competence by seeking challenging tasks, increasing effort in the face of difficulty, extending their learning processes beyond the minimum required, and engaging in the learning process. Furthermore, findings reported by various researchers show that a mastery-goal orientation has a positive effect on students’ academic achievement in classroom courses (e.g., Bandalos et al., 2003; Grant & Dweck, 2003; Greene & Miller, 1996; Meece & Holt, 1993; Schraw, Horn, Thorndike-Christ, & Bruning, 1995). In the context of online learning the findings regarding mastery-goal orientation are mixed. Cho and Shen (2013) used a structural equation modelling analysis to show that intrinsic goal orientation predicted self-regulated learning strategies, which in turn predicted online course grades. In contrast, results obtained by different scholars suggest that endorsing a mastery goal orientation is not related to students' performance in online courses (e.g., Husman & Hilpert, 2007; Neroni, Meijs, Leontjevas, Kirschner, & De Groot, 2018).

The expectancy component of motivation refers to students’ beliefs that they can accomplish a learning task, which in turn influences their motivation for doing the task. Expectancy includes control of learning beliefs and self-efficacy beliefs for learning and performance (Garcia & Pintrich, 1996; Pintrich & De Groot, 1990). Control of learning beliefs refers to students' beliefs that their efforts to learn will result in positive, desired outcomes and that their efforts to study makes a difference in their learning (Pintrich et al., 1991). In addition, some researchers explicitly distinguish between positive effort beliefs (i.e., the belief that effort is important for overcoming obstacles and achieving success) and negative effort beliefs (i.e., the belief that having ability is a sufficient condition for learning and effort should not be needed to succeed) (e.g., Blackwell et al., 2007; Dweck, 1999; Dweck & Master, 2008). We are not aware of studies investigating the effect of effort beliefs on achievement in online learning environments. In the context of classroom learning, prior studies have shown that positive effort beliefs have an indirect positive impact on grades (Blackwell et al., 2007; Jones et al., 2012). For instance, a path modelling analysis by Blackwell et al. (2007) showed that positive effort beliefs, predicted positive learning strategies, which in turn predicted high school grades.

Self-efficacy beliefs, the other aspect of expectancy in addition to control of learning beliefs, are an individuals' perceptions of their abilities to successfully complete a specific task (Bandura, 2007). Therefore, self-efficacy is not what an individual is able to do, but rather what an individual perceives itself to be capable of doing. A meta-analysis conducted by Multon, Brown, and Lent (1991), who examined the relationship between self-efficacy beliefs and students' academic achievement in classroom courses across 38 published and unpublished studies, found that self-efficacy accounted for approximately 14% of the variance in academic performance across a variety of student samples, experimental designs, and criterion measures. More recently, regression analysis showed that self-efficacy strongly predicted grades for college students in classroom courses (e.g., Komarraju & Nadler, 2013; Lynch, 2006). In addition, a structural equation modeling analysis confirmed that self-efficacy predicted final English and math grades for secondary school students (Bae, 2014).

Bandura (1997) proposed that self-efficacy beliefs are context-specific rather than a generalized expectancy. Thus, in the context of online learning, online learning self-efficacy can be conceptualized as an individual's perceptions of his or her abilities to successfully complete specific tasks required of online learners (Zimmerman & Kulikowich, 2016). The findings regarding the relationship between self-efficacy in online contexts and academic achievement are mixed. Puzziferro (2008) examined the relationship between students' performance (measured as a function of grade and course satisfaction) and students' online learning self-efficacy. The author did not find a significant link between self-efficacy and performance. In contrast, Wang et al. (2013) found that students with higher levels of technology self-efficacy (which measured general computer self-efficacy and online learning platform-related self-efficacy) received better grades.

The affective component of motivation refers to students' feelings about learning tasks, and specifically test anxiety or fear of assessment (Garcia & Pintrich, 1996; Pintrich & De Groot, 1990). Several researchers have found a significant negative correlation between test anxiety and college students classroom course grades (e.g., Chapell et al., 2005; Pintrich et al., 1993; Rana & Mahmood, 2010). Along these lines, using an analysis of variance, Cassady and Johnson (2002) found that university students who reported higher levels of test anxiety received lower grades, compared to students who reported lower levels of test anxiety and received higher grades. More recently, a correlation analysis by Stowell and Bennett (2010) revealed that test anxiety was also negatively correlated with students' online exam score.

2.1.3 Self-theory of intelligence

Students hold different "theories" about the nature of intelligence, also called implicit theories or mindset (Dweck & Master, 2008). Those who hold an entity mindset believe that intelligence is an unchangeable, fixed "entity". In contrast, students who hold an incremental mindset think of intelligence as a malleable quality that can be developed and cultivated through learning (Dweck, 1999). These mindsets shape students' goals and values, change the meaning of failure, and guide their response to setbacks (Dweck & Master, 2008).

Classroom studies have shown that individuals with an incremental mindset believe in the value of effort, have mastery-oriented goals, and tend to do well academically. Furthermore, students endorsing an incremental mindset do better in difficult courses, especially ones that require self-regulated learning. In contrast, entity individuals see effort as evidence of a lack of ability and have been associated with lower academic performance than incremental minded individuals (e.g., Dweck & Master, 2008; Henderson & Dweck, 1990; Robins & Pals, 2002).

Students' endorsement of a particular mindset is relatively stable over time (Robins & Pals, 2002). However, mindsets can be manipulated. For instance, researchers informed participants that the tasks involved either inherent ability that was not malleable or ability that could be improved with practice (Martocchio, 1994; Wood & Bandura, 1989), or instilled either an entity or incremental mindset by having participants read persuasive scientific articles (Hong et al., 1999; Niiya et al., 2004). Results indicate that participants in the entity condition were outperformed by those in the incremental condition. Other work has aimed at teaching students to adopt the beneficial incremental mindset, for instance through workshops in classroom settings (Aronson, Fried, & Good, 2002; Blackwell et al., 2007). As demonstrated by hierarchical linear modelling (Blackwell et al., 2007) and analysis of covariance (Aronson et al., 2002), these interventions resulted in improvements of students' grades.

More recently, researchers investigated the potential of online mindset interventions. Paunesku et al. (2015) delivered brief growth-mindset interventions through online modules to 1,594 students at different high schools in the United States. The intervention was intended to help students persist when they experienced academic difficulty in one of their classroom-based courses. Results obtained through a regression analysis showed that among students at risk of dropping out of high school (one third of the sample), the intervention raised students' semester GPAs significantly in core academic courses. Their findings are in line with work from Yeager et al. (2016), who also used regression analysis to show that a growth mindset intervention that was delivered online to a census of students in ten different American high schools improved students' achievement (a census is defined as an attempt to reach all individuals in an organization, and is contrasted with a sample, which does not).

2.1.4 Summary

In conclusion, there is evidence that self-regulation, motivation, and self-theory of intelligence are important predictors of achievement in both traditional classroom and online classes. To date, however, to the best of our knowledge there are no published studies investigating the effects of all the above-described constructs on students' grades when combined into one regression model or whether the different constructs have a comparable effect in both classroom and online contexts.

2.2 Other established variables influencing grades in classroom and online courses

The present thesis aims to broaden the understanding of the relationship between the target psychological constructs (described in section 2.1) and grades, both in classroom and online courses. However, we acknowledge that there are additional established variables beyond the scope of the present thesis that have been linked with academic achievement in classroom and online learning environments, a selection of which are described below.

2.2.1 Age

Research exploring the relationship between students' age and academic achievement in higher education has shown that mature-age students generally outperform young students (e.g., McKenzie & Gow, 2004; Sheard, 2009). However, the findings about the relation between age and academic performance in online courses are not consistent. Some studies did not find age to be a significant predictor of academic performance (Coldwell, Craig, Paterson, & Mustard, 2008; Kotey & Anderson, 2006; Lu, Yu, & Liu, 2003). In contrast, Wojciechowski and Palmer (2005) found age to be a strong predictor of grade, with mature-aged students performing better than younger students.

2.2.2 Grade point average

In the context of traditional classroom learning, numerous studies have identified cumulative grade point average (GPA) as a significant predictor of students' future academic success (e.g., Bode & Gates, 2001; Peterson, 2009; Shulruf, Hattie, & Tumen, 2008). In addition, GPA has been found to be positively and significantly related to grades in online courses. Thus, students with higher GPAs do better in online courses compared to students with lower GPAs (e.g., Cheung & Kan, 2002; Jost, Rude-Parkins, & Githens, 2012; Wojciechowski & Palmer, 2005).

2.2.3 Student participation

Students in traditional classroom environments who actively participate (e.g., attend class, pay attention, complete homework, or participate vocally in class) earn higher grades than students who participate less (Handelsman, Briggs, Sullivan, & Towler, 2005; Kuh, Cruce, Shoup, Kinzie, & Gonyea, 2008). The findings transfer to the online context. Research using learning analytics shows that students who participate more actively in an online course achieve higher grades, compared to students who participate less actively and therefore receive lower grades (Coldwell et al., 2008). One way to operationalize participation in online courses is through discussion forum submission and indeed discussion board usage is positively and significantly related to higher grades (Alstete & Beutell, 2004; Hoskins & Van Hooff, 2005; Koç, 2017).

Chapter 3: Method

To investigate the relationships between psychological constructs and performance in classroom and online settings, we collected data on the target constructs and final grades from students enrolled in classroom and online courses.

3.1 Participants

Participants were undergraduate students at Carleton University enrolled in either a first year "Introduction to Psychology" classroom-based class (that had seven sections), or in a first year "Introduction to Psychology" for-credit online class (that had four sections).[1] The "Introduction to Psychology" class was divided into two half courses (PSYC 1001 and PSYC 1002), each focusing on sub-fields within psychology. The seven classroom-based sections were taught by two different instructors (referred to as Instructor A and Instructor B), who are Carleton faculty members. Specifically, Instructor A taught four classroom sections (three PSYC 1001 courses and one PSYC 1002 course), while Instructor B taught three PSYC 1002 classroom courses. The four online-based sections (two PSYC 1001 courses and two PSYC 1002 courses) were all taught by Instructor B. While the low-level topics in the PSYC 1001 and PSYC 1002 courses were distinct, at a broad level both instructors taught similar topics. More precisely, as specified in the course syllabi, PSYC 1001 covered topics related to the biology of behavior, learning and behavior, sensation, perception, memory and consciousness, whereas PSYC 1002 introduced students to human development, motivation, emotion, personality, social interaction, psychological disorders, stress and health and, therapy.

[1] We do not have information about how many students who originally consented subsequently withdrew from the class (the present analysis is based only on students who completed the class).

Participants were recruited through the university SONA experiment sign-up system and obtained 0.5% bonus course credit as a token of appreciation for their participation. The recruitment took place during the 2017 Fall term as well as the 2018 Winter term and lasted about six months (from September 6th to December 8th, 2017, as well as from January 10th to April 11th, 2018).

In total, 1557 students signed-up to complete an online personality traits questionnaire and gave their consent to share their final "Introduction to Psychology" course grade with us. Of the 1557 students who signed up, 63 students did not do the online questionnaire, and 32 participants withdrew during the study by not finishing the questionnaire. Furthermore, we deleted the datasets of 9 participants because their answers were unrelated to the questions asked (i.e., they answered all questions of the questionnaire with the same Likert-scale value). Thus, complete datasets from 1453 participants were included in the analysis, of which 707 participants were enrolled in one of the classroom-based sections (referred to as the classroom sample), and 746 participants were enrolled in one of the for-credit online sections (referred to as the online sample). The research ethics board clearance for the present study was received and is included in Appendix A (#107077; July 24, 2017).

3.2 Measures

To gather data on personality traits, participants completed an online questionnaire, consisting of 109 items (see Appendix B). The questionnaire included items from several established instruments, described below, to measure students' motivational beliefs, use of self-regulated learning strategies, online learning self-efficacy, as well as their self-theory of intelligence. To assess the instrument reliability, Cronbach's alpha was computed for the classroom sample and the online sample. Values below .50 are considered unacceptable, whereas values between .65 and .80 are considered reasonable. In addition to the questionnaire data, participants' final term grades were obtained from the instructors as a measure of academic achievement.

3.2.1 Motivation

Students motivation was measured with the established Motivated Strategies for Learning Questionnaire (MSLQ). The MSLQ consist of two sections, a motivation section and a learning strategies section (Garcia & Pintrich, 1996; Pintrich & De Groot, 1990; Pintrich et al., 1991, 1993). Moreover, Pintrich et al. (1993) demonstrated that the scales are robust and confirmatory factor analyses supported a good factor structure.

To measure motivation, all six scales from the motivation section of the MSLQ were used, which includes 31 items measuring students' motivational beliefs (i.e., intrinsic goal orientation, extrinsic goal orientation, task value), their beliefs about their skills to succeed (i.e., control of learning beliefs, self-efficacy for learning and performance), as well as their anxiety about tests (i.e., test anxiety). Items were rated on a 7-point Likert scale from 1 (not at all true of me) to 7 (very true of me). The scales were constructed by taking the mean of the items that make up the specific scale. Higher mean scores indicate higher levels of motivation. The only exception is the test anxiety scale, where a high mean score indicates high anxiety about tests. Cronbach's alpha was used to examine the internal consistency of scores for each subscale and reliability coefficients for the classroom sample ranged from .67 to .92, and from .72 to .89 for the online sample (for details see Appendix C).

3.2.2 Self-regulated learning

Students self-reported use of self-regulated learning strategies was measured with all nine scales from the learning strategies section of the Motivated Strategies for Learning Questionnaire (MSLQ) (Garcia & Pintrich, 1996; Pintrich & De Groot, 1990; Pintrich et al., 1991, 1993). The learning strategies section consists of 50 items assessing students' use of different cognitive and metacognitive strategies (i.e., rehearsal, elaboration, organization, critical thinking, metacognitive self-regulation), as well as their resource management strategies (i.e., time and study environment, effort regulation, peer learning, help seeking). Items were rated on a 7-point Likert scale from 1 (not at all true of me) to 7 (very true of me). As is standard, the scales were scored by reversing negatively worded items and computing a mean of the items that make up the specific scale, whereby higher mean scores indicate higher levels of strategy use. Cronbach's alpha was used to examine the internal consistency of scores for each subscale and reliability coefficients for the classroom sample ranged from .58 to .86, and from .58 to .85 for the online sample (for details see Appendix C).

3.2.3 Online learning self-efficacy

To measure students' perceptions of their ability to successfully complete specific tasks required in online courses (i.e., their self-efficacy), the Online Learning Self-Efficacy Scale (OLSES) was used (Zimmerman, 2017; Zimmerman & Kulikowich, 2016). We used the OLSES instead of measuring students' self-efficacy with the self-efficacy sub-scale of the MSLQs' motivational section in order to take the context in which self-efficacy is measured into account. Specifically, the tasks required by online learners differ from those of classroom students (e.g., besides managing required course work, online learners also need to be able to interact with technology to successfully complete a course). Therefore, the OLSES is a more appropriate instrument for the online sample because it was designed for the online context. The OLSES consists of 22 items on three subscales: (1) learning in the online environment (e.g., “Learn without being in the same room as the instructor”); (2) time management (e.g., “Develop and follow a plan for completing all required work on time”); and (3) technology use (e.g., “Navigate online course materials efficiently”). Students rated the items on a 6-point Likert scale from 1 (believe that they would perform poorly) to 6 (believe that they would perform the task at expert level). A mean score of the items that make up each scale was calculated, with a higher score indicating higher online learning self-efficacy. In addition, Cronbach’s alpha was used to examine the internal consistency of scores for each subscale and reliability coefficients for the online sample ranged from .86 to .90 (for details see Appendix C).

3.2.4 Self-theory of intelligence

To measure students’ self-theory of intelligence, Dweck’s established Implicit Theories of Intelligence Scale (Dweck, 1999) was used. The scale consists of three entity theory statements (e.g., “You have a certain amount of intelligence, and you can’t really do much to change it”) and three incremental theory statements (e.g., “No matter who you are, you can significantly change your intelligence level”). Participants rated the statements using a 6-point Likert scale from 1 (strongly agree) to 6 (strongly disagree). Following the method in Blackwell et al. (2007), the incremental theory items were reversed, and a mean theory of intelligence score was calculated for the six items, with the low end representing an endorsement of pure entity theory, and the high end representing an endorsement of pure incremental theory (classroom sample: $\alpha = .86$; online sample: $\alpha = .80$).

3.2.5 Academic achievement

Students' final grades are commonly used to determine academic achievement (Kuh, Kinzie, Buckley, Bridges, & Hayek, 2006). Accordingly, in the present study, academic achievement will be operationalized as final course grade in percentage. The grades were obtained from the course instructors and used as the measure of academic achievement. The final grades were based on a combination of tests and/or assignments.

3.3 Procedure

To collect data about students' personality traits an online questionnaire was created using Qualtrics, an online survey software. Participants were recruited via the universities' SONA experiment sign-up system and used a provided link to access the questionnaire. Once they accepted the online consent form at the beginning of the survey (see Appendix D), the survey was administered. Once they finished the survey, which took approximately 30 to 45 minutes, Qualtrics sent participants back to the SONA system, where their credit was assigned automatically. Participation was completely voluntary, and participants could withdraw from the online questionnaire at any time before submitting their answers at the end of the survey. If participants wished to withdraw from the study after completing the online questionnaire, they could do so by reaching out to us during the term (none did).

At the end of the term, students' anonymized final course grades were collected by the thesis author from two course instructors (i.e., Instructor A and Instructor B), who agreed to the collection. That is, even though the present study obtained ethics approval and the participating students agreed as well, it was left up to each instructor's discretion as to whether they decided to share the grades of those students who consented. Two out of eight instructors approached by the thesis author agreed to share the grades for those students who consented to this

To collect the grades, the thesis author prepared a list with participants' ID numbers and met both instructors in person. During the meeting, the instructor provided the thesis author with a USB drive containing an excel file with the ID numbers and final grades in percentage from all students enrolled in their "Introduction to Psychology" courses. After connecting the USB drive to her computer, the thesis author extracted only the grades of those students from that list who participated in the present study and consented to share their final course grade based on their student ID numbers, using an excel function (VLOOKUP). Afterwards, the thesis author returned the USB drive to the instructor, without saving the full lists provided by the instructors on her computer.

3.4 Analysis

Statistical analysis was performed using R version 3.3.2, a free language and software environment for statistical computing and RStudio, an integrated development environment for R. In the present thesis, both descriptive and inferential statistics were applied. The inferential evaluation was conducted using hierarchical regression analysis. The alpha level (i.e., threshold for significance) in the following analyses was set at .05.

3.4.1 Hierarchical regression analysis

Hierarchical regression analysis is a method to test whether an independent variable or a set of independent variables account for a statistically significant amount of variance in a dependent variable, over and beyond that accounted for by previously entered independent variables (Cohen, Cohen, West, Aiken, & others, 1983). In a hierarchical regression analysis, the variables are selected based on previous work and research findings. The order of entry is chosen prior to analysis of the data and should be made based on a rationale (Wampold & Freund, 1987). More precisely, Cohen et al. (1983) suggested that the variables should be entered according to their relevance, whereby the independent variables of primary importance to the researcher or those that have a previously established relation with the dependent variable should be entered first. Furthermore, hierarchical regression analysis should not be used in an exploratory matter but rather to evaluate specific theoretically based hypotheses (Aron & Aron, 1994; Cohen, 2008). Thus, researchers need to generate a clear and logical rationale for the selection of predictor variables and their specific order of entry (Petrocelli, 2003).

Chapter 4: Results

The aim of the following analysis is to broaden the understanding of the relationship between student-related constructs and students' grades in classroom and online learning settings as well as to shed light on whether those variables have a comparable influence in both learning environments. The target constructs were selected based on prior work highlighting their importance in academic settings (see section 4.1 and 4.2 in present chapter), and included motivation, self-regulated learning, online learning self-efficacy, and self-theory of intelligence. As described in section 3.4.1 above, our main method of analysis was hierarchical regression. For the primary analysis presented in section 4.1 and 4.2, we conducted two hierarchical regression analysis for each context (classroom, online), with one model containing the broad-level constructs and the other constituted specific sub-constructs prior work has identified as important. Section 4.3 reports on additional analysis to clarify interpretations of our findings. We begin by presenting the findings from the classroom setting.

4.1 Classroom setting: Relationships between target constructs and grade

Complete data were available for 707 participants; thus, the present analysis is based on this sample. We begin with the descriptive statistics.

4.1.1 Descriptive statistics and relation between target constructs

The means, standard deviations, and range of scores for the target constructs are shown in Table 1. As described in section 3.2, the motivation construct consists of six scales (i.e., intrinsic goal orientation, extrinsic goal orientation, task value, control of learning beliefs, self-efficacy for learning and performance, test anxiety) and the self-regulated learning construct of nine scales (i.e., rehearsal, elaboration, organization, critical thinking, metacognitive self-regulation, time and study environment, effort regulation, peer learning, help seeking); these scales are shown in Table 1.

Table 1. Descriptive statistics for the target constructs in the classroom sample

Variable	M	SD	Range of scores	Skewness	Kurtosis
1. Grade	69.07	13.97	3.00 - 103.00	-0.13	0.18
2. M: Intrinsic Goal Orientation	4.71	1.04	1.25 - 7.00	-0.27	-0.03
3. M: Extrinsic Goal Orientation	5.37	1.02	1.75 - 7.00	-0.44	-0.08
4. M: Task Value	5.51	1.06	1.67 - 7.00	-0.58	-0.08
5. M: Control of Learning Beliefs	5.50	0.93	2.00 - 7.00	-0.43	-0.30
6. M: Self-Efficacy for Learning & Performance	4.92	1.08	1.00 - 7.00	-0.50	0.40
7. M: Test Anxiety	4.73	1.27	1.00 - 7.00	-0.26	-0.55
8. SRL: Rehersal	4.97	1.09	1.50 - 7.00	-0.27	-0.32
9. SRL: Elaboration	5.00	1.07	1.83 - 7.00	-0.22	-0.47
10. SRL: Organization	4.93	1.09	1.75 - 7.00	-0.22	-0.41
11. SRL: Critical Thinking	4.20	1.21	1.00 - 7.00	-0.19	-0.30
12. SRL: Metacognitive Self-Regulation	4.57	0.84	2.08 - 6.83	-0.07	-0.03
13. SRL: Time & Study Environment	4.87	0.96	1.75 - 7.00	-0.12	-0.24
14. SRL: Effort Regulation	4.96	1.10	1.25 - 7.00	-0.20	-0.26
15. SRL: Peer Learning	3.56	1.49	1.00 - 7.00	0.11	-0.79
16. SRL: Help Seeking	3.56	1.17	1.00 - 6.50	-0.07	-0.66
17. Self-Theory of Intelligence	4.29	0.85	1.00 - 6.00	-0.18	-0.06

Note 1. Score for grade is out of 100; scores for item 2 to 16 are out of 7; scores for item 17 are out of 6.

Skewness and kurtosis for all variables were close to zero and within acceptable limits (i.e., +- 1.0) (see e.g., George & Mallery, 2016; Wilcox, 2011). The obtained mean scores indicated moderate levels of motivation and self-regulated learning. The mean values for self-theory of intelligence indicated that the classroom sample on average tended towards the endorsement of an incremental mindset. Overall, significant correlations occurred in the expected directions (see Appendix E for details). The final course grade was significantly correlated with most constructs but with a noticeable exception: course grade was not significantly correlated with self-theory of intelligence.

4.1.2 Classroom setting: What constructs uniquely predict grade?

To examine the relationships between classroom course grades and the target constructs as well which constructs uniquely contribute to performance (i.e., grade), we conducted a three-step hierarchical regression with course grade as the dependent variable and the target psychological constructs as independent variables. Before presenting the results, we justify the inclusion of the variables in our model.

4.1.2.1 Theoretical background

Students' motivation is a key factor influencing academic achievement: students who approach their classes with an intrinsic goal for learning, who believe that the material is interesting and important (i.e., task value), who have high self-efficacy beliefs, and who rate themselves as in control of their learning are more likely to receive higher grades (Garcia & Pintrich, 1996; Pintrich et al., 1993). In addition to motivation, self-regulated learning strategies play an important role in influencing outcomes. Students who rely on deeper processing strategies (i.e., elaboration, organization, critical thinking, and metacognitive self-regulation), and successfully manage their time and study environment, as well as their own efforts, are more likely to receive higher grades (Garcia & Pintrich, 1996; Pintrich et al., 1993).

The remaining construct we included in our model is self-theory of intelligence. In prior work students' self-theory of intelligence was correlated with final grades (e.g., Blackwell et al., 2007; J. A. Chen & Pajares, 2010; De Castella & Byrne, 2015; Gonida et al., 2006; Niiya et al., 2004; Paunesku et al., 2015; Yeager et al., 2016). In general, there is evidence that self-theory of intelligence, is associated with student grades, although the strength of these variables to explain outcomes over and beyond motivation and self-regulated learning is unclear.

4.1.2.2 Outliers, influential cases, and verification of assumptions

Before running the analysis, we verified that our data did not include outliers that could bias the results. A thorough examination of the data revealed no influential outliers (see Appendix G.1 for detailed outlier analysis). Furthermore, we verified that the assumptions of the regression were met, including multicollinearity, homoscedasticity, linearity, and the normally distributed errors assumptions (see Appendix G.1 for details).

4.1.2.3 Classroom setting: Results with full model

To determine which constructs uniquely explain variance in students' performance (i.e., grade) in classroom settings, we carried out a three-step hierarchical regression with "grade" as the dependent variable and the different constructs as independent variables entered in the following order (new variables in a given step shown in italics):

Step 1: motivational construct

Step 2: motivational construct + *self-regulated learning construct*

Step 3: motivational construct + self-regulated learning construct + *self-theory of intelligence*

In the first step, all the motivational variables from the motivation section of the MSLQ (items 2 to 7 in Table 1) were entered into the model. As shown in Table 2, intrinsic goal orientation, task value, control of learning beliefs, self-efficacy and test anxiety were significant predictors, with self-efficacy obtaining the largest regression coefficient (β =

0.27). Overall, model 1 was significant, $F(6, 700) = 19.06$, $p < .001$, accounting for 13.3% of variance in grade (*adjusted* $R^2 = 0.133$).

In the second step, all self-regulated learning variables from the self-regulated learning section of the MSLQ (items 8 to 16 in Table 1) were entered into the model. In model 2, the newly entered effort regulation was a significant predictor, while only self-efficacy remained a significant predictor of grade, with coefficients of $\beta = 0.22$ and $\beta = 0.17$, respectively (see Table 2). Model 2 was overall significant, $F(15, 691) = 10.84$, $p < .001$, and explained 17.3% of the variance in grade (*adjusted* $R^2 = 0.173$). Importantly, model 2 resulted in a significant increase of the R^2-value and therefore the amount of variance accounted for in grade, compared to model 1, $F(9, 691) = 4.74$, $p < .001$. This indicates that the self-regulated learning construct explained unique variance in course grades over and beyond the motivational construct.

Finally, in the third step, self-theory of intelligence was entered as an additional predictor of grade. In model 3, self-efficacy, effort regulation and control of learning beliefs were significant positive predictors, with coefficients of $\beta = 0.23$, $\beta = 0.18$ and $\beta = 0.09$, respectively. In addition, critical thinking was also a significant predictor but with a negative coefficient of $\beta = -0.10$ (see Table 2), indicating that if students' self-reported use of critical thinking increases by one standard deviation, their grade decreases by 0.1 standard deviations. The standard deviation for classroom grade is 13.97 grade points. Thus, a one standard deviation increase in critical thinking would lower classroom grade by 1.4 points. Model 3 was overall significant, $F(16, 690) = 10.21$, $p < .001$, accounting for 17.3% of the variance in final grade (*adjusted* $R^2 = 0.173$). However, model 3 did not significantly improve the R^2-value compared to model 2, $F(1, 690) = 0.84$, $p = .36$.

Table 2. Results of three-step hierarchical regression analysis

	R^2	$R^2_{adjusted}$	F	sigΔF	B	95% CI	β	p
Step 1	0.141	0.133	19.06					< .001
Constant					45.80	[38.63; 52.96]		< .001
Intrinsic Goal Orientation (M)					-1.91	[-3.22; -0.59]	-0.14	< .01
Extrinsic Goal Orientation (M)					0.14	[-1.04; 1.33]	0.01	.81
Task Value (M)					2.02	[0.66; 3.38]	0.15	< .01
Control of Learning Beliefs (M)					1.44	[0.13; 2.7]	0.10	< .05
Self-Efficacy (M)					3.46	[2.16; 4.76]	0.27	< .001
Test Anxiety (M)					-0.97	[-1.85; -0.09]	-0.09	< .05
Step 2	0.190	0.173	10.84	< .001				< .001
Constant					38.44	[30.14; 46.74]		< .001
Intrinsic Goal Orientation (M)					-0.98	[-2.39; 0.43]	-0.07	.17
Extrinsic Goal Orientation (M)					0.07	[-1.11; 1.25]	0.01	.91
Task Value (M)					0.39	[-1.05; 1.83]	0.03	.60
Control of Learning Beliefs (M)					1.23	[-0.08; 2.55]	0.08	.07
Self-Efficacy (M)					2.90	[1.56; 4.23]	0.22	< .001
Test Anxiety (M)					-0.23	[-1.13; 0.68]	-0.02	.62
Rehersal (SRL)					-0.09	[-1.32; 1.14]	-0.01	.88
Elaboration (SRL)					0.82	[-0.71; 2.35]	0.06	.29
Organisation (SRL)					-0.47	[-1.81; 0.88]	-0.04	.50
Critical Thinking (SRL)					-1.17	[-2.35; 0.004]	-0.10	.05
Metacognitive Self-Regulation (SRL)					0.21	[-1.86; 2.28]	0.01	.84
Time and Study Environment (SRL)					1.08	[-0.38; 2.55]	0.07	.15
Effort Regulation (SRL)					2.21	[0.87; 3.54]	0.17	< .01
Peer Learning (SRL)					-0.44	[-1.34; 0.47]	-0.05	.35
Help Seeking (SRL)					0.19	[-0.86; 1.25]	0.02	.72
Step 3	0.191	0.173	10.21	.36				< .001
Constant					39.76	[30.99; 48.53]		< .001
Intrinsic Goal Orientation (M)					-0.96	[-2.37; 0.45]	-0.07	.18
Extrinsic Goal Orientation (M)					0.02	[-1.17; 1.20]	0.001	.98
Task Value (M)					0.39	[-1.05; 1.84]	0.03	.59
Control of Learning Beliefs (M)					1.37	[0.02; 2.72]	0.09	< .05
Self-Efficacy (M)					2.92	[1.59; 4.25]	0.23	< .001
Test Anxiety (M)					-0.21	[-1.11; 0.70]	-0.02	.66
Rehersal (SRL)					-0.10	[-1.32; 1.13]	-0.01	.88
Elaboration (SRL)					0.79	[-0.74; 2.32]	0.06	.31
Organisation (SRL)					-0.44	[-1.79; 0.91]	-0.03	.52
Critical Thinking (SRL)					-1.18	[-2.35; -0.004]	-0.10	< .05
Metacognitive Self-Regulation (SRL)					0.19	[-1.88; 2.26]	0.01	.86
Time and Study Environment (SRL)					1.14	[-0.33; 2.60]	0.08	.13
Effort Regulation (SRL)					2.24	[0.90; 3.58]	0.18	< .01
Peer Learning (SRL)					-0.44	[-1.35; 0.46]	-0.05	.34
Help Seeking (SRL)					0.21	[-0.84; 1.27]	0.02	.69
Self-Theory of Intelligence					-0.55	[-1.73; 0.63]	-0.03	.36

4.1.3 Classroom setting: Detailed analysis

The analysis above provides insight into the contribution of the *overall* motivation and self-regulated learning constructs, as well as of self-theory of intelligence. To better understand the contribution of selected individual sub-constructs from these scales to classroom course grades, we conducted a second hierarchical regression analysis with individual sub-constructs that prior work has indicated to be highly predictive of grades in classroom settings.

4.1.3.1 Theoretical background

A correlational analysis including all MSLQ scales with final classroom grade performed by Pintrich et al. (1991) showed that the self-efficacy scale had the strongest relationship with grade. Since then, various researchers have found that self-efficacy strongly predicts grades in classroom courses (e.g., Bae, 2014; Komarraju & Nadler, 2013; Lynch, 2006). In a meta-analysis, Multon et al. (1991) examined the effect of efficacy beliefs on academic achievement based on 38 published and unpublished studies that measured academic performance. They found that self-efficacy accounted for approximately 14% of the variance in academic performance across a variety of experimental designs, student samples, and criterion measures.

In addition to self-efficacy, effort and metacognitive self-regulation (sub-constructs of the MSLQ self-regulated learning strategies section) are also strong predictors of grade. Pintrich and De Groot (1990) performed a regression analysis to predict classroom grades. The significant predictors were effort and metacognitive self-regulation, as well as self-efficacy.

Yet another variable associated with grades is self-theory of intelligence, measured by the Implicit Theories of Intelligence Scales. We acknowledge that in the above analysis (section 4.1.2.3) this variable was not significant, but the variables chosen for a hierarchical regression should be based on prior theory rather than the present data. The positive relationship between this variable and grades was described in section 4.1.2.1.

We included two additional predictors in our model: intrinsic goal orientation and control of learning beliefs (both from the motivational section of the MSLQ). Having an intrinsic goal orientation towards an academic task has been shown to be beneficial for students' academic achievement. Pintrich et al. (1991) found a significant correlation between the intrinsic goal orientation scale of the MSLQ (which measures the degree to which students perceive themselves to be participating in a task for reasons such as challenge, curiosity and mastery) and grade. Furthermore, students who adopt mastery goals perform better, especially in the face of challenge (Bandalos et al., 2003; Grant & Dweck, 2003; Greene & Miller, 1996; Meece & Holt, 1993; Schraw et al., 1995). As far as control of learning beliefs, Pintrich et al. (1991) reported a significant positive correlation between the control of learning beliefs scale of the MSLQ, which measures students belief that their efforts to study make a difference in their learning and course grade. Many of the studies cited above used zero-order correlations, therefore we acknowledge that the relationships may change in the context of a multiple regression.

4.1.3.2 Outliers, influential cases, and verification of assumptions

No influential outliers were found. In addition, we verified that the assumptions of multicollinearity, homoscedasticity, linearity, and normally distributed errors were met (see Appendix G.2 for details).

4.1.3.3 Classroom setting: Results with detailed model

To understand the contribution of the selected sub-constructs to course grade, a five-step hierarchical regression was conducted with "grade" as the dependent variable and self-efficacy, effort regulation, metacognitive self-regulation, self-theory of intelligence, intrinsic goal orientation and control of learning beliefs as independent variables entered in the following order (new variables in a given step shown in italics):

Step 1: self-efficacy

Step 2: self-efficacy + *effort regulation* + *metacognitive self-regulation*

Step 3: self-efficacy + effort regulation + metacognitive self-regulation + *self-theory of intelligence*

Step 4: self-efficacy + effort regulation + metacognitive self-regulation + self-theory of intelligence + *intrinsic goal orientation*

Step 5: self-efficacy + effort regulation + metacognitive self-regulation + self-theory of intelligence + intrinsic goal orientation + *control of learning beliefs*

In the first step of the model building process, self-efficacy was entered as a predictor variable. As shown in Table 3, self-efficacy was a significant predictor ($\beta = 0.33$); overall, model 1 was significant, $F(1, 705) = 88.42$, $p < .001$, and accounted for 11% of the variance in final course grade (*adjusted* $R^2 = 0.11$).

In the second step, effort regulation and metacognitive self-regulation were entered into the model. In model 2, self-efficacy remained significant, but of the new variables only effort regulation was significant (see Table 3). Model 2 was overall significant, $F(3, 703) = 46.94$, $p < .001$, accounting for 16.3% of variance in grade (*adjusted* $R^2 = 0.163$).

Moreover, model 2 significantly increased the R^2-value and thus the amount of unique variance accounted for in grades, compared to model 1, $F(2, 703) = 23.63$, $p < .001$.

In the next step, self-theory of intelligence was entered as an additional predictor of grade. In model 3, self-efficacy and effort regulation remained significant predictors and were the only significant predictors, i.e., self-theory was not (see Table 3). Overall, model 3 was significant, $F(4, 702) = 35.18$, $p < .001$, accounting for 16.2% of the variance in final grade (*adjusted* $R^2 = 0.162$). However, model 3 did not significantly improve the value of R^2 compared to model 2, $F(1, 702) = 0.09$, $p = .77$.

In step 4, intrinsic goal orientation was entered as a predictor of grade. In model 4, self-efficacy and effort regulation remained significant predictors, but none of the other variables were, mirroring the pattern in model 2 and model 3 (see Table 3). Model 4 was significant, $F(5, 701) = 28.79$, $p < .001$, accounting for 16.4% of the variance in final grade (*adjusted* $R^2 = 0.164$). However, model 4 did not significantly improve the value of R^2 compared to model 3, $F(1, 701) = 2.75$, $p = .10$.

In the final step, control of learning beliefs was entered as an additional predictor of grade. In model 5, self-efficacy ($\beta = 0.23$), effort regulation ($\beta = 0.27$), and control of learning beliefs ($\beta = 0.11$) were significant positive predictors. In addition, intrinsic goal orientation was also a significant predictor but with a negative coefficient of $\beta = -0.09$ (see Table 3), indicating that if intrinsic goal orientation increases by one standard deviation, grade decreases by 0.09 standard deviations. The standard deviation for classroom grade is 13.97 grade points. Thus, a one standard deviation increase in intrinsic goal orientation would lower the grade by 1.26 points. Model 5 was significant, $F(6, 700) = 25.41$, $p < .001$, accounting for 17.2% of variance in final grade (*adjusted* $R^2 = 0.172$).

Model 5 significantly increased the R^2-value and therefore the amount of variance accounted for in final grade, compared to model 4, $F(1, 700) = 7.36$, $p < .01$. This indicates that control of learning beliefs explained unique variance in course grades over and beyond intrinsic goal orientation and self-theory of intelligence.

Table 3. Results of five-step hierarchical regression analysis

	R^2	$R^2_{adjusted}$	F	sigΔF	B	95% CI	β	p
Step 1	0.111	0.110	88.42					< .001
Constant					47.32	[43.40; 52.44]		< .001
Self-Efficacy (M)					4.30	[3.40; 5.20]	0.33	< .001
Step 2	0.167	0.163	46.94	< .001				< .001
Constant					41.09	[35.31; 46.87]		< .001
Self-Efficacy (M)					3.04	[1.97; 4.11]	0.24	< .001
Effort Regulation (SRL)					3.54	[2.52; 4.57]	0.28	< .001
Meta-Cognitive Self-Regulation (SRL)					-1.00	[-2.40; 0.41]	-0.06	.16
Step 3	0.167	0.162	35.18	.77				< .001
Constant					41.65	[34.76; 48.54]		< .001
Self-Efficacy (M)					3.06	[1.99; 4.14]	0.24	< .001
Effort Regulation (SRL)					3.56	[2.53; 4.60]	0.28	< .001
Meta-Cognitive Self-Regulation (SRL)					-1.00	[-2.41; 0.40]	-0.06	.16
Self-Theory of Intelligence					-0.17	[-1.32; 0.97]	-0.01	.77
Step 4	0.170	0.164	28.76	.10				< .001
Constant					42.45	[35.51; 49.40]		< .001
Self-Efficacy (M)					3.50	[2.30; 4.71]	0.27	< .001
Effort Regulation (SRL)					3.53	[2.50; 4.57]	0.28	< .001
Meta-Cognitive Self-Regulation (SRL)					-0.64	[-2.11; 0.84]	-0.04	.40
Self-Theory of Intelligence					-0.11	[-1.26; 1.03]	-0.01	.85
Intrinsic Goal Orientation (M)					-1.01	[-2.21; 0.19]	-0.08	.10
Step 5	0.179	0.172	25.41	< .01				< .001
Constant					38.63	[31.18; 46.08]		< .001
Self-Efficacy (M)					3.01	[1.76; 4.26]	0.23	< .001
Effort Regulation (SRL)					3.46	[2.43; 4.49]	0.27	< .001
Meta-Cognitive Self-Regulation (SRL)					-0.64	[-2.10; 0.83]	-0.04	.39
Self-Theory of Intelligence					-0.47	[-1.64; 0.70]	-0.03	.43
Intrinsic Goal Orientation (M)					-1.24	[-2.44; -0.03]	-0.09	< .05
Control of Learning Beliefs (M)					1.67	[0.46; 2.88]	0.11	< .01

4.2 Online setting: Relationship between target constructs and grade

After investigating the relationship between the target constructs and grade in a classroom learning context using hierarchical regression analysis, we repeated the analysis with the online students. Complete data were available for 746 participants; thus, the following analysis is based on this sample.

4.2.1 Descriptive statistics and relation between target constructs

The descriptive statistics for the target constructs are shown in Table 4. Because self-efficacy beliefs are context-specific (Bandura, 1997), the self-efficacy variable (measured by the MSLQ) was replaced with the online learning self-efficacy construct. As introduced in section 3.2, the online learning self-efficacy construct consist of three scales (i.e., learning in the online environment, time management, technology use).

Examination of the data revealed that skewness and kurtosis for all construct variables were close to zero and within acceptable limits (i.e., +- 1.0) (see e.g., George & Mallery, 2016; Wilcox, 2011). However, the distribution of the dependent variable (i.e., grade) was negatively skewed (skewness = -2.05) and leptokurtic (kurtosis = 5.19). The obtained mean scores indicated relatively high levels of online learning self-efficacy and motivation as well as moderate levels of self-regulated learning. The mean values for self-theory of intelligence indicated that the online sample on average tended towards the endorsement of an incremental mindset. Overall, significant correlations between the different constructs occurred in the expected directions, but with one exception: final online grade was only significantly correlated with the time management scale of the online learning self-efficacy construct (see Appendix F for details).

Table 4. Descriptive statistics for the target constructs in the online sample

Variable	M	SD	Range of scores	Skewness	Kurtosis
1. Grade	67.79	14.80	1.00 - 93.00	-2.05	5.51
2. M: Intrinsic Goal Orientation	4.65	1.10	1.00 - 7.00	-0.29	-0.07
3. M: Extrinsic Goal Orientation	5.13	1.15	1.00 - 7.00	-0.46	-0.12
4. M: Task Value	5.11	1.16	1.00 - 7.00	-0.51	0.06
5. M: Control of Learning Beliefs	5.30	1.06	1.50 - 7.00	-0.34	-0.35
6. M: Test Anxiety	4.79	1.21	1.00 - 7.00	-0.19	-0.33
7. SRL: Rehersal	4.70	1.17	1.00 - 7.00	-0.21	-0.24
8. SRL: Elaboration	4.79	1.15	1.00 - 7.00	-0.22	-0.17
9. SRL: Organization	4.72	1.21	1.00 - 7.00	-0.18	-0.21
10. SRL: Critical Thinking	4.40	1.19	1.20 - 7.00	-0.21	-0.09
11. SRL: Metacognitive Self-Regulation	4.51	0.84	1.00 - 6.92	-0.08	0.22
12. SRL: Time & Study Environment	4.51	0.92	1.38 - 7.00	0.27	0.40
13. SRL: Effort Regulation	4.63	1.05	1.75 - 7.00	0.23	-0.34
14. SRL: Peer Learning	3.49	1.60	1.00 - 7.00	0.11	-0.88
15. SRL: Help Seeking	3.44	1.25	1.00 - 7.00	-0.15	-0.69
16. OLSE: Learning in Online Environment	4.38	0.90	1.60 - 6.00	-0.23	-0.55
17. OLSE: Time Management	4.18	1.04	1.00 - 6.00	-0.36	-0.31
18. OLSE: Technology Use	4.80	0.95	1.86 - 6.00	-0.65	-0.48
19. Self-Theory of Intelligence	4.10	0.87	1.00 - 6.00	0.11	-0.20

Note 2. Score for grade is out of 100; scores for item 2 to 15 are out of 7; scores for item 16 to 19 out of 6.

4.2.2 Online setting: What constructs uniquely predict grade?

In contrast to the previous analysis with the classroom sample, we included online learning self-efficacy as an additional construct in the analysis with the online sample (measured by the OLSES instrument). Therefore, the target constructs for this analysis were motivation, self-regulated learning, online learning self-efficacy as well as self-theory of intelligence.

There are no studies examining the relationship between the afore mentioned constructs and student achievement in online courses when combined into one hierarchical regression model. To determine the relationship between course grades in an online learning environment and the target constructs, as well which constructs uniquely contribute to performance (i.e., grade), we conducted a four-step hierarchical regression with online course grade as the dependent variable and the target psychological constructs as the independent variables. Before presenting the results, we justify the inclusion of the variables in our model.

4.2.2.1 Theoretical background

Previous work established the importance of motivational constructs in the context of academic achievement in online courses and established a positive effect of motivation on online course grades (see e.g., Basila, 2016; Cho & Heron, 2015; Kim et al., 2014; Wang et al., 2013). In addition to motivation, self-regulated learning has a positive impact on online grades as well (see e.g., Basila, 2016; Broadbent & Poon, 2015; Lin et al., 2017). Moreover, online learning self-efficacy has been shown to have a positive impact on online grades (see e.g., McGhee, 2010; Wang et al., 2013). We are not aware of studies examining self-theory of intelligence as a predictor for academic performance in online learning environments. However, as demonstrated in section 4.1.2.1, prior research studies conducted in classroom settings established a positive relationship between this variables and students' grades.

4.2.2.2 Outliers, influential cases, and verification of assumptions

No influential outliers were found. Moreover, we verified that the assumptions of multicollinearity, homoscedasticity, and linearity were met. In contrast, the assumption of normally distributed errors was violated (see Appendix G.3 for details). However, the central limit theorem states that a sampling distribution, given an adequate sample size, will approximate a standard normal distribution, regardless of the shape of the population distribution. The given sample size (*N* = 746) is adequately large, which allows the reasonable assumption that the sample errors are normally distributed.

4.2.2.3 Online setting: Results with full model

To determine which constructs uniquely explain variance in student performance (i.e., grade) in online settings, we conducted a four-step hierarchical regression with "grade" as the dependent variable and the different constructs as the independent variables entered in the following order (new variables in a given step shown in italics):

Step 1: motivational construct

Step 2: motivational construct + *self-regulated learning construct*

Step 3: motivational construct + self-regulated learning construct + *online learning self-efficacy construct*

Step 4: motivational construct + self-regulated learning construct + online learning self-efficacy construct + *self-theory of intelligence*

In the first step, all motivational variables (except self-efficacy) from the motivation section of the MSLQ (items 2 to 6 in Table 4) were entered into the model. As shown in Table 5, control of learning beliefs was the only significant predictor of grade ($\beta = 0.12$). Overall, model 1 was not significant, $F(5, 740) = 1.90$, $p = .09$.

In the second step, all self-regulated learning variables from the self-regulated learning section of the MSLQ (items 7 to 15 in Table 4) were entered into the model. In model 2, control of learning beliefs remained the only motivation-related significant positive predictor of grade ($\beta = 0.12$). In addition, organization was also a significant predictor but with a negative coefficient of β = - 0.17 (see Table 5).[2] This indicates that if organization increases by one standard deviation, grade decreases by 0.17 standard deviations. The standard deviation for online grade is 14.80 grade points. Thus, a one standard deviation increase in organization lowers online grade by 2.5 points. Overall, model 2 was significant, $F(14, 731) = 3.05$, $p < .001$, and significantly increased the R^2-value compared to model 1, $F(9, 731) = 3.67$, $p < .001$, but only accounted for 3.7% of variance in grade (*adjusted* $R^2 = 0.037$).

In the third step, all online learning self-efficacy variables from the Online Learning Self-Efficacy Scale (items 16 to 18 in Table 4) were entered as predictors. In model 3, organization was the only significant predictor (β = - 0.18) but none of the online learning self-efficacy variables were (see Table 5). Overall, model 3 was significant, $F(17, 728) = 2.86$, $p < .001$, accounting for 4.1% of variance in grade (*adjusted* $R^2 = 0.041$). However, model 3 did not significantly improve the R^2-value compared to model 2, $F(3, 728) = 1.91$, $p = .13$.

Finally, in the fourth step, self-theory of intelligence was entered as an additional predictor of grade. In model 4, organization was again the only significant predictor (β = - 0.21) (see Table 6). Overall, model 4 was significant, $F(18, 727) = 2.72$, $p < .001$, and accounted for 4% of variance in grade (*adjusted* $R^2 = 0.04$), but did not result in a significant increase in the R^2-value compared to model 3, $F(1, 727) = 0.39$, $p = .53$.

[2] Effort regulation (a self-regulated learning variable) was just above the significance threshold at $p = .05$.

Table 5. Results of four-step hierarchical regression analysis

	R^2	$R^2_{adjusted}$	F	sigΔF	B	95% CI	β	p
Step 1	0.013	0.006	1.90					.09
Constant					67.30	[60.69; 73.90]		< .001
Intrinsic Goal Orientation (M)					-0.15	[-1.54; 1.24]	-0.01	.84
Extrinsic Goal Orientation (M)					0.34	[-0.83; 1.50]	0.03	.57
Task Value (M)					-1.15	[-2.66; 0.36]	-0.09	.14
Control of Learning Beliefs (M)					1.67	[0.37; 2.96]	0.12	< .05
Test Anxiety (M)					-0.73	[-1.71; 0.26]	-0.06	.15
Step 2	0.055	0.037	3.05	< .001				< .001
Constant					53.92	[45.37; 62.46]		< .001
Intrinsic Goal Orientation (M)					-0.56	[-2.13; 1.01]	-0.04	.48
Extrinsic Goal Orientation (M)					0.11	[-1.08; 1.30]	0.01	.86
Task Value (M)					-1.47	[-3.03; 0.09]	-0.11	.07
Control of Learning Beliefs (M)					1.68	[0.29; 3.06]	0.12	< .05
Test Anxiety (M)					0.01	[-1.03; 1.05]	0.001	.99
Rehersal (SRL)					-0.78	[-2.22; 0.67]	-0.06	.29
Elaboration (SRL)					1.51	[-0.26; 3.28]	0.12	.10
Organisation (SRL)					-2.09	[-3.62; -0.57]	-0.17	< .01
Critical Thinking (SRL)					-0.73	[-2.27; 0.81]	-0.06	.35
Metacognitive Self-Regulation (SRL)					1.40	[-1.14; 3.93]	0.08	.28
Time and Study Environment (SRL)					1.26	[-0.30; 2.83]	0.08	.11
Effort Regulation (SRL)					1.45	[-0.02; 2.92]	0.10	.05
Peer Learning (SRL)					0.62	[-0.47; 1.71]	0.07	.27
Help Seeking (SRL)					0.92	[-0.33; 2.18]	0.08	.15
Step 3	0.063	0.041	2.860	.13				< .001
Constant					52.67	[43.74; 61.60]		< .001
Intrinsic Goal Orientation (M)					-0.75	[-2.36; 0.86]	-0.06	.36
Extrinsic Goal Orientation (M)					-0.06	[-1.26; 1.14]	-0.005	.92
Task Value (M)					-1.29	[-2.86; 0.29]	-0.10	.11
Control of Learning Beliefs (M)					1.38	[-0.13; 2.88]	0.10	.07
Test Anxiety (M)					-0.02	[-1.06; 1.03]	-0.001	.97
Rehersal (SRL)					-0.81	[-2.26; 0.64]	-0.06	.27
Elaboration (SRL)					1.49	[-0.29; 3.26]	0.12	.10
Organisation (SRL)					-2.19	[-3.72; -0.67]	-0.18	< .01
Critical Thinking (SRL)					-0.56	[-2.11; 0.99]	-0.05	.48
Metacognitive Self-Regulation (SRL)					1.36	[-1.18; 3.91]	0.08	.29
Time and Study Environment (SRL)					0.77	[-0.89; 2.44]	0.05	.36
Effort Regulation (SRL)					1.16	[-0.33; 2.65]	0.08	.13
Peer Learning (SRL)					0.62	[-0.48; 1.71]	0.07	.27
Help Seeking (SRL)					0.95	[-0.31; 2.22]	0.08	.14
Learning in Online Environment (OLSE)					-0.97	[-3.33; 1.38]	-0.06	.42
Time Management (OLSE)					1.28	[-0.45; 3.00]	0.09	.15
Technology Use (OLSE)					1.31	[-0.72; 3.33]	0.08	.21

Table 6. Results of four-step hierarchical regression analysis (continued)

	R^2	$R^2_{adjusted}$	F	sigΔF	B	95% CI	β	p
Step 4	0.063	0.040	2.720	.53				< .001
Constant					53.78	[44.19; 63.37]		< .001
Intrinsic Goal Orientation (M)					-0.72	[-2.33; 0.90]	-0.05	.38
Extrinsic Goal Orientation (M)					-0.04	[-1.24; 1.16]	-0.03	.95
Task Value (M)					-1.28	[-2.86; 0.29]	-0.10	.11
Control of Learning Beliefs (M)					1.42	[-0.09; 2.93]	0.10	.07
Test Anxiety (M)					-0.04	[-1.09; 1.01]	-0.003	.94
Rehersal (SRL)					-0.81	[-2.26; 0.64]	-0.06	.27
Elaboration (SRL)					1.47	[-0.31; 3.25]	0.11	.11
Organisation (SRL)					-2.20	[-3.73; -0.68]	-0.18	< .01
Critical Thinking (SRL)					-0.58	[-2.14; 0.97]	-0.05	.46
Metacognitive Self-Regulation (SRL)					1.37	[-1.18; 3.91]	0.08	.29
Time and Study Environment (SRL)					0.80	[-0.86; 2.47]	0.05	.34
Effort Regulation (SRL)					1.20	[-0.29; 2.70]	0.09	.12
Peer Learning (SRL)					0.58	[-0.52; 1.68]	0.06	.30
Help Seeking (SRL)					0.96	[-0.30; 2.22]	0.08	.14
Learning in Online Environment (OLSE)					-0.93	[-3.29; 1.43]	-0.06	.44
Time Management (OLSE)					1.24	[-0.49; 2.97]	0.09	.16
Technology Use (OLSE)					1.35	[-0.68; 3.37]	0.09	.19
Self-Theory of Intelligence					-0.42	[-1.75; 0.90]	-0.02	.53

4.2.3 Online setting: Detailed analysis

The analysis above provides insight into the relationship between online course grade and the target constructs. To better understand the contribution of selected sub-constructs from these scales to online course grades, we conducted a second hierarchical regression with specific sub-constructs that previous work has indicated to be predictive of grades in online settings.

4.2.3.1 Theoretical background

Bandura (1997) proposed that self-efficacy beliefs are context-specific rather than a generalized expectancy, which is why researchers began investigating students' self-efficacy within an online learning context. The results show, that online learning self-efficacy is positively correlated with online course grades (see e.g., McGhee, 2010; Wang et al., 2013). Besides online learning self-efficacy, previous research revealed that effort regulation (as measured by the MSLQ) was positively correlated with academic achievement in online courses and that students with higher levels of effort regulation received higher grades (Bell & Akroyd, 2006; Moon-Heum Cho & Shen, 2013; Kim, Park, Cozart, & Lee, 2015; Puzziferro, 2008).

4.2.3.2 Outliers, influential cases, and verification of assumptions

No influential outliers were found. We determined that the assumptions of multicollinearity, homoscedasticity, and linearity were met. However, the assumption of normally distributed errors was violated (see Appendix G.4 for details). Based on the central limit theorem the given sample size ($N = 746$) is adequately large, which allows the reasonable assumption that the sample errors are normally distributed.

4.2.3.3 Online setting: Results with detailed model

To better understand the contribution of the selected variables to online course grades, a two-step hierarchical regression was conducted, with "grade" as the dependent variable and online learning self-efficacy and effort regulation as independent variables, entered in the following order (new variables in a given step shown in italics):

Step 1: online learning self-efficacy construct

Step 2: online learning self-efficacy construct + *effort regulation*

In the first step, all online learning self-efficacy variables from the Online Learning Self-Efficacy Scale were entered as predictors. As shown in Table 7, in model 1, only time management emerged as a significant predictor ($\beta = 0.12$). Overall, model 1 was significant, $F(3, 742) = 4.41$, $p < .01$, but accounted only for a very small amount of the variance in student's final online course grade (*adjusted* $R^2 = 0.014$).

In the second step, effort regulation (measured by the MSLQ) was entered as a predictor. In model 2, none of the variables were significant predictors and even though model 2 was significant, $F(4, 741) = 4.02$, $p < .01$, it accounted for a very small amount of the variance in grade (*adjusted* $R^2 = 0.016$). In addition, model 2 did not significantly improve the value of R^2 compared to model 1, $F(1, 741) = 2.82$, $p = .09$).

Table 7. Results of two-step hierarchical regression analysis

	R^2	$R^2_{adjusted}$	F	sigΔF	B	95% CI	β	p
Step 1	0.018	0.014	4.41					< .01
Constant					58.98	[53.24; 64.71]		< .001
Learning in Online Environment (OLSE)					-0.75	[-2.92; 1.42]	-0.05	.50
Time Management (OLSE)					1.75	[0.28; 3.21]	0.12	< .05
Technology Use (OLSE)					1.00	[-0.70; 2.70]	0.06	.25
Step 2	0.021	0.016	4.02	.09				< .01
Constant					56.76	[50.47; 63.05]		< .001
Learning in Online Environment (OLSE)					-0.62	[-2.80; 1.56]	-0.04	.58
Time Management (OLSE)					1.33	[-0.21; 2.88]	0.09	.09
Technology Use (OLSE)					0.76	[-0.97; 2.48]	0.05	.39
Effort Regulation (SRL)					0.98	[-0.17; 2.13]	0.07	.09

4.3 Instructor influence: Checking for potential bias

While there was some overlap in the models obtained from the face-to-face and online classes, there were also substantial differences in terms of the significant predictors of course grade and overall model fit as measured by R^2. This suggests that context (face-to-face vs. online) influences the relationship between the target psychological constructs and student grades. However, there is an alternative explanation: the online classes were all taught by one instructor (Instructor B), while the face-to-face classes were taught by two instructors (Instructor A and B). In theory, an instructor could influence the relationship between grades and constructs (e.g., if an instructor is very motivating, then perhaps the influence of the student motivational variables is affected). Thus, to verify that the difference in findings for the classroom and online sample were due to the context and not caused by the instructor, we checked for instructor influence on variance in grade. Specifically, we repeated the hierarchical regression analysis for the *classroom sample* but for each instructor separately. If the instructor was the reason for the different results (face-to-face vs. online), the results for each instructors' individual classroom sample should be different as well. On the other hand, if the obtained models for the two instructors turn out comparable, we have some indication that the instructor is not the reason for the differing online model. We are focusing on the classroom sample because we have those data from both instructors. We acknowledge that ideally we could also check for differences between instructors' online samples (we do not have data to do so).

For the present analysis, we created the detailed model only (analogous to the one created in section 4.1.3). This decision was based on the fact that we had a smaller sample size for this analysis (specifically for Instructor B, see section 4.3.2), and the fine-grained analysis involved fewer predictors than the high-level model. In this five-step hierarchical regression, the independent variables were entered in the same order as in section 4.1.3.3 (new added variables shown in italics):

Step 1: self-efficacy

Step 2: self-efficacy + *effort regulation* + *metacognitive self-regulation*

Step 3: self-efficacy + effort regulation + metacognitive self-regulation + *self-theory of intelligence*

Step 4: self-efficacy + effort regulation + metacognitive self-regulation + self-theory of intelligence + *intrinsic goal orientation*

Step 5: self-efficacy + effort regulation + metacognitive self-regulation + self-theory of intelligence + intrinsic goal orientation + *control of learning beliefs*

4.3.1 Classroom setting: Instructor A

Instructor A taught four classroom-based "Introduction to Psychology" sections. Complete data were available for 557 participants; thus, the present analysis is based on this sample.

4.3.1.1 Outliers, influential cases, and verification of assumptions

No influential outliers were found. In addition, we verified that the assumptions of multicollinearity, homoscedasticity, linearity, and normally distributed errors were met (see Appendix G.5 for details).

4.3.1.2 Instructor A: Results with detailed classroom model

In the first step of the model, self-efficacy was entered as a predictor variable. As shown in Table 8, self-efficacy was a significant predictor ($\beta = 0.34$); overall, model 1 was significant, $F(1, 555) = 73.56$, $p < .001$, and accounted for 11.5% of the variance in final grade (*adjusted* $R^2 = 0.115$).

In the second step, effort regulation and metacognitive self-regulation were entered into the model. In model 2, self-efficacy remained significant ($\beta = 0.23$), but of the new variables only effort regulation was significant ($\beta = 0.27$) (see Table 8). Model 2 was overall significant, $F(3, 553) = 37.13$, $p < .001$, and accounted for 16.1% of variance in final grade (*adjusted* $R^2 = 0.161$). In addition, model 2 significantly increased the amount of unique variance accounted for in final grade, compared to model 1, $F(2, 553) = 17.02$, $p < .001$.

In the next step, self-theory of intelligence was entered as an additional predictor. In model 3, self-efficacy and effort regulation remained significant predictors, but self-theory was not (see Table 8). Overall, model 3 was significant, $F(4, 552) = 27.80$, $p < .001$, accounting for 16.2% of the variance in final grades (*adjusted* $R^2 = 0.162$). However, model 3 did not significantly improve the value of R^2 compared to model 2, $F(1, 552) = 0.01$, $p = .97$.

In step 4, intrinsic goal orientation was entered as a predictor of grade. In model 4, self-efficacy and effort regulation remained significant positive predictors. In addition, intrinsic goal orientation was also as significant predictor but with a negative coefficient ($\beta = -0.10$) (see Table 8). Model 4 was significant, $F(5, 551) = 23.14$, $p < .001$, accounting for 16.6% of the variance in final grade (*adjusted* $R^2 = 0.166$), and did significantly improve the R^2-value compared to model 3, $F(1, 551) = 3.95$, $p = < .05$. This indicates that intrinsic goal orientation explained unique variance over and beyond self-theory of intelligence.

In the final step, control of learning beliefs was entered as an additional predictor. In model 5, self-efficacy, effort regulation, and control of learning beliefs were significant positive predictors. In addition, intrinsic goal orientation remained a significant negative predictor (see Table 8). Model 5 was significant, $F(6, 550) = 20.35$, $p < .001$, accounting for 17.2% of variance in final grades (*adjusted* $R^2 = 0.172$). Model 5 significantly increased the R^2-value compared to model 4, $F(1, 550) = 5.45$, $p < .05$, indicating that control of learning beliefs explained unique variance in course grades over and beyond intrinsic goal orientation.

Table 8. Results of detailed classroom model (classroom sample Instructor A)

	R^2	$R^2_{adjusted}$	F	sigΔF	B	95% CI	β	p
Step 1	0.117	0.115	73.56					< .001
Constant					47.79	[42.51; 53.07]		< .001
Self-Efficacy (M)					4.53	[3.49; 5.57]	0.34	< .001
Step 2	0.168	0.163	37.13	< .001				< .001
Constant					40.40	[33.68; 47.12]		< .001
Self-Efficacy (M)					3.02	[1.77; 4.28]	0.23	< .001
Effort Regulation (SRL)					3.56	[2.33; 4.80]	0.27	< .001
Meta-Cognitive Self-Regulation (SRL)					-0.67	[-2.34; 0.99]	-0.04	.43
Step 3	0.168	0.162	27.80	.91				< .001
Constant					40.66	[32.52; 48.80]		< .001
Self-Efficacy (M)					3.03	[1.77; 4.30]	0.23	< .001
Effort Regulation (SRL)					3.57	[2.32; 4.82]	0.27	< .001
Meta-Cognitive Self-Regulation (SRL)					-0.68	[-2.34; 0.99]	-0.04	.43
Self-Theory of Intelligence					-0.08	[-1.43; 1.28]	-0.004	.91
Step 4	0.174	0.166	23.14	< .05				< .001
Constant					41.75	[33.56; 49.94]		< .001
Self-Efficacy (M)					3.65	[2.25; 5.06]	0.28	< .001
Effort Regulation (SRL)					3.54	[2.30; 4.78]	0.27	< .001
Meta-Cognitive Self-Regulation (SRL)					-0.20	[-1.93; 1.53]	-0.01	.82
Self-Theory of Intelligence					0.02	[-1.33; 1.38]	0.001	.97
Intrinsic Goal Orientation (M)					-1.40	[-2.78; -0.01]	-0.10	< .05
Step 5	0.182	0.172	20.35	< .05				< .001
Constant					37.75	[28.93; 46.58]		< .001
Self-Efficacy (M)					3.20	[1.75; 4.65]	0.24	< .001
Effort Regulation (SRL)					3.50	[2.26; 4.74]	0.27	< .001
Meta-Cognitive Self-Regulation (SRL)					-0.21	[-1.93; 1.51]	-0.01	.81
Self-Theory of Intelligence					-0.33	[-1.71; 1.05]	-0.02	.64
Intrinsic Goal Orientation (M)					-1.67	[-3.07; -0.27]	-0.12	< .05
Control of Learning Beliefs (M)					1.67	[0.27; 3.08]	0.11	< .05

4.3.2 Classroom setting: Instructor B

Instructor B taught three classroom-based “Introduction to Psychology” sections. Complete data were available for 150 participants; therefore, the present analysis is based on this sample.

4.3.2.1 Outliers, influential cases, and verification of assumptions

No influential outliers were found. Furthermore, we verified that the assumptions of multicollinearity, linearity, homoscedasticity, and normally distributed errors were met (see Appendix G.6 for details).

4.3.2.2 Instructor B: Results with detailed classroom model

In the first step, self-efficacy was entered as a predictor variable. As shown in Table 9, self-efficacy was a significant predictor ($\beta = 0.23$), model 1 was significant, $F(1, 148) = 8.34$, $p < .01$, and accounted for 4.7% of the variance in grade (*adjusted* $R^2 = 0.047$).

In the second step, effort regulation and metacognitive self-regulation were entered into the model. In model 2, all predictor variables were significant (see Table 9). Model 2 was overall significant, $F(3, 146) = 5.82$, $p < .001$, accounting for 8.8% of variance in grade (*adjusted* $R^2 = 0.088$). Moreover, model 2 significantly increased the R^2-value compared to model 1, $F(2, 146) = 4.45$, $p < .05$, indicating that both effort regulation and meta-cognitive self-regulation explained unique variance in final grade over and beyond self-efficacy.

In the next step, self-theory of intelligence was entered as an additional predictor of grade. In model 3, self-efficacy, effort regulation, and meta-cognitive self-regulation remained significant predictors, whereas self-theory was not significant (see Table 9). Overall, model 3 was significant, $F(4, 145) = 5.10$, $p < .001$, accounting for 9.9% of the variance in final grade (*adjusted* $R^2 = 0.099$). However, model 3 did not significantly improve the value of R^2 compared to model 2, $F(1, 145) = 2.74$, $p = .09$.

In step 4, intrinsic goal orientation was entered as a predictor of grade. In model 4, self-efficacy and effort regulation remained significant predictors, but none of the other variables were (see Table 9). Model 4 was significant, $F(5, 144) = 4.06$, $p < .01$, accounting for 9.2% of the variance in grade (*adjusted* $R^2 = 0.092$). Model 4 did not significantly improve the R^2-value compared to model 3, $F(1, 144) = 0.03$, $p = .87$.

In the final step, control of learning beliefs was entered as an additional predictor of grade. In model 5, self-efficacy (β = 0.22) and effort regulation (β = 0.20) remained as significant positive predictors. In addition, self-theory of intelligence was also a significant predictor but with a negative coefficient (β = -0.16) (see Table 9). Even though model 5 was significant, $F(6, 143) = 3.92$, $p < .01$, and accounted for 10.5% of variance in final grade (*adjusted* R^2 = 0.105), model 5 did not significantly increase the R^2-value compared to model 4, $F(1, 143) = 2.95$, $p = .09$. Overall, the results from the models on a per-instructor basis were comparable – we describe these below and summarize the other findings related to the classroom and online models.

Table 9. Results of detailed classroom model (classroom sample Instructor B)

	R^2	$R^2_{adjusted}$	F	sigΔF	B	95% CI	β	p
Step 1	0.053	0.047	8.34					< .01
Constant					52.97	[44.95; 61.00]		< .001
Self-Efficacy (M)					2.43	[0.77; 4.10]	0.23	< .01
Step 2	0.107	0.088	5.82	< .05				< .001
Constant					52.11	[41.08; 63.15]		< .001
Self-Efficacy (M)					2.70	[0.82; 4.59]	0.26	< .01
Effort Regulation (SRL)					2.20	[0.46; 3.93]	0.21	< .05
Meta-Cognitive Self-Regulation (SRL)					-2.39	[-4.77; -0.0002]	-0.18	< .05
Step 3	0.123	0.099	5.10	.10				< .001
Constant					57.58	[44.80; 70.35]		< .001
Self-Efficacy (M)					3.01	[1.10; 4.91]	0.28	< .01
Effort Regulation (SRL)					2.28	[0.56; 4.01]	0.22	< .01
Meta-Cognitive Self-Regulation (SRL)					-2.50	[-4.88; -0.12]	-0.19	< .05
Self-Theory of Intelligence					-1.68	[-3.70; 0.33]	-0.13	.10
Step 4	0.123	0.093	4.06	.87				< .01
Constant					57.79	[44.73; 70.86]		< .001
Self-Efficacy (M)					3.08	[0.96; 5.21]	0.29	< .01
Effort Regulation (SRL)					2.27	[0.53; 4.01]	0.21	< .05
Meta-Cognitive Self-Regulation (SRL)					-2.42	[-4.98; 0.15]	-0.18	.06
Self-Theory of Intelligence					-1.69	[-3.71; 0.34]	-0.13	.10
Intrinsic Goal Orientation (M)					-0.19	[-2.44; 2.05]	-0.02	.87
Step 5	0.141	0.105	3.92	.09				< .01
Constant					54.10	[40.44; 67.76]		< .001
Self-Efficacy (M)					2.33	[0.04; 4.61]	0.22	< .05
Effort Regulation (SRL)					2.08	[0.33; 3.82]	0.20	< .05
Meta-Cognitive Self-Regulation (SRL)					-2.44	[-4.99; 0.11]	-0.18	.06
Self-Theory of Intelligence					-2.06	[-4.12; -0.01]	-0.16	< .05
Intrinsic Goal Orientation (M)					-0.25	[-2.48; 1.98]	-0.02	.82
Control of Learning Beliefs (M)					1.89	[-0.29; 4.06]	0.16	.09

4.4 Overall summary

In the classroom context, the analysis with the full sample and the model that contained all the target constructs (section 4.1.2.3) showed that the self-regulated learning construct did explain unique variance in grades over and beyond the motivational construct. In contrast, the self-theory of intelligence construct did not account for a significant amount of unique variance in grades. In this model, self-efficacy (a motivational sub-construct), effort regulation (a self-regulated learning sub-construct), and control of learning beliefs (a motivational sub-construct) were the strongest positive predictor variables for grades in classroom courses. Unexpectedly, critical thinking (a self-regulated learning sub-construct) turned out to be a significant *negative* predictor, indicating that an increase in critical thinking results in a decrease in classroom course grade. This full model accounted for approximately 17% of the variance in course grades.

A subsequent analysis also involving the full classroom sample but with selected sub-constructs (section 4.1.3.3) accounted for a similar amount of variance in grade as the full model. This analysis revealed the same three sub-constructs to be the strongest positive predictors as in the full model. In addition, intrinsic goal orientation was also a significant predictor of students' grades but with a *negative* coefficient, indicating that an increase in intrinsic goal orientation results in a decrease in classroom course grade.

For the online sample, mirroring the findings for the classroom results, the model that contained all the target constructs (section 4.2.2.3) showed that the self-regulated learning construct did explain unique variance in grade over and beyond the motivational construct. However, the online learning self-efficacy construct did not account for a significant amount of unique variance in grade. Also, as was the case for the classroom data, self-theory of intelligence did not explain unique variance in grade. In this model, organization (a self-regulated learning sub-construct) was the only significant predictor but with a *negative* coefficient, indicating that an increase in organization leads to a decrease in online course grade. Also in contrast to the classroom results, the full model accounted only for approximately 4% of variance in online grades. A second detailed analysis (section 4.2.3.3) aimed to investigate if model fit would be improved by the inclusion of specific sub-constructs, namely the online learning self-efficacy sub-construct and effort regulation (a self-regulated learning sub-construct). The detailed model was overall significant but accounted for an even smaller amount (1.6%) of variance in online grades.

In summary, our results indicate that variables accounting for a significant amount of variance in classroom course grades are not applicable for explaining variance in online course grades. To ensure that the difference in findings for the classroom and online sample were due to the context (classroom, online) and not caused by the instructor (Instructor B taught all online courses), we tested for a potential instructor influence on variance in classroom grade. In both instructor's classroom samples, self-efficacy and effort regulation were significant predictors of grade, obtaining the largest positive standardized regression coefficients. Furthermore, for both samples, the value of the standardized coefficients (i.e., whether they are negative or positive) were almost identical. Thus, these results allow the reasonable assumption that the instructor was not responsible for the noticeable difference in the results of the classroom and online sample, which we will further discuss in the next chapter.

Chapter 5: Discussion

In the following chapter, we discuss our results concerning the relationship between the target constructs and students' grades in classroom and online courses as well as the limitations of our study. We conclude the chapter by highlighting potential directions for future research.

5.1 Classroom context: The relationship between target constructs and course grade

Our analysis with the full hierarchical regression model with all the target constructs revealed that both the motivational construct as well as the self-regulated learning construct explained unique variance in classroom grade, and that self-regulated learning accounts for unique variance over and beyond motivation. These results are in line with prior work showing that motivation and self-regulated learning explain a significant amount of variance in classroom grade (e.g., Bae, 2014; Komarraju & Nadler, 2013; Lynch, 2006; Pintrich & De Groot, 1990). In contrast, self-theory of intelligence did not significantly improve the model fit over and beyond the self-regulation and motivation constructs. This was somewhat unexpected given that prior research found the positive association between self-theory of intelligence and classroom grades, albeit with different analysis techniques as compared to the ones used here (e.g., Blackwell et al., 2007; J. A. Chen & Pajares, 2010; De Castella & Byrne, 2015; Dweck & Master, 2008; Gonida et al., 2006; Hong et al., 1999; Niiya et al., 2004; Paunesku et al., 2015; Yeager et al., 2016). One possible reason why our findings differed from previous research is that the ability of self-theory of intelligence to predict grade might be less pronounced compared to the predictive power of the motivation and self-regulated learning constructs. In fact, Costa and Faria (2018) conducted a recent meta-analysis of 46 studies published between 2002 and 2017, that examined the relationship between self-theory of intelligence and students' academic achievement. The mean weighted effect size of all included studies revealed that in general self-theory of intelligence is significantly positively related to academic achievement, but the effect is small ($r = 0.07$). Moreover, they found that this positive effect was at the limit of significance ($p = .05$) for students in North America.

An implication that can be derived from our findings is that focusing on interventions that aim to foster students' ability to apply self-regulated learning strategies and control their motivation could be even more effective in positively influencing grades in classroom courses than interventions focusing on students' self-theory of intelligence. In fact, Pintrich et al. (1991) stated that both motivational beliefs and the use of self-regulated learning strategies are learnable. Furthermore, a meta-analysis on intervention studies aiming to foster self-regulated learning among primary and secondary school students by Dignath and Büttner (2008) revealed that self-regulated learning can be effectively promoted through teaching interventions to improve students' performance. However, there is a caveat to our interpretation, in that self-theory of intelligence may not have an effect in the present domain of psychology but may have a stronger effect in other domains. Indeed, Paunesku et al. (2015) found that students' self-theory of intelligence is particularly important in the domains of math and science, as compared to, for instance, social studies. An alternative explanation is that we did not obtain accurate measure of students' self-theory of intelligence. This could have happened if, for instance, the Implicit Theories of Intelligence Scale instrument appeared at the end of the online questionnaire and participants were fatigued by the time they got to it (while the questions within a given instrument were randomized, the MSLQ, OLSES, and Implicit

Theories of Intelligence Scale instruments were administered in a specific order that was fixed for all participants). However, the Implicit Theories of Intelligence Scale was one of the first instruments participants encountered when completing the questionnaire, and thus the lack of relation between grades and self-theory of intelligence in our study was not due to instrument order in the questionnaire. In fact, the MSLQ was administered last, but both the related motivational and self-regulated learning constructs accounted for a unique amount of variance in grade.

An unanticipated result with the full hierarchical regression model was the negative relationship between course grades and critical thinking, indicating that students who think less critically about the topics in their class receive higher grades. Our findings contradict previous research that identified a positive relationship between critical thinking and students' academic achievement in classroom courses, based on correlation, multiple regression, and path analysis (e.g., Lun, Fischer, & Ward, 2010; Pintrich et al., 1993; Stupnisky, Renaud, Daniels, Haynes, & Perry, 2008; Villavicencio, 2011). To the best of our knowledge, there are no studies reporting a negative relationship between the two variables. A reason for our obtained result might be that participants were undergraduate students freshly coming from high school, where their critical thinking skills may not have been fully shaped and so while students may report using them, the skills themselves need refinement. There is some evidence pointing to the fact that critical thinking skills further develop during a four-year undergrad experience (Giancarlo & Facione, 2001). A complementary explanation is that students are not yet good at assessing their critical thinking strategies and accurately self-reporting it. Yet another possibility is that critical thinking was not beneficial for the type of multiple choice assessments that were used to evaluate students in this class, i.e., students with higher critical thinking skills overthought the question options to their detriment. In general, more research is needed to address our speculations.

Our analysis with the detailed hierarchical regression model containing selected sub-constructs revealed another unexpected result: a negative relationship between classroom course grades and intrinsic goal orientation (also conceptualized as mastery-goal orientation), indicating that students with lower levels of intrinsic motivation receive higher grades. While the relationship was weak as indicated by the small standardized regression coefficient, it was significant. Our results again contradict some research in traditional classroom settings. Specifically, prior work has found that mastery-goal orientation has a positive effect on students' academic achievement in classroom courses and positively predicts students' grades (e.g., Grant & Dweck, 2003; Greene & Miller, 1996; Meece & Holt, 1993; Schraw et al., 1995). However, there is also some evidence that mastery-goal orientation does not predict student's academic achievement (Elliot & Church, 1997; Harackiewicz et al., 1997; Miltiadou, 2001). The question why mastery-goal orientation is sometimes unrelated to class grades has been assessed by Senko and Miles (2008). They hypothesized that mastery-oriented students allow their individual interests to dictate their study efforts such that they neglect boring topics in favor of preferred ones. Results of a path analysis supported their reasoning, showing that mastery-oriented students allocated their study efforts disproportionately to the personally interesting material, and this in turn predicted low grades. This may have also been the case for the students in our data, thus explaining the negative relationship between course grade and intrinsic goal orientation.

One other explanation for our findings pertains to the instrument used to measure intrinsic goal orientation and critical thinking, the MSLQ, and specifically that it did not measure the constructs it was designed to measure. However, this instrument has been shown to be a valid, reliable measure and has been widely used in research investigating the role of motivational and self-regulated learning constructs in traditional classroom settings (Pintrich & De Groot, 1990; Pintrich et al., 1993). Therefore, it is unlikely that the MSLQ was the reason for the divergent findings related to the negative relationships between grade and intrinsic goal orientation, as well as grade and critical thinking in the classroom context.

5.2 Online context: The relationship between target constructs and course grade

Mirroring the findings for the classroom results, in the online context the hierarchical regression analysis with the full model containing all the target constructs showed that the self-regulated learning construct did explain unique variance in grades over and beyond the motivational construct, whereas self-theory of intelligence did not. However, compared to the classroom model, the online model explained a smaller amount of variance in students' online course grade, highlighting a noticeable difference between the classroom and the online sample. These results are surprising and somewhat contradictory to prior work stating that online learning requires an even higher level of motivation and self-regulation than traditional classroom learning (Dabbagh & Kitsantas, 2004; Hartley & Bendixen, 2001). We expected online learning self-efficacy and the use of self-regulated learning strategies to be especially important predictors of online course grades, because prior work has shown their importance and positive influence on academic achievement in the context of online courses (e.g., Broadbent & Poon, 2015;

Cho & Heron, 2015; Kim et al., 2014; Lin et al., 2017; Wang et al., 2013). As far as self-theory of intelligence, we are not aware of studies examining this construct as a predictor for students' grades in online learning environments. Thus, our study is the first to explore this relationship.

The detailed online model, containing only the online learning self-efficacy construct and effort regulation construct (a self-regulated learning sub-construct) was significant but revealed that effort regulation did not explain unique variance in students' online grades over and beyond online learning self-efficacy. Furthermore, the overall model also accounted for a very small amount of variance in online course grades. Thus, even though prior work stated that higher levels of online learning self-efficacy and effort regulation are associated with higher online grades (Kim et al., 2015; Puzziferro, 2008; Wang et al., 2013), our results show that those constructs do not explain a significant amount of variance in students' finale online course grades.

5.3 Does context matter?

In general, our analysis shows that the constructs accounting for a significant amount of variance in classroom grades were not applicable for explaining variance in online course grades. Therefore, our findings have implications for the design of online learning environments. In general, HCI researchers can not assume results obtained in traditional classroom settings will transfer to the online context. Furthermore, because we did not find the psychological constructs to be good predictors, our results do not allow us to propose design guidelines to support students when learning online based on these constructs.

Our findings raise the question of what factors do have a positive influence on students' academic achievement in online learning environments, i.e., what are good predictors of online course grades? As previously mentioned (see section 2.2), students' GPA is positively and significantly related to their grades in online courses (e.g., Cheung & Kan, 2002; Jost et al., 2012; Wojciechowski & Palmer, 2005). However, this might not be a suitable predictor when faced with a population that has no or little experience with higher education. Another potential predictor might be students' age, but there is not that much variation in age in online courses, and in general findings about the relation between age and academic performance in online courses are mixed. While some studies did not find age to be a significant predictor of academic performance (Coldwell et al., 2008; Kotey & Anderson, 2006; Lu et al., 2003), other researchers found age to be a strong predictor of grade, with mature-aged students performing better than younger students (Alstete & Beutell, 2004; Wojciechowski & Palmer, 2005).

The above-mentioned factors have one thing in common: they are fixed characteristics that are already assigned to students when they enroll in an online course. However, other variables that may affect performance shift during students' experience with the class, such as students' level of participation. Students who participate more actively in an online course achieve higher grades, compared to students who participate less actively (Coldwell et al., 2008). One way instructors can foster participation in online courses is through discussion forums. Prior work shows that the usage of a discussion board is positively and significantly related to higher grades (Alstete & Beutell, 2004; Hoskins & Van Hooff, 2005; Koç, 2017). Moreover, providing students with explicit discussion prompts has been shown to improve the quality of online discussions and encourage more in-depth student interactions (Hara, Bonk, & Angeli, 2000; Spatariu, Hartley, Schraw, Bendixen, & Quinn, 2007).

Another factor that may affect grade is interaction. Students' interactions with both their instructor and their peers could positively influence online course grades (Beaudoin, 2002; Jaggars & Xu, 2016). For instance, Lammers and Gillaspy (2013) developed a measurement instrument to assess the relationship between student-instructor rapport and university students online course grades. The results of a hierarchical regression analysis showed that this instrument accounted for approximately 16% of variance in online course grade. In a classroom setting, interaction between students and instructors happens naturally, as they listen to each other's comments, ask questions, and build rapport through frequent contact. In an online learning environment, instructors can foster interaction e.g., through guided introductions, exchanges of personal information, and activities that require students to work with one another, share results, and go beyond the typical course discussion.

Related to the discussion above, another noticeable question is whether the differences between the classroom and online sample are instructor-related and which other factors could have contributed to the present results. We presented arguments against the possibility of the instructor strongly biasing our analysis, because the results of the fine-grained model for the classroom samples of both instructors revealed a similar pattern (see section 4.3). Specifically, in both samples self-efficacy and effort regulation were significant predictors of grade, obtaining by far the largest standardized regression coefficients. Furthermore, the values of the standardized coefficients were similar in both samples. Interestingly, however, besides self-efficacy and effort regulation, for the classroom sample of Instructor B self-theory of intelligence was also a significant but negative predictor of grade. In contrast to the classroom sample of Instructor B, for the classroom sample of Instructor A only intrinsic goal orientation (with a negative coefficient) and control of learning beliefs were additional significant predictors of grade. That some of the predictor variables in the models were not overlapping between the two instructors may point to the fact that both student and instructor traits may influence grades. In general, the findings related to some prior work have shown that instructor qualities have little impact on students' classroom course grades (e.g., Hoffmann & Oreopoulos, 2009; Kim, Dar-Nimrod, & MacCann, 2017). For instance, Kim et al. (2018) performed a multiple regression analysis, which showed that instructor's big five personality traits (i.e., openness, conscientiousness, extraversion, agreeableness, neuroticism) did not predict students' academic achievement. In the context of online learning, a multiple regression analysis conducted by Martin (2017) revealed that instructors' experience and level of education accounted for only a very small amount of variance in students' online course grades. However, other scholars have highlighted that instructors do play a role in helping students learn through their ability to establish and maintain a personal connection and empathy with students, impart the fact they care about students' learning outcomes, and encourage students' motivation, involvement and persistence (Lepper & Woolverton, 2002; W. B. Wood & Tanner, 2012). In terms of the present study, in which only one instructor (Instructor B) taught all online courses, this indicates that the online instructors' individual characteristics (e.g., teaching style or the way the instructor designed the online course) could have potentially influenced online course grade. Thus, it is likely that instructor characteristics do explain some variance in student performance, although it is an open question as to what degree.

Another possible explanation for the differing results related to the classroom and online samples is that both instructors used slightly different grading schemes but as we argue below, this is not likely to be the cause of the difference in results. Specifically, Instructor A evaluated students through two mid-term exams, one final exam, as well as through participation in research projects. Instructor B’s grading scheme mirrors the evaluation of Instructor A in terms of exams and participation in research projects (which in total make up approximately 70% of students’ final grade) but includes additional evaluation measures like short quizzes and assignments (which make up the remaining 30% of students’ final course grade). Furthermore, Instructor B applied the same grading scheme in both his online and classroom courses. However, we did not find a substantial difference between the classroom samples of Instructor A and Instructor B in terms of the variables predicting grade. This suggests that the slight disparity in grading schemes was not responsible for the noticeable difference between the classroom and online sample.

A supplementary explanation for the different results in the two contexts (classroom, online) might be related to the MSLQ instrument. The MSLQ has been designed as a self-report instrument to assess motivation and use of self-regulated learning strategies by college students. Even though the MSLQ can be used in various courses, it was developed for the use and in the context of classroom learning (Pintrich et al., 1991, 1993). Thus, one could argue that the MSLQ is not an appropriate measurement tool in online learning settings. Besides using the MSLQ to assess motivation and self-regulation for the classroom sample, we chose to also use it for the online sample for three reasons: (1) to be able to compare the results of the classroom and online samples; (2) to be able to compare our results with regard to prior findings; (3) the MSLQ is an established measurement instrument in the field of psychology and cognitive science, and some research has validated the MSLQ in online learning environments (Moon-Heum Cho & Summers, 2012; Jansen, Van Leeuwen, Janssen, Kester, & Kalz, 2017). If we were to replace the MSQL with an online version, it is not clear what that would be - we are aware of only one instrument assessing analogous constructs in online learning settings created by Jansen et al. (2017), but the authors conclude that further development of their questionnaire is necessary. As mentioned above, researchers have used the MSLQ to measure students' motivation and self-regulation in the context of online courses (e.g., Artino Jr & Stephens, 2009; Moon-Heum Cho & Shen, 2013; Colorado & Eberle, 2010; Wang et al., 2013). In addition, our result show that the correlations between the different scales of the MSLQ and the computed Cronbach's alpha values show a similar pattern in both contexts, indicating that the instrument in itself is reliable.

5.4 Limitations

We did not collect demographic information because we were interested in the relationships between psychological constructs and grade as well as specific sub-constructs and grade, unrelated to demographical characteristics (such as age, gender, experience with higher education, full-time or part-time student, or external commitments). Our findings obtained particularly in the online context raise the question whether demographical factors might have had an influence on online course grade and whether including that information might improve the models. For instance, fourth-year undergraduate students have more university-relevant experience compared to first-year undergraduate students, which might result in the fourth-year students being more successful in online courses compared to first-year undergraduate students. Furthermore, time intensive external commitments (such as work or family) might influence students' preferences for online courses over face-to-face courses, and their online course grade.

In the present study, only datasets of students who completed their online or classroom "Introduction to Psychology" course were included in the analysis, because we did not obtain the grades achieved (if any) by students who withdrew from the online and classroom courses before completion. This might have influenced our results to the extent that potential differences between those who did and did not withdraw were not taken into account, so that the obtained results are only picturing the factors influencing grade for students who are able to persist in a course. To examine whether there is a difference regarding the influence of psychological constructs on online and classroom course grade between those who withdraw and those who complete the course, future studies could compare the influence psychological constructs have on both groups midterm grades, as well as whether a similar pattern emerges for midterm grades of students who withdrew compared to the final grades of students who completed the course.

Another limitation of our study is the number of participating instructors. While we present analysis arguing that the instructor was not responsible for the noticeable difference in the results of the classroom and online sample, a larger number of instructors would strengthen the analysis and allow us to draw stronger conclusions about the generality of our findings. In addition, due to the non-experimental nature of the study, we were limited in our ability to control for grading schemes, course content, and the context in which each instructor taught. Finally, although the student sample sizes in both contexts are large, all participants were enrolled in undergraduate introductory psychology courses at the same university. Thus, samples drawn from other fields, institutions, courses and cohorts would help to draw a richer picture of the relationship between psychological constructs and course performance.

5.5 Future work

The results of the present thesis point to several directions for future work. One potential area of research is to evaluate whether the results hold with classroom and online samples drawn from other institutions, disciplines, courses and with different levels of experience with higher education (e.g., graduate students) to determine whether our results are generalizable to a wider population. In addition, future researchers should replicate the present study with a larger number of online and classroom instructors participating. Another interesting future research direction relates to the design of online learning platforms and specifically the development of design guidelines for promoting students' self-regulation, motivation as well as other constructive behaviors, such as participation or interaction. Therefore, following a user-centered approach, an approach that takes users' characteristics into account as well as the virtual environments the user is interacting with, could be especially promising. We believe that interdisciplinary research at the intersection of the learning sciences and HCI has the potential to unveil interesting findings that in turn will lead to the development of effective and engaging online courses as well as to novel approaches to foster learning online.

Appendices

Appendix A Ethics board clearance

A.1 Original ethics board clearance

Carleton
UNIVERSITY
Canada's Capital University

Office of Research Ethics and Compliance
5110 Human Computer Interaction Bldg | 1125 Colonel By Drive
| Ottawa, Ontario K1S 5B6
613-520-2600 Ext: 4085
ethics@carleton.ca

CERTIFICATION OF INSTITUTIONAL ETHICS CLEARANCE

The Carleton University Research Ethics Board-B (CUREB-B) has granted ethics clearance for the research project described below and research may now proceed. CUREB-B is constituted and operates in compliance with the *Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans* (TCPS2).

Ethics Protocol Clearance ID: Project # 107077

Faculty Supervisor: Ms. Anna-Lena Theus

Research Team: Ms. Anna-Lena Theus (Primary Investigator)
Dr. Katarzyna (Kasia) Muldner (Research Supervisor)
Bruce Tsuji (Collaborator)

Project Title: Investigating student learning in online and face to face contexts [Anna-Lena Theus]

Funding Source (If applicable):

Effective: **July 24, 2017** Expires: **July 31, 2018**.

Restrictions:

This certification is subject to the following conditions:

1. Clearance is granted only for the research and purposes described in the application.
2. Any modification to the approved research must be submitted to CUREB-B via a Change to Protocol Form. All changes must be cleared prior to the continuance of the research.
3. An Annual Status Report for the renewal of ethics clearance must be submitted and cleared by the renewal date listed above. Failure to submit the Annual Status Report will result in the closure of the file.If funding is associated, funds will be frozen.
4. A closure request must be sent to CUREB-B when the research is complete or terminated.

5. Should any participant suffer adversely from their participation in the project you are required to report the matter to CUREB-B.

Failure to conduct the research in accordance with the principles of the *Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans 2ndedition* and the *Carleton University Policies and Procedures for the Ethical Conduct of Research* may result in the suspension or termination of the research project.

Please contact the Research Compliance Coordinators, at ethics@carleton.ca, if you have any questions or require a clearance certificate with a signature.

CLEARED BY: **Date: July 24, 2017**

Andy Adler, PhD, Chair, CUREB-B

Bernadette Campbell, PhD, Vice-Chair, CUREB-B

A.2 Ethics clearance renewal

Carleton UNIVERSITY
Canada's Capital University

Office of Research Ethics
5110 Human Computer Interaction Bldg | 1125 Colonel By Drive
| Ottawa, Ontario K1S 5B6
613-520-2600 Ext: 4085
ethics@carleton.ca

CERTIFICATION OF INSTITUTIONAL ETHICS CLEARANCE

The Carleton University Research Ethics Board-B (CUREB-B) at Carleton University has renewed ethics clearance for the research project detailed below. CUREB-B is constituted and operates in compliance with the *Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans* (TCPS2).

Title: Investigating student learning in online and face to face contexts [Anna-Lena Theus]

Protocol #: 107077

Principal Investigator: Ms. Anna-Lena Theus

Department and Institution: Faculty of Science\Computer Science (School of), Carleton University

Project Team (and Roles): Ms. Anna-Lena Theus (Primary Investigator)
Dr. Katarzyna (Kasia) Muldner (Research Supervisor)
Bruce Tsuji (Collaborator)

Funding Source (If applicable):

Effective: **July 13, 2018** Expires: **July 31, 2019**.

Please ensure the study clearance number is prominently placed in all recruitment and consent materials: CUREB-B Clearance # 107077.

<u>Restrictions:</u>

This certification is subject to the following conditions:

1. Clearance is granted only for the research and purposes described in the application.

2. Any modification to the approved research must be submitted to CUREB-B. All changes must be approved prior to the continuance of the research.

3. An Annual Application for the renewal of ethics clearance must be submitted and cleared by the above date. Failure to submit the Annual Status Report will result in the closure of the file. If funding is associated, funds will be frozen.

4. A closure request must be sent to CUREB-B when the research is complete or terminated.

5. Should any participant suffer adversely from their participation in the project you are required to report the matter to CUREB-B.

6. It is the responsibility of the student to notify their supervisor of any adverse events, changes to their application, or requests to renew/close the protocol.

7. Failure to conduct the research in accordance with the principles of the *Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans 2nd edition* and the *Carleton University Policies and Procedures for the Ethical Conduct of Research* may result in the suspension or termination of the research project.

Upon reasonable request, it is the policy of CUREB, for cleared protocols, to release the name of the PI, the title of the project, and the date of clearance and any renewal(s).

Please email the Research Compliance Coordinators at ethics@carleton.ca if you have any questions.

CLEARED BY: **Date: July 13, 2018**

Bernadette Campbell, PhD, Chair, CUREB-B

Andy Adler, PhD, Vice-Chair, CUREB-B

Appendix B Questionnaires used in online survey

B.1 MSLQ – Motivation section

1. In a class like this,I prefer course material that challenges me,so I can learn new things.
2. If I study in appropriate ways, then I will be able to learn the material in this course.
3. When I take a test I think about how poorly I am doing compared with other students.
4. I think I will be able to use what I learn in this course in other courses.
5. I believe I will receive an excellent grade in this class.
6. I'm certain I can understand the most difficult material presented in the readings for this course.
7. Getting a good grade in this class is the most satisfying thing for me right now.
8. When I take a test I think about items on other parts of the test I can't answer.
9. It is my own fault if I don't learn the material in this course.
10. It is important for me to learn the course material in this class.
11. The most important thing for me right now is improving my overall grade point average, so my main concern in this class is getting a good grade.
12. I'm confident I can learn the basic concepts taught in this course.
13. If I can, I want to get better grades in this class than most of the other students.
14. When I take tests I think of the consequences of failing.
15. I'm confident I can understand the most complex material presented by the instructor in this class.
16. In a class like this, I prefer course material that arouses my curiosity, even if it is difficult to learn.
17. I am very interested in the content area of this course.
18. If I try hard enough, then I will understand the course material.
19. I have an uneasy, upset feeling when I take an exam.
20. I'm confident I can do an excellent job on the assignments and tests in this course.
21. I expect to do well in this class.
22. The most satisfying thing for me in this course is trying to understand the content as thoroughly as possible.
23. I think the course material in this classis useful for me to learn.
24. When I have the opportunity in this class, I choose course assignments that I can learn from even if they don't guarantee a good grade.
25. If I don't understand the course material, it is because I didn't try hard enough.
26. I like the subject matter of this course.
27. Understanding the subject matter of this course is very important to me.
28. I feel my heart beating fast when I take an exam.
29. I'm certain I can master the skills being taught in this class.

30. I want to do well in this class because itis important to show my ability to my family, friends, employer, or others.
31. Considering the difficulty of the class, the teacher and my skills, I think I will do well in this class.

B.2 MSLQ – Learning strategies section

32. When I study the readings for this course, I outline the material to help me organize my thoughts.
33. During class time I often miss important points because I'm thinking of other things.
34. When I study for this course, I often try to explain the material to classmate or friend.
35. I usually study in a place where I can concentrate on my course work.
36. When reading for this course, I make up questions to help focus my reading.
37. I often feel lazy or bored when I study for this class that I quit before I finish what I planned to do.
38. I often find myself questioning things I hear or read in the class to decide if I find them convincing
39. When I study for this class, I practice saying the material to myself over and over.
40. Even if I have trouble learning the material in this class, I try to do the work on my own, without help from anyone.
41. When I get confused about something I'm reading for this class, I go back and try to figure it out.
42. When I study for this course, I go through the readings and my class notes and try to find the most important ideas.
43. I make good use of my study time for this course.
44. If course readings are difficult to understand, I change the way I read the material.
45. I try to work with other students from this class to complete the course assignments.
46. When studying for this course, I read my class notes and the course readings over and over again.
47. When a theory, interpretation, or conclusion is presented in class or in the readings, I try to decide if there is good supporting evidence.
48. I work hard to do well in this class even if I don't like what we are doing.
49. I make simple charts, diagrams, or tables to help me organize course material.
50. When studying for this course, I often set aside time to discuss course material with a group of students from the class.
51. I treat the course material a: a starting point and try to develop my own ideas about it.
52. I find it hard to stick to a study schedule.
53. When I study for this class, I pull together information from different sources, such as lectures, readings, and discussions.
54. Before I study new course material thoroughly, I often skim it to see how it is organized.
55. I ask myself questions to make sure I understand the material I have been studying in this class.
56. I try to change the way I study to fit the course requirements and the instructor's teaching style.
57. I often find that I have been reading for this class but don't know what it was about.

58. I ask the instructor to clarify concepts I don't understand well.

59. I memorize key words to remind me of important concepts in this class.

60. When course work is difficult, I either give up or only study the easy parts.

61. I try to think through a topic and decide what I am supposed to learn from it rather than just reading it over when studying for this course.

62. I try to relate ideas in this subject to those in other courses whenever possible.

63. When I study for this course, I go over my class notes and make an outline of important concepts.

64. When reading for this class, I try to relate the material to what I already know.

65. I have a regular place set aside for studying.

66. I try to play around with ideas of my own related to what I am learning in this course.

67. When I study for this course, I write brief summaries of the main ideas from the readings and my class notes.

68. When I can't understand the material in this course, I ask another student in this class for help.

69. I try to understand the material in this class by making connections between the reading sand the concepts from the lectures.

70. I make sure that I keep up with the weekly readings and assignments for this course.

71. Whenever I read or hear an assertion or conclusion in this class, I think about possible alternatives.

72. I make lists of important items for this course and memorize the lists.

73. I attend this class regularly.

74. Even when course materials are dull and uninteresting, I manage to keep working until I finish.

75. I try to identify students in this class whom I can ask for help if necessary.

76. When I study for this course I try to determine which concept I don't understand well.

77. I often find that I don't spend very much time on this course because of other activities.

78. When I study for this class, I set goals for myself to direct my activities in each study period.

79. If I get confused taking notes in class, I make sure I sort it out afterwards.

80. I rarely find time to review my notes or readings before an exam.

81. I try to apply ideas from course readings in other class activities such as lecture and discussion.

B.3 Online Learning Self-Efficacy Scale

1. Navigate online course materials efficiently
2. Find the course syllabus online
3. Communicate effectively with my instructor via e-mail
4. Communicate effectively with technical support via e-mail, telephone, live online chat
5. Submit assignments to an online drop box
6. Overcome technical difficulties on my own
7. Navigate the online grade book

8. Manage time effectively
9. Complete all assignments on time
10. Learn to use a new type of technology efficiently
11. Learn without being in the same room as the instructor
12. Learn without being in the same room as other students
13. Search the Internet to find the answer to a course-related question
14. Search the online course materials
15. Communicate using asynchronous technologies (e.g., discussion boards, e-mail)
16. Meet deadlines with very few reminders
17. Complete a group project entirely online
18. Use synchronous technology to communicate with others (such as Skype)
19. Focus on schoolwork when faced with distractions
20. Develop and follow a plan for completing all required work on time
21. Use the library's online resources efficiently
22. When a problem arises, I promptly ask questions in the appropriate forum (e.g., discussion boards, e-mail)

B.4 Implicit Theories of Intelligence Scale

1. You have a certain amount of intelligence, and you can't really do much to change it*
2. Your intelligence is something about you that you can't change very much*
3. To be honest, you can't really change how intelligent you are*
4. No matter who you are, you can significantly change your intelligence level
5. No matter how much intelligence you have, you can always change it quite a bit
6. You can change even your basic intelligence level considerably

* entity items

Appendix C Cronbach's alpha values for all construct scales

Variable	Cronbach's alpha classroom sample	Cronbach's alpha online sample
1. M: Intrinsic Goal Orientation	0.71	0.72
2. M: Extrinsic Goal Orientation	0.67	0.73
3. M: Task Value	0.88	0.89
4. M: Control of Learning Beliefs	0.71	0.78
5. M: Self-Efficacy for Learning & Performance	0.92	-
6. M: Test Anxiety	0.80	0.79
7. SRL: Rehersal	0.66	0.75
8. SRL: Elaboration	0.82	0.85
9. SRL: Organization	0.66	0.78
10. SRL: Critical Thinking	0.82	0.83
11. SRL: Metacognitive Self-Regulation	0.78	0.80
12. SRL: Time & Study Environment	0.77	0.72
13. SRL: Effort Regulation	0.69	0.58
14. SRL: Peer Learning	0.76	0.80
15. SRL: Help Seeking	0.58	0.69
16. OLSE: Learning in Online Environment	-	0.88
17. OLSE: Time Management	-	0.86
18. OLSE: Technology Use	-	0.90
19. Self-Theory of Intelligence	0.86	0.80

Appendix D Online consent form

Online Consent

Title: Investigating student learning in online and face to face contexts
Funding Source: Funding is pending
Date of ethics clearance: July 24, 2017
Ethics Clearance for the Collection of Data Expires: July 31, 2018

This study investigates factors influencing how students learn in various contexts, including face to face and online classes. One of the goals is to build predictive models that can identify when students are facing difficulty. The researcher for this study is Anna-Lena Theus in the School of Computer Science. She is working under the supervision of Dr. Kasia Muldner in the Institute of Cognitive Science.

This study involves an approximately 30-45 minute online survey that will ask you to self report on some personality-related traits, such as the goals you set in school settings. Participating in this research means also agreeing to let researchers analyze your Introduction to Psychology class-related data (e.g., your cuLearn interactions, grade). All of the data will be anonymized, meaning your name will be removed from all the data and so will NOT appear anywhere. Participation is completely voluntary. Participation will not affect personal or professional relationships in any way. The course instructor won't have information on who consented to have their data analyzed – once final grades are posted, they will have access to only the anonimized data and/or results.

You have the right to end your participation in the survey at any time, for any reason. You can withdraw from the survey by closing the browser window with the survey at any time before completing it. If you close the survey before it is completed, you will not receive the extra course credit. If you wish to withdraw after you complete the survey, you may do so anytime during the present term by mailing the lead researcher Theus. If you withdraw from the study, the information you provided will be destroyed.

The ethics protocol for this project was reviewed by the Carleton University Research Ethics Board, which provided clearance to carry out the research (CUREB-B Clearance #107077). If you have any ethical concerns with the study, please contact Dr. Andy Adler, Chair, Carleton University Research Ethics Board-B (by phone at 613-520-2600 ext. 4085 or via email at ethics@carleton.ca).

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Appendix E Classroom setting: Results of correlation analysis

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.
1. Grade	-																
2. M: Intrinsic Goal Orientation	.16**	-															
3. M: Extrinsic Goal Orientation	.14**	.27***	-														
4. M: Task Value	.26***	.65***	.42***	-													
5. M: Control of Learning Beliefs	.25***	.41***	.43***	.55***	-												
6. M: Self-Efficacy for L+P	.33***	.61***	.37***	.57***	.50***	-											
7. M: Test Anxiety	-.09	.02	.38***	.15**	.11	-.14*	-										
8. SRL: Rehersal	.13	.28***	.33***	.39***	.23***	.31***	.18***	-									
9. SRL: Elaboration	.22***	.53***	.29***	.56***	.96***	.53***	.07	.59***	-								
10. SRL: Organization	.17***	.44***	.36***	.48***	.32***	.44***	.13	.63***	.67***	-							
11. SRL: Critical Thinking	.01	.51***	.18***	.29***	.15**	.39***	.07	.37***	.55***	.43***	-						
12. SRL: Metacognitive SR	.20***	.53***	.28***	.48***	.31***	.53***	-.03	.57***	.73***	.61***	.64***	-					
13. SRL: T+ S Environment	.30***	.31***	.21***	.44***	.26***	.43***	-.11	.38***	.47***	.49***	.19***	.51***	-				
14. SRL: Effort Regulation	.36***	.33***	.21***	.48***	.30***	.47***	-.18***	.32***	.44***	.35***	.11	.48***	.69***	-			
15. SRL: Peer Learning	-.08	.22***	.11	.07	-.04	.13*	.12	.29***	.27***	.33***	.45***	.36***	.05	-.09	-		
16. SRL: Help Seeking	-.01	.18**	.02	.05	-.08	.12	.02	.14*	.22***	.21***	.34***	.30***	.13	.03	.62***	-	
17. Self-theory of Intelligence	.09	.17***	.08	.22***	.30***	.21***	.01	.09	.14*	.15**	.03	.12	.20***	.21***	-.03	.01	-

Signif. codes: * = p<.05, ** = p<.01, *** = p<.001

Appendix F Online setting: Results of correlation analysis

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.	17.	18.	19.	20
1. Grade	-																			
2. M: Intrinsic Goal Orientation	-.02	-																		
3. M: Extrinsic Goal Orientation	.003	.39***	-																	
4. M: Task Value	-.03	.71***	.51***	-																
5. M: Control of Learning Beliefs	.06	.49***	.44***	.61***	-															
6. M: Self-Efficacy for L+P	.10	.59***	.50***	.59***	.63***	-														
7. M: Test Anxiety	-.05	.21***	.45***	.31***	.24***	.06	-													
8. SRL: Rehersal	-.02	.53***	.44***	.53***	.39***	.48***	.29***	-												
9. SRL: Elaboration	.04	.62***	.42***	.63***	.49***	.54***	.26***	.66***	-											
10. SRL: Organization	-.04	.57***	.45***	.58***	.44***	.49***	.28***	.74***	.73***	-										
11. SRL: Critical Thinking	.01	.63***	.35***	.47***	.31***	.49***	.21***	.55***	.71***	.58***	-									
12. SRL: Metacognitive SR	.06	.62***	.38***	.57***	.46***	.56***	.15**	.67***	.78***	.71***	.71***	-								
13. SRL: T+ S Environment	.11	.30***	.20***	.34***	.30***	.36***	.01	.40***	.41***	.42***	.24***	.51***	-							
14. SRL: Effort Regulation	.12	.27***	17***	.37***	.38***	.41***	-.12*	.31***	.37***	.34***	.16**	.45***	.63***	-						
15. SRL: Peer Learning	.03	.32***	.22***	.15**	-.05	.26***	.11	.38***	.34***	.34***	.53***	.37***	.02	-.17**	-					
16. SRL: Help Seeking	.06	.20**	.17***	.04	-.15**	.16***	.03	.24***	.22***	.21***	.41***	.24***	.02	-.11	.72***	-				
17. OLSE: Learning in OE	.09	.41***	.29***	.39***	.46***	.57***	.07	.39***	.47***	.44***	.33***	.48***	.36***	.36***	.18***	.14*	-			
18. OLSE: Time Management	.13*	.41***	.25***	.31***	.29***	.48***	.02	.38***	.41***	.43***	.34***	.49***	.56***	.46***	.19***	.16**	.72***	-		
19. OLSE: Technology Use	.10	.25***	.32***	.37***	.55***	.46***	.15**	.30***	.33***	.32***	.13*	.30***	.31***	.37***	-.10	-.13*	.76***	.55***	-	
20. Self-theory of Intelligence	.01	.12	.10	.18***	.28***	.20***	-.04	.07	.08	.08	-.03	.10	.20***	.29***	-.21***	-.17*	.21***	.14**	.28***	-

Signif. codes: * = p<.05, ** = p<.01, *** = p<.001

Appendix G Outliers analysis and assumption checking

G.1 Classroom setting: Full model

Outliers in the context of the present analysis would have large residuals. To define a cut-off point for what constitutes a large residual, standardized residuals are used (i.e., residuals divided by their standard deviation estimate) (Field, Miles, & Field, 2012). Standardized residuals with an absolute value greater than +-3.29 are a cause for concern because in an average sample a value this high is unlikely to happen by chance. Moreover, if more than 1% of the sample cases have standardized residuals with a value greater than +-2.5, there is evidence that the level of error within the model is unacceptable (i.e., the model is a poor fit for the sample data). Lastly, if more than 5% of cases have standardized residual values greater than +-1.96, there is also evidence that the model is a poor representation of the actual data. Given the size of the classroom sample ($N = 707$), 1% corresponds to a total of seven cases, whereas 5% corresponds to 35 cases.

The outlier analysis revealed one case with a standardized residual value greater than +-3.29, four cases with standardized residual values outside the +-2.5 threshold, as well as 33 cases with standardized residual values outside the +-1.96 threshold. Overall, less than 5% of cases lie outside the threshold of +-1.96, which indicates that our model is a good representation of the actual data. Nevertheless, to ensure none of these cases have an undue influence on the model, Cook's distance (or Cook's D_i) was calculated.

Cook's D_i measures the influence of the i^{th} observation on a regression model. A large D_i indicates an observation that has more than the average influence on the estimation of the parameters (Scanlon, 1994). There is no formal definition which value can be considered as a "large D_i". However, Cook and Weisberg (1982) suggested that values greater than 1 are a cause for concern. Overall, none of the 707 cases of the classroom sample had a Cook's D-value greater than 1. Thus, none of the data points in question had a Cook's D-value greater 1 and therefore did not have undue influence on the model.

We verified that the assumptions of the regression were met. To check the multicollinearity assumption, the variance of inflation factor (VIF) was used. For all predictor variables the VIF values were considerably smaller than 10 and the tolerance values were not below 0.2, which would indicate potential problems. The average VIF value was not substantially greater than 1, which suggests that the regression was not biased. Furthermore, the result of the Durbin-Watson test indicated that the assumption of independent errors had been met (d = 1.90, p = .19).

To assess the assumptions of homoscedasticity, linearity, and normally distributed errors, two plots were generated. Figure 1 shows the residuals plotted against the predicted outcome values (i.e., grade). The pattern indicates that the assumptions of homoscedasticity and linearity have been met, because the data points are evenly dispensed around zero (Field et al., 2012). Figure 2 shows a Q-Q plot that represents the errors' potential deviation from normality. The pattern indicates that the assumption of normally distributed errors has been met, because the data points lie on or close to the dotted line, which represents a normal distribution (Field et al., 2012).

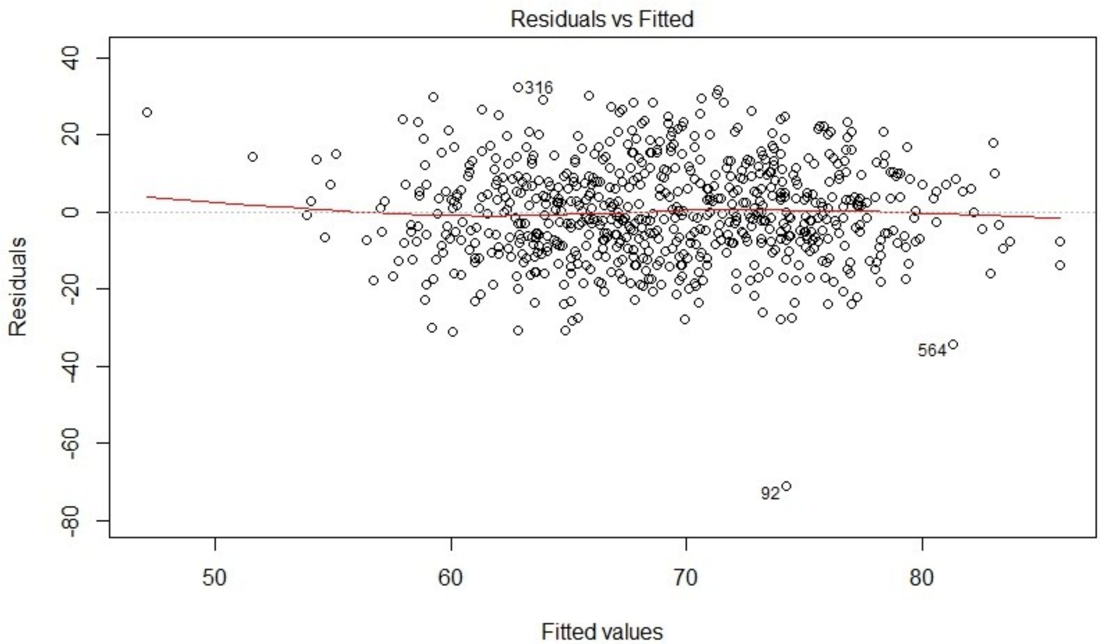

Figure 1. Residuals plotted against the predicted outcome values (i.e., grade)

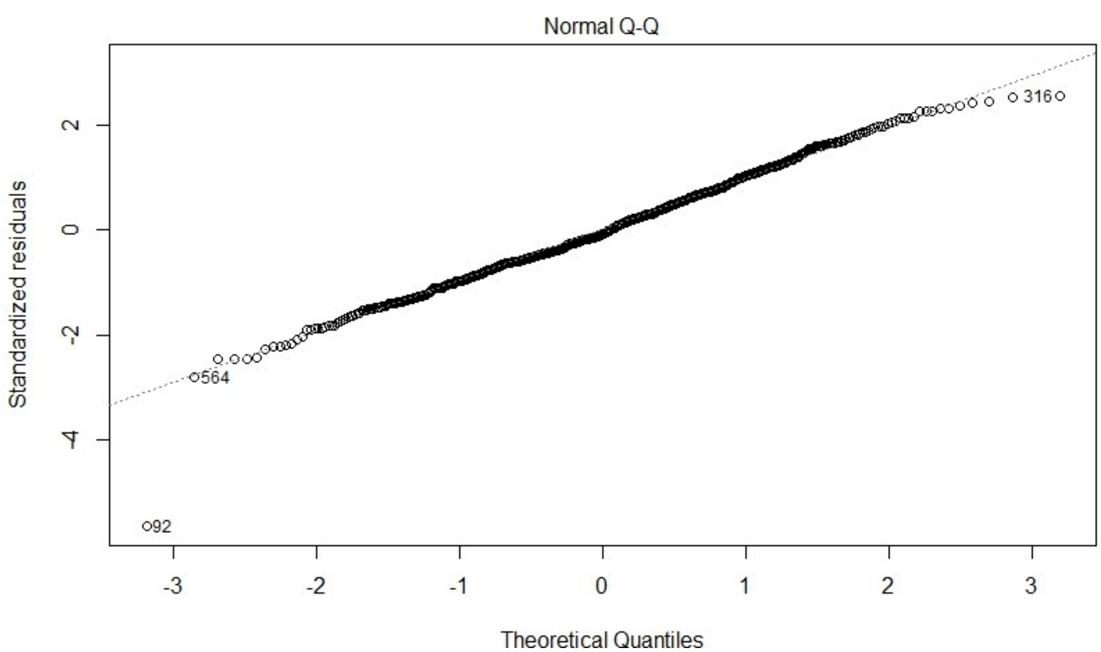

Figure 2. Error distribution

G.2 Classroom setting: Detailed model

The outlier analysis revealed one case with a standardized residual value greater than +-3.29, five cases with standardized residual values outside the +-2.5 threshold, as well as 37 cases with standardized residuals outside the +-1.96 threshold. In summary, approximately 5% of cases lie outside the threshold of +-1.96, which indicates that the model still is a good representation of the data. In addition, none of the 707 cases of the classroom sample did have a Cook's D-value greater than 1. Thus, none of the data points in question had a Cook's D-value greater 1 and therefore did not have more than the average influence on the model.

We verified that the assumptions of the regression were met. For all predictor variables the VIF values were considerably smaller than 10, the tolerance values were not below 0.2, and the average VIF value was not substantially greater than 1, indicating that the no-multicollinearity assumption had been met. The result of the Durbin-Watson test indicated that the assumption of independent errors had been met (d = 1.92, p = .30).

To assess the assumptions of homoscedasticity, linearity, and normally distributed errors two plots were generated. The pattern of the first plot (Figure 3) indicates that the assumptions of homoscedasticity and linearity have been met, because the data points are evenly dispensed around zero. The pattern of the Q-Q plot (Figure 4) indicates that the assumption of normally distributed errors has been met, because the data points lie on or close to the dotted line, which represents a normal distribution (Field et al., 2012).

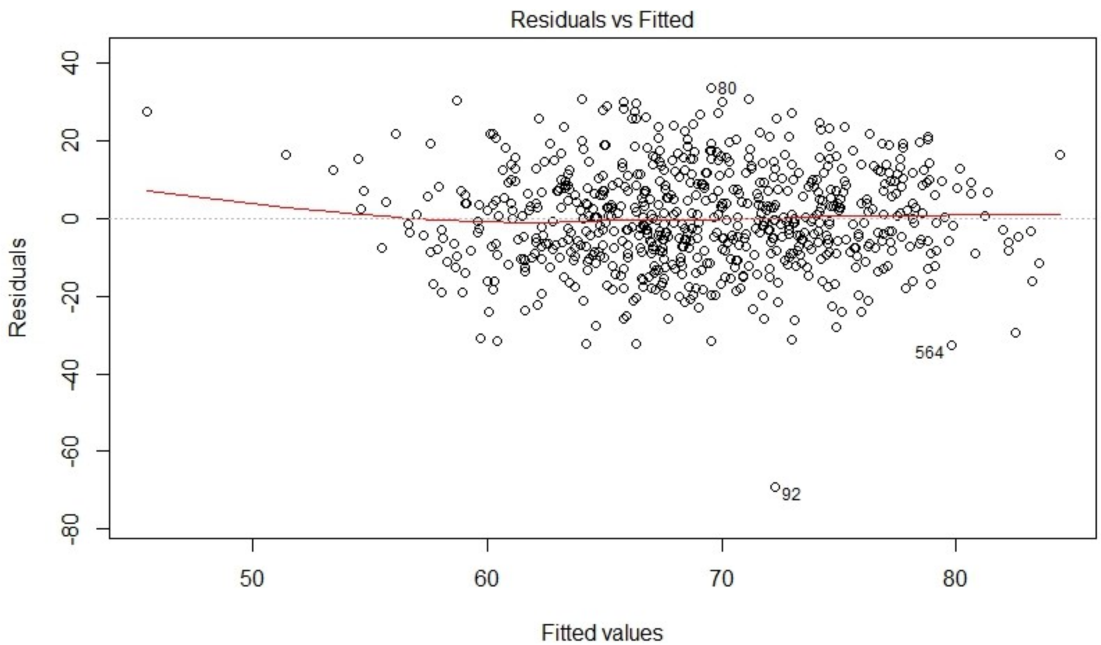

Figure 3. Residuals plotted against the predicted outcome values (i.e., grade)

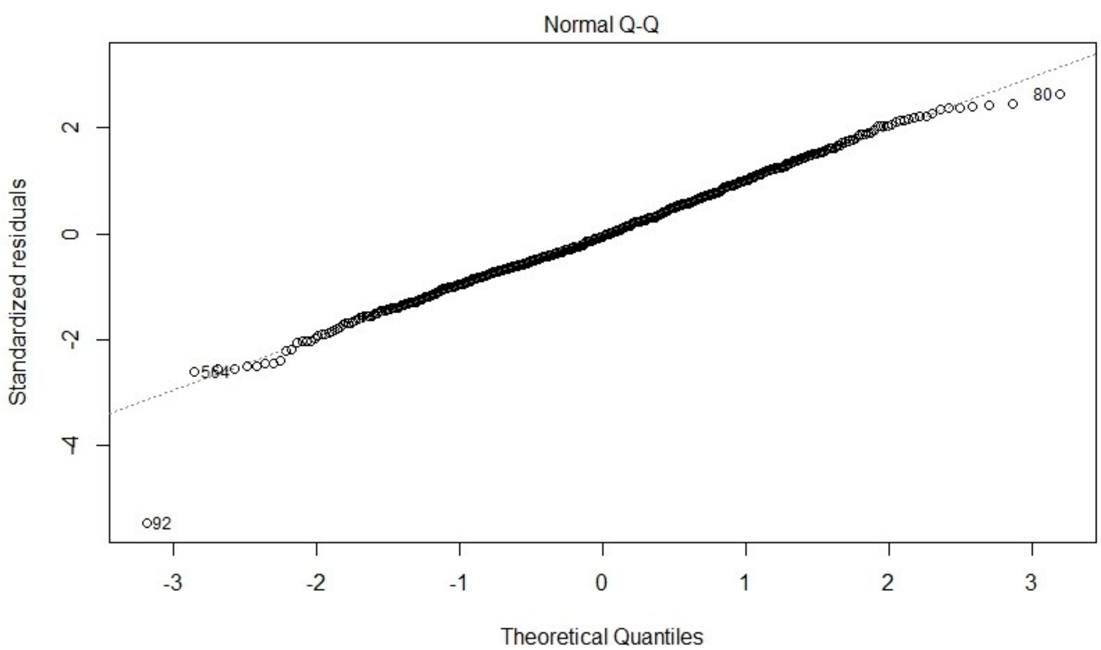

Figure 4. Error distribution

G.3 Online setting: Full model

Given the size of the online sample (N = 746), 1% corresponds to a total of eight cases, whereas 5% corresponds to 37 cases. The outlier analysis revealed a total number of 17 cases with a standardized residual value greater than +-3.29, 30 cases with standardized residual values outside the +-2.5 threshold, as well as 36 cases with standardized residual values outside the +-1.96 threshold. In general, almost 5% of cases lie outside the threshold of +-1.96, which indicates that the model may still be a good representation of the actual data. However, 17 cases have standardized residual values greater than +-3.29, which is a cause for concern. None of the 746 cases of the online sample did have a Cook's D-value greater than 1. Thus, none of the data points in question had a Cook's D-value greater 1 and therefore did not have more than the average influence on the model.

We verified that the assumptions of the regression were met. For all predictor variables in the VIF values were considerably smaller than 10, the tolerance values were not below 0.2, and the average VIF value was not substantially greater than 1, indicating that the no-multicollinearity assumption had been met. The result of the Durbin-Watson test indicated that the assumption of independent errors had been met (d = 1.88, p = .11).

To assess the assumptions of homoscedasticity, linearity, and normally distributed errors two plots were generated. The pattern of the first plot (Figure 5) shows that the assumptions of homoscedasticity and linearity have been met, because the data points are evenly dispensed around zero. The pattern of the second plot (Figure 6) indicates that the assumption of normally distributed errors has been violated, because at one of the extremes the data points are very distant from the dotted line, which represents a normal distribution (Field et al., 2012). However, the central limit theorem states that the sampling distribution of the mean for any population, given an adequate sample size, will approximate a standard normal distribution. The given sample size ($N = 746$) is adequately large, which allows the reasonable assumption that the sample means are normally distributed.

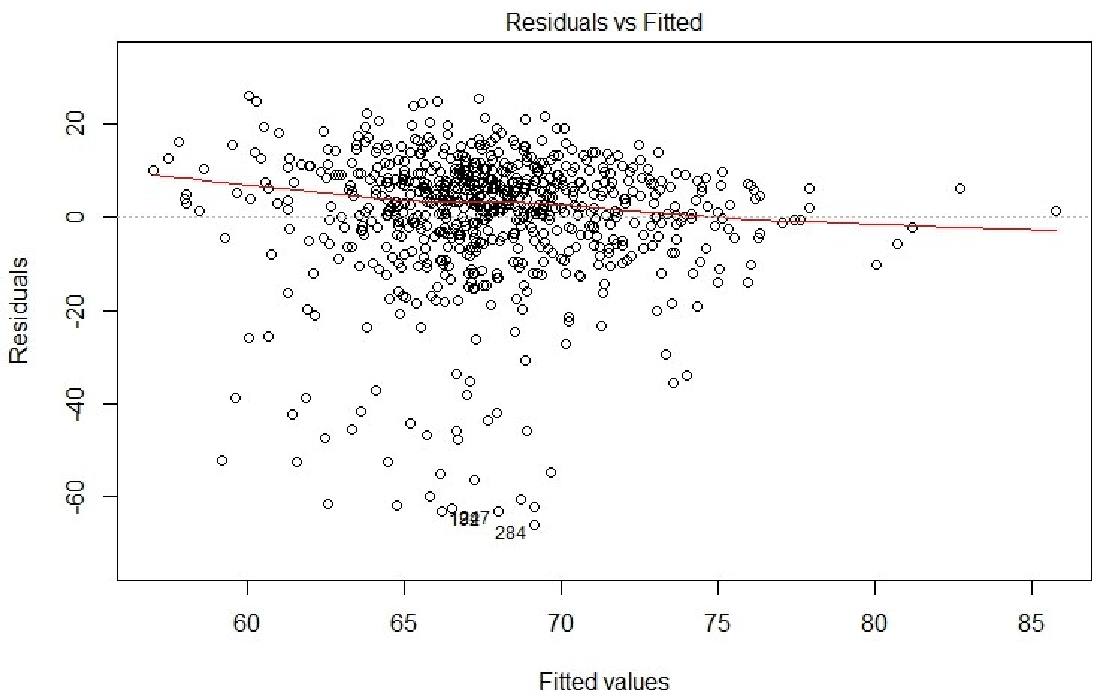

Figure 5. Residuals plotted against the predicted outcome values (i.e., grade)

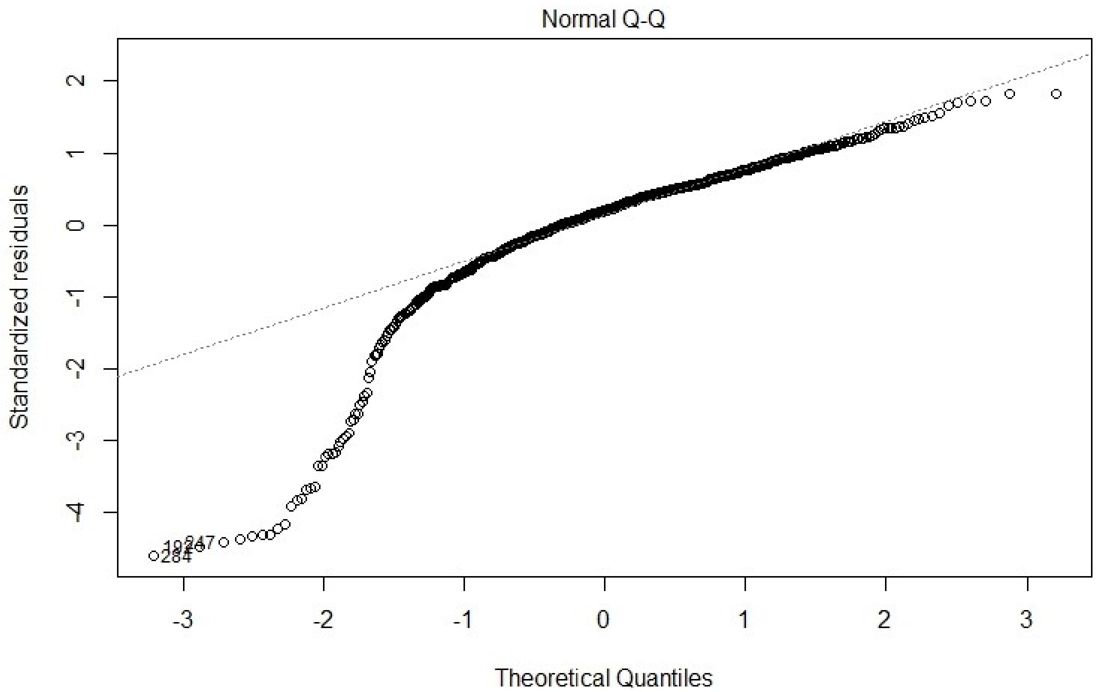

Figure 6. Error distribution

G.4 Online setting: Detailed model

The outlier analysis revealed a total number of 19 cases with a standardized residual value greater than +-3.29, 31 cases with standardized residual values outside the +-2.5 threshold, as well as 37 cases with standardized residual values outside the +-1.96 threshold. In general, 5% of cases lie outside the threshold of +-1.96, which indicates that the model may still be a good representation of the actual data. 19 cases had standardized residual values greater than +-3.29, which is a cause for concern. However, none of the 746 cases of the online sample did have a Cook's D-value greater than 1. Thus, none of the data points in question had a Cook's D-value greater 1 and therefore did not have more than the average influence on the model.

We verified that the assumptions of the regression were met. For all predictor variables in the VIF values were considerably smaller than 10, the tolerance values were not below 0.2, and the average VIF value was not substantially greater than 1, indicating that the no-multicollinearity assumption had been met. The result of the Durbin-Watson test indicated that the assumption of independent errors had been met (d = 1.86, p = .06).

To assess the assumptions of homoscedasticity, linearity, and normally distributed errors two plots were generated. The pattern of the first plot (Figure 7) indicates that the assumptions of homoscedasticity and linearity have been met, because the data points are evenly dispensed around zero. The second plot pictures the deviation from normality (Figure 8). The pattern indicates that the assumption of normally distributed errors has been violated, because at one of the extremes the data points are very distant from the dotted line, which represents a normal distribution (Field et al., 2012). Considering the central limit theorem, the given sample size (N = 746) is adequately large, which allows the reasonable assumption that the sample means are still normally distributed.

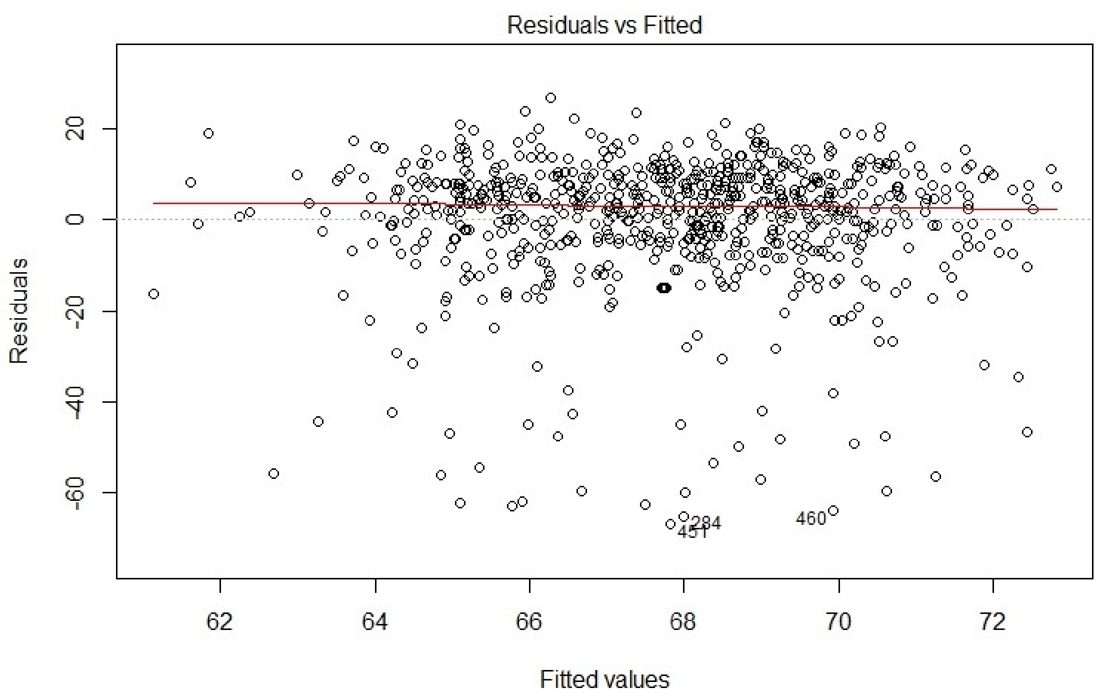

Figure 7. Residuals plotted against the predicted outcome values (i.e., grade)

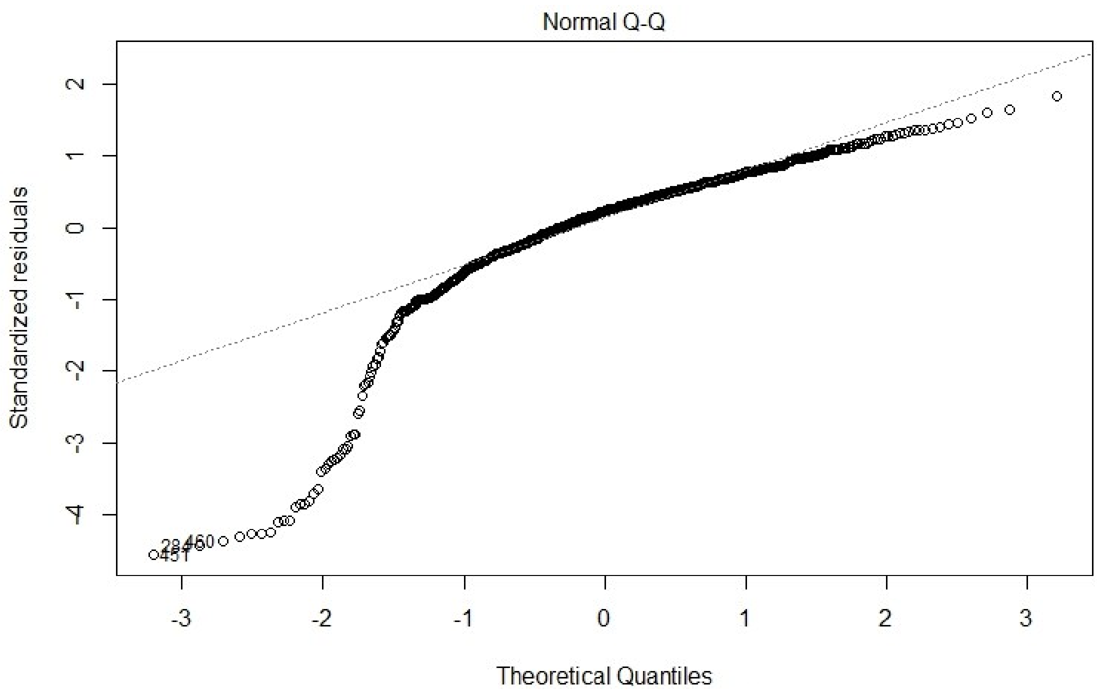

Figure 8. Error distribution

G.5 Classroom setting: Detailed model Instructor A

Given the size of the Instructor A's classroom sample (*N* = 557), 1% corresponds to a total of six cases, whereas 5% corresponds to 28 cases. The outlier analysis revealed one case with a standardized residual value greater than +-3.29, three cases with standardized residual values outside the +-2.5 threshold, as well as 25 cases with standardized residuals outside the +-1.96 threshold. In summary, less than 5% of cases lie outside the threshold of +-1.96, which indicates that the model is a good representation of the actual data. In addition, none of the 557 cases and therefore none of the data points in question had a Cook's D-value greater 1 and therefore did not have more than the average influence on the model.

We verified that the assumptions of the regression were met. For all predictor variables the VIF values were considerably smaller than 10, the tolerance values were not below 0.2, and the average VIF value was not substantially greater than 1, indicating that the no-multicollinearity assumption had been met. The result of the Durbin-Watson test indicated that the assumption of independent errors had been met (d = 1.95, p = .57).

To assess the assumptions of homoscedasticity, linearity, and normally distributed errors two plots were generated. The pattern of the first plot (Figure 9) indicates that the assumptions of homoscedasticity and linearity have been met, because the data points are evenly dispensed around zero. The pattern of the Q-Q plot (Figure 10) indicates that the assumption of normally distributed errors has been met, because the data points lie on or close to the dotted line, which represents a normal distribution (Field et al., 2012).

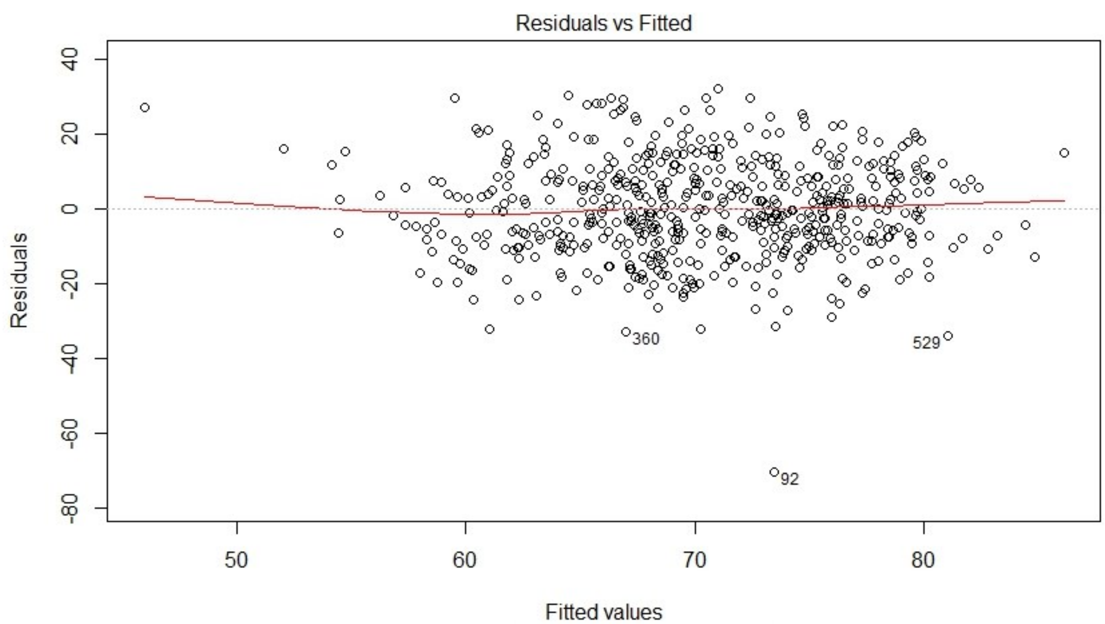

Figure 9. Residuals plotted against the predicted outcome values (i.e., grade)

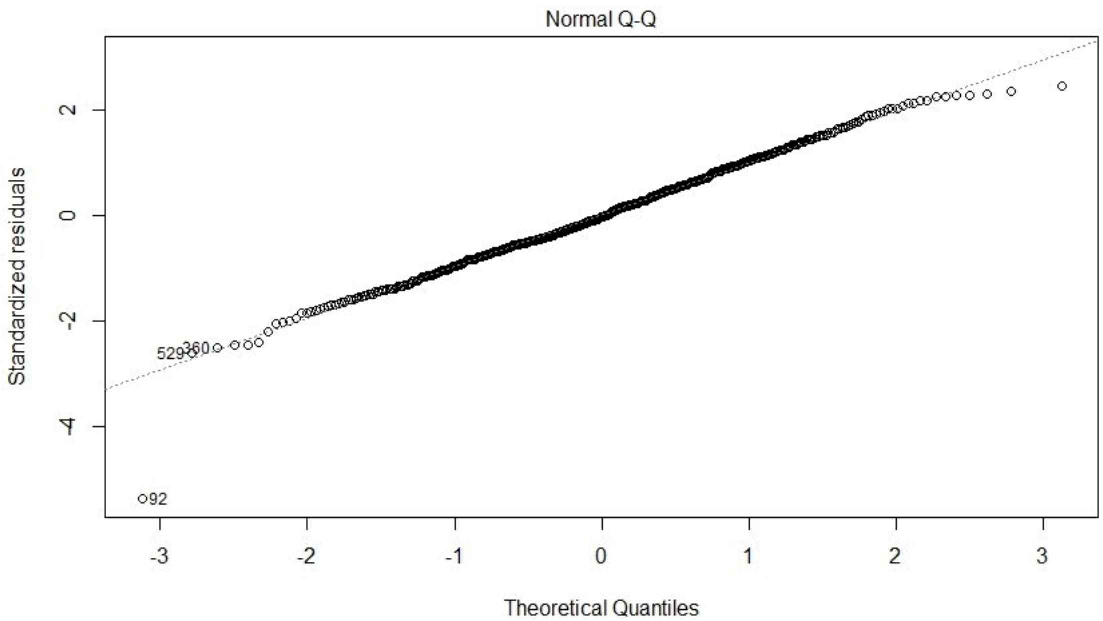

Figure 10. Error distribution

G.6 Classroom setting: Detailed model Instructor B

Given the size of Instructor B's classroom sample ($N = 150$), 1% corresponds to a total of two cases, whereas 5% corresponds to eight cases. The outlier analysis revealed no cases with a standardized residual value greater than +-3.29, two cases with standardized residual values outside the +-2.5 threshold, as well as 12 cases with standardized residuals outside the +-1.96 threshold. In summary, more than 5% of cases lie outside the threshold of +-1.96, which indicates that the model may not be a good representation of the actual data. None of the 150 cases of the classroom sample had a Cook's D-value greater than 1. Thus, none of the data points in question had a Cook's D-value greater 1 and therefore did not have more than the average influence on the model.

We verified that the assumptions of the regression were met. For all predictor variables the VIF values were considerably smaller than 10, the tolerance values were not below 0.2, and the average VIF value was not substantially greater than 1, indicating that the no-multicollinearity assumption had been met. The result of the Durbin-Watson test indicated that the assumption of independent errors had been met (d = 1.88, p = .43).

To assess the assumptions of homoscedasticity, linearity, and normally distributed errors two plots were generated. The pattern of the first plot (Figure 11) indicates that the assumptions of homoscedasticity and linearity have been met, because the data points are evenly dispensed around zero. The pattern of the Q-Q plot (Figure 12) indicates that the assumption of normally distributed errors has been met, because the data points lie on or close to the dotted line, which represents a normal distribution (Field et al., 2012).

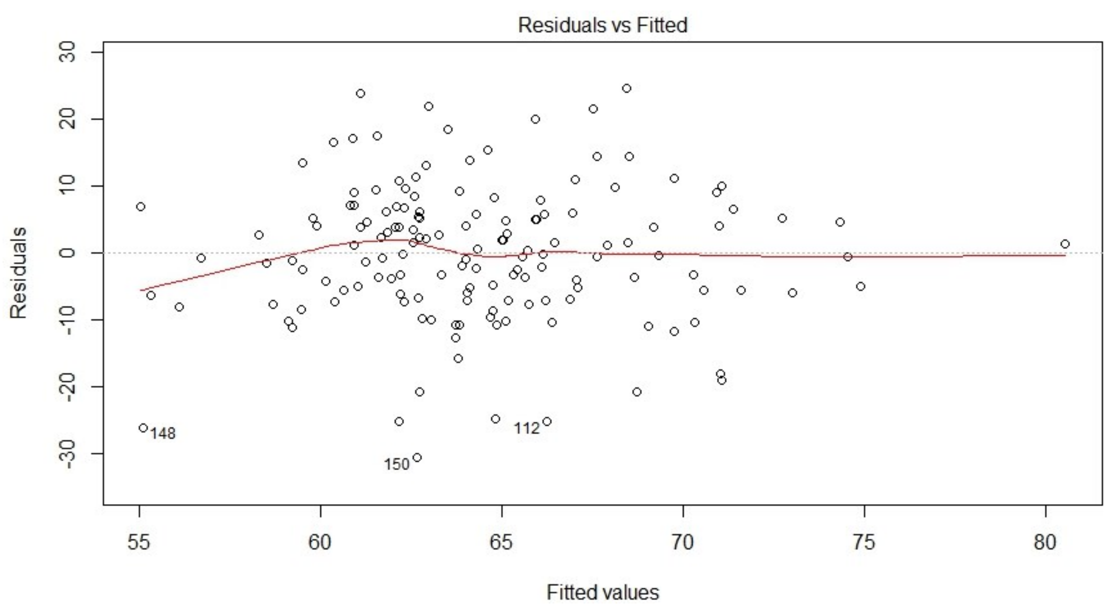

Figure 11. Residuals plotted against the predicted outcome values (i.e., grade)

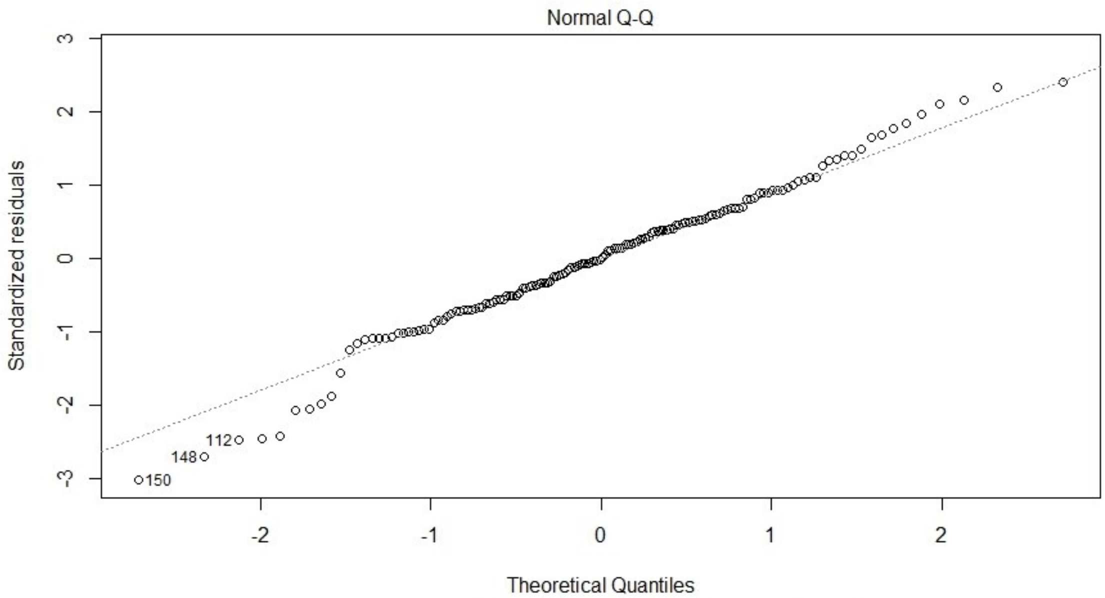

Figure 12. Error distribution

References

Alstete, J. W., & Beutell, N. J. (2004). Performance indicators in online distance learning courses: a study of management education. *Quality Assurance in Education*, *12*(1), 6-14.

Aron, A., & Aron, E. N. (1994). *Statistics for psychology.* Upper Saddle River, NJ: Prentice-Hall.

Aronson, J., Fried, C. B., & Good, C. (2002). Reducing the effects of stereotype threat on African American college students by shaping theories of intelligence. *Journal of Experimental Social Psychology*, *38*(2), 113–125.

Artino Jr, A. R., & Stephens, J. M. (2009). Academic motivation and self-regulation: A comparative analysis of undergraduate and graduate students learning online. *The Internet and Higher Education*, *12*(3–4), 146–151.

Bae, Y. (2014). *The relationships among motivation, self-regulated learning, and academic achievement*. Doctoral dissertation, Texas A & M University.

Bandalos, D. L., Finney, S. J., & Geske, J. A. (2003). A model of statistics performance based on achievement goal theory. *Journal of Educational Psychology*, *95*(3), 604-616.

Bandura, A. (1997). *Self-Efficacy: The Exercise of Control*. Worth Publishers.

Bandura, A. (2007). Much ado over a faulty conception of perceived self--efficacy grounded in faulty experimentation. *Journal of Social and Clinical Psychology*, *26*(6), 641–658.

Basila, C. L. (2016). *Academic performance in college online courses: The role of self-regulated learning, motivation and academic self-efficacy*. Doctoral dissertation, State University of New York at Albany.

Beaudoin, M. F. (2002). Learning or lurking?: Tracking the “invisible” online student. *The Internet and Higher Education*, *5*(2), 147–155.

Bell, P. D., & Akroyd, D. (2006). Can factors related to self-regulated learning predict learning achievement in undergraduate asynchronous Web-based courses. *International Journal of Instructional Technology and Distance Learning*, *3*(10), 5-16.

Blackwell, L. S., Trzesniewski, K. H., & Dweck, C. S. (2007). Implicit theories of intelligence predict achievement across an adolescent transition: A longitudinal study and an intervention. *Child Development*, *78*(1), 246–263.

Bode, S. K., & Gates, G. E. (2001). Correlates of success on the registered dietetic technician credentialing examination. *Journal of the Academy of Nutrition and Dietetics*, *101*(12), 1473-1474.

Broadbent, J., & Poon, W. L. (2015). Self-regulated learning strategies & academic achievement in online higher education learning environments: A systematic review. *The Internet and Higher Education*, *27*, 1–13.

Cassady, J. C., & Johnson, R. E. (2002). Cognitive test anxiety and academic performance. *Contemporary Educational Psychology*, *27*(2), 270–295.

Chapell, M. S., Blanding, Z. B., Silverstein, M. E., Takahashi, M., Newman, B., Gubi, A., & McCann, N. (2005). Test anxiety and academic performance in undergraduate and graduate students. *Journal of Educational Psychology*, *97*(2), 268-274.

Chen, C. S. (2002). Self-regulated learning strategies and regulated learning strategies and achievement in an introduction to information systems course. *Information Technology, Learning, and Performance Journal*, *20*(1), 11–25.

Chen, J. A., & Pajares, F. (2010). Implicit theories of ability of Grade 6 science students: Relation to epistemological beliefs and academic motivation and achievement in science. *Contemporary Educational Psychology*, *35*(1), 75–87.

Cheung, L. L. W., & Kan, A. C. N. (2002). Evaluation of factors related to student performance in a distance-learning business communication course. *Journal of Education for Business*, *77*(5), 257–263.

Cho, M.-H., & Heron, M. L. (2015). Self-regulated learning: the role of motivation, emotion, and use of learning strategies in students' learning experiences in a self-paced online mathematics course. *Distance Education*, *36*(1), 80–99.

Cho, M.-H., & Shen, D. (2013). Self-regulation in online learning. *Distance Education*, *34*(3), 290–301.

Cho, M.-H., & Summers, J. (2012). Factor validity of the Motivated Strategies for Learning Questionnaire (MSLQ) in asynchronous online learning environments. *Journal of Interactive Learning Research*, *23*(1), 5–28.

Cohen, B. H. (2008). *Explaining psychological statistics*. John Wiley & Sons.

Cohen, J., Cohen, P., West, S. G., Aiken, L. S., & others. (1983). *Applied multiple regression/correlation analysis for the behavioral sciences*. Hillsdale, NJ: Lawrence Erlbaum

Coldwell, J., Craig, A., Paterson, T., & Mustard, J. (2008). Online students: Relationships between participation, demographics and academic performance. *Electronic Journal of E-Learning*, *6*(1), 19–30.

Colorado, J. T., & Eberle, J. (2010). Student demographics and success in online learning environments. *Emporia State Research Studies*, *46*(1), 4–10.

Cook, R. D., & Weisberg, S. (1982). *Residuals and influence in regression*. New York: Chapman and Hall.

Costa, A., & Faria, L. (2018). Implicit theories of intelligence and academic achievement: A meta-analytic review. *Frontiers in Psychology*, *9*. doi: 10.3389/fpsyg.2018.00829

Dabbagh, N., & Kitsantas, A. (2004). Supporting self-regulation in student-centered web-based learning environments. *International Journal on E-Learning*, *3*(1), 40–47.

De Castella, K., & Byrne, D. (2015). My intelligence may be more malleable than yours: The revised implicit theories of intelligence (self-theory) scale is a better predictor of achievement, motivation, and student disengagement. *European Journal of Psychology of Education*, *30*(3), 245–267.

Dignath, C., & Büttner, G. (2008). Components of fostering self-regulated learning among students. A meta-analysis on intervention studies at primary and secondary school level. *Metacognition and Learning*, *3*(3), 231–264.

Dweck, C. S. (1986). Motivational processes affecting learning. *American Psychologist*, *41*(10), 1040-1048.

Dweck, C. S. (1999). *Self-theories: Their role in motivation, personality, and development*. Philadelphia, PA: Psychology Press.

Dweck, C. S., & Elliott, E. S. (1983). Achievement motivation. *Handbook of Child Psychology*, *4*, 643–691.

Dweck, C. S., & Leggett, E. L. (1988). A social-cognitive approach to motivation and personality. *Psychological Review*, *95*(2), 256-273.

Dweck, C. S., & Master, A. (2008). Self-theories motivate self-regulated learning. In D.H. Schunk & B.J. Zimmerman (Eds.), *Motivation and Self-Regulated Learning: Theory, Research, and Applications*, 31–51. New York: Taylor & Francis.

Elliot, A. J., & Church, M. A. (1997). A hierarchical model of approach and avoidance achievement motivation. *Journal of Personality and Social Psychology*, *72*(1), 218-232.

Elliot, A. J., McGregor, H. A., & Gable, S. (1999). Achievement goals, study strategies, and exam performance: A mediational analysis. *Journal of Educational Psychology*, *91*(3), 549-563.

Elliott, E. S., & Dweck, C. S. (1988). Goals: An approach to motivation and achievement. *Journal of Personality and Social Psychology*, *54*(1), 5-12.

Field, A. P., Miles, J., & Field, Z. (2012). *Discovering statistics using R*. London;Thousand Oaks, Calif;: Sage.

Garcia, T., & Pintrich, P. R. (1996). Assessing students' motivation and learning strategies in the classroom context: The Motivated Strategies for Learning Questionnaire. In *Alternatives in assessment of achievements, learning processes and prior knowledge*, 319–339. Springer.

George, D., & Mallery, P. (2016). *IBM SPSS statistics 23 step by step: A simple guide and reference*. New York: Routledge.

Giancarlo, C. A., & Facione, P. A. (2001). A look across four years at the disposition toward critical thinking among undergraduate students. *The Journal of General Education, 50*(1), 29-55.

Gonida, E., Kiosseoglou, G., & Leondari, A. (2006). Implicit theories of intelligence, perceived academic competence, and school achievement: Testing alternative models. *The American Journal of Psychology*, *119*(2), 223-238.

Grant, H., & Dweck, C. S. (2003). Clarifying achievement goals and their impact. *Journal of Personality and Social Psychology*, *85*(3), 541-553.

Greene, B. A., & Miller, R. B. (1996). Influences on achievement: Goals, perceived ability, and cognitive engagement. *Contemporary Educational Psychology*, *21*(2), 181–192.

Handelsman, M. M., Briggs, W. L., Sullivan, N., & Towler, A. (2005). A measure of college student course engagement. *The Journal of Educational Research*, *98*(3), 184–192.

Hara, N., Bonk, C. J., & Angeli, C. (2000). Content analysis of online discussion in an applied educational psychology course. *Instructional Science*, *28*(2), 115–152.

Harackiewicz, J. M., Barron, K. E., Carter, S. M., Lehto, A. T., & Elliot, A. J. (1997). Predictors and consequences of achievement goals in the college classroom: Maintaining interest and making the grade. *Journal of Personality and Social Psychology*, *73*(6), 1284-1295.

Harackiewicz, J. M., Barron, K. E., Tauer, J. M., Carter, S. M., & Elliot, A. J. (2000). Short-term and long-term consequences of achievement goals: Predicting interest and performance over time. *Journal of Educational Psychology*, *92*(2), 316-330.

Hartley, K., & Bendixen, L. D. (2001). Educational research in the Internet age: Examining the role of individual characteristics. *Educational Researcher*, *30*(9), 22-26.

Henderson, V. L., & Dweck, C. S. (1990). Motivation and achievement. In. S. Feldman & GR Elliott (Eds.), *At the Threshold: The Developing Adolescent*, 308–329. Cambridge, Mass: Harvard University Press.

Hoffmann, F., & Oreopoulos, P. (2009). Professor qualities and student achievement. *The Review of Economics and Statistics*, *91*(1), 83–92.

Hong, Y., Chiu, C., Dweck, C. S., Lin, D. M.-S., & Wan, W. (1999). Implicit theories, attributions, and coping: A meaning system approach. *Journal of Personality and Social Psychology*, *77*(3), 588-599.

Hoskins, S. L., & Van Hooff, J. C. (2005). Motivation and ability: which students use online learning and what influence does it have on their achievement? *British Journal of Educational Technology*, *36*(2), 177–192.

Husman, J., & Hilpert, J. (2007). The intersection of students' perceptions of instrumentality, self-efficacy, and goal orientations in an online mathematics course. *Zeitschrift Für Pädagogische Psychologie*, *21*(3/4), 229–239.

Jaggars, S. S., & Xu, D. (2016). How do online course design features influence student performance? *Computers & Education*, *95*, 270–284.

Jansen, R. S., Van Leeuwen, A., Janssen, J., Kester, L., & Kalz, M. (2017). Validation of the self-regulated online learning questionnaire. *Journal of Computing in Higher Education*, *29*(1), 6–27.

Jones, B. D., Wilkins, J. L. M., Long, M. H., & Wang, F. (2012). Testing a motivational model of achievement: How students' mathematical beliefs and interests are related to their achievement. *European Journal of Psychology of Education*, *27*(1), 1–20.

Jost, B., Rude-Parkins, C., & Githens, R. P. (2012). Academic performance, age, gender, and ethnicity in online courses delivered by two-year colleges. *Community College Journal of Research and Practice*, *36*(9), 656–669.

Kim, C., Park, S. W., & Cozart, J. (2014). Affective and motivational factors of learning in online mathematics courses. *British Journal of Educational Technology*, *45*(1), 171–185.

Kim, C., Park, S. W., Cozart, J., & Lee, H. (2015). From motivation to engagement: The role of effort regulation of virtual high school students in mathematics courses. *Journal of Educational Technology & Society*, *18*(4), 261-272.

Kim, L. E., Dar-Nimrod, I., & MacCann, C. (2018). Teacher personality and teacher effectiveness in secondary school: Personality predicts teacher support and student self-efficacy but not academic achievement. *Journal of Educational Psychology, 110*(3), 309-323.

Koç, M. (2017). Learning Analytics of Student Participation and Achievement in Online Distance Education: A Structural Equation Modeling. *Educational Sciences: Theory & Practice*, *17*(6), 1893-1910.

Komarraju, M., & Nadler, D. (2013). Self-efficacy and academic achievement: Why do implicit beliefs, goals, and effort regulation matter? *Learning and Individual Differences*, *25*, 67–72.

Kotey, B., & Anderson, P. (2006). Performance of distance learning students in a small business management course. *Education+ Training*, *48*(8/9), 642–653.

Kuh, G. D., Cruce, T. M., Shoup, R., Kinzie, J., & Gonyea, R. M. (2008). Unmasking the effects of student engagement on first-year college grades and persistence. *The Journal of Higher Education*, *79*(5), 540–563.

Kuh, G. D., Kinzie, J. L., Buckley, J. A., Bridges, B. K., & Hayek, J. C. (2006). *What matters to student success: A review of the literature* (Vol. 8). Washington, DC: National Postsecondary Education Cooperative.

Lammers, W. J., & Gillaspy Jr, J. A. (2013). Brief measure of student-instructor rapport predicts student success in online courses. *International Journal for the Scholarship of Teaching and Learning*, *7*(2), 16. doi:10.20429/ijsotl.2013.070216

Lepper, M. R., & Woolverton, M. (2002). The wisdom of practice: Lessons learned from the study of highly effective tutors. In *Improving Academic Achievement: Impact of Psychological Factors on Education*, 135–158. San Diego, CA: Academic Press.

Lin, C.-H., Zhang, Y., & Zheng, B. (2017). The roles of learning strategies and motivation in online language learning: A structural equation modeling analysis. *Computers & Education*, *113*, 75–85.

Lu, J., Yu, C.-S., & Liu, C. (2003). Learning style, learning patterns, and learning performance in a WebCT-based MIS course. *Information & Management*, *40*(6), 497–507.

Lun, V. M.-C., Fischer, R., & Ward, C. (2010). Exploring cultural differences in critical thinking: Is it about my thinking style or the language I speak? *Learning and Individual Differences*, *20*(6), 604–616.

Lynch, D. J. (2006). Motivational Factors, Learning Strategies and Resource Management as Predictors of Course Grades. *College Student Journal*, *40*(2), 423-428.

Martel, C., Dupont, D., & Bédard, J. (2015). *Online and distance education capacity of Canadian universities: Analysis and review*. Montréal, Quebec: EduConsillium.

Martin, A. M. (2017). *The Impact of Instructor Qualities in Higher Education Online Courses*. Doctoral dissertation, Kent State University.

Martocchio, J. J. (1994). Effects of conceptions of ability on anxiety, self-efficacy, and learning in training. *Journal of Applied Psychology*, *79*(6), 819-825.

McGhee, R. M. H. (2010). *Asynchronous interaction, online technologies self-efficacy and self-regulated learning as predictors of academic achievement in an online class*. Doctoral dissertation, Southern University and Agricultural and Mechanical College.

McKenzie, K., & Gow, K. (2004). Exploring the first year academic achievement of school leavers and mature-age students through structural equation modelling. *Learning and Individual Differences*, *14*(2), 107–123.

Meece, J. L., & Holt, K. (1993). A pattern analysis of students' achievement goals. *Journal of Educational Psychology*, *85*(4), 582-590.

Middleton, M. J., & Midgley, C. (1997). Avoiding the demonstration of lack of ability: An underexplored aspect of goal theory. *Journal of Educational Psychology*, *89*(4), 710-718.

Midgley, C., Kaplan, A., Middleton, M., Maehr, M. L., Urdan, T., Anderman, L. H., … Roeser, R. (1998). The development and validation of scales assessing students' achievement goal orientations. *Contemporary Educational Psychology*, *23*(2), 113–131.

Midgley, C., Maehr, M. L., Hruda, L. Z., Anderman, E., Anderman, L., Freeman, K. E., & Urdan, T. (2000). *Manual for the patterns of adaptive learning scales*. Ann Arbor: University of Michigan.

Miltiadou, M. (2001). *Motivational constructs as predictors of success in the online classroom.* Doctoral dissertation, Arizona State University.

Multon, K. D., Brown, S. D., & Lent, R. W. (1991). Relation of self-efficacy beliefs to academic outcomes: A meta-analytic investigation. *Journal of Counseling Psychology*, *38*(1), 30-38.

Neroni, J., Meijs, C., Leontjevas, R., Kirschner, P. A., & De Groot, R. H. M. (2018). Goal Orientation and Academic Performance in Adult Distance Education. *The International Review of Research in Open and Distributed Learning*, *19*(2). doi: http://dx.doi.org/10.19173/irrodl.v19i2.3440

Niiya, Y., Crocker, J., & Bartmess, E. N. (2004). From vulnerability to resilience: Learning orientations buffer contingent self-esteem from failure. *Psychological Science*, *15*(12), 801–805.

Paunesku, D., Walton, G. M., Romero, C., Smith, E. N., Yeager, D. S., & Dweck, C. S. (2015). Mind-set interventions are a scalable treatment for academic underachievement. *Psychological Science*, *26*(6), 784–793.

Peterson, V. M. (2009). Predictors of academic success in first semester baccalaureate nursing students. *Social Behavior and Personality: An International Journal*, *37*(3), 411–417.

Petrocelli, J. V. (2003). Hierarchical multiple regression in counseling research: Common problems and possible remedies. *Measurement and Evaluation in Counseling and Development*, *36*(1), 9–22.

Pintrich, P. R. (1999). The role of motivation in promoting and sustaining self-regulated learning. *International Journal of Educational Research*, *31*(6), 459–470.

Pintrich, P. R., & De Groot, E. V. (1990). Motivational and self-regulated learning components of classroom academic performance. *Journal of Educational Psychology*, *82*(1), 33-40.

Pintrich, P. R., Smith, D. A. F., Garcia, T., & McKeachie, W. J. (1991). *A manual for the use of the Motivated Strategies for Learning Questionnaire (MSLQ)*. Ann Arbor: University of Michigan.

Pintrich, P. R., Smith, D. A. F., Garcia, T., & McKeachie, W. J. (1993). Reliability and predictive validity of the Motivated Strategies for Learning Questionnaire (MSLQ). *Educational and Psychological Measurement*, *53*(3), 801–813.

Puzziferro, M. (2008). Online technologies self-efficacy and self-regulated learning as predictors of final grade and satisfaction in college-level online courses. *The American Journal of Distance Education*, *22*(2), 72–89.

Rana, R. A., & Mahmood, N. (2010). The Relationship between Test Anxiety and Academic Achievement. *Bulletin of Education and Research*, *32*(2), 63-74.

Robins, R. W., & Pals, J. L. (2002). Implicit self-theories in the academic domain: Implications for goal orientation, attributions, affect, and self-esteem change. *Self and Identity*, *1*(4), 313–336.

Scanlon, E. S. (1994). Residuals and influence in regression. *Proceedings of the Casualty Actuarial Society 154/155*, 123-153.

Schraw, G., Horn, C., Thorndike-Christ, T., & Bruning, R. (1995). Academic goal orientations and student classroom achievement. *Contemporary Educational Psychology*, *20*(3), 359–368.

Seaman, J. E., Allen, I. E., & Seaman, J. (2018). Grade Increase: Tracking Distance Education in the United States. Wellesley: Babson Survey Research Group. Retrieved from http://www.onlinelearningsurvey.com/highered.html

Senko, C., & Miles, K. M. (2008). Pursuing their own learning agenda: How mastery-oriented students jeopardize their class performance. *Contemporary Educational Psychology*, *33*(4), 561–583.

Sheard, M. (2009). Hardiness commitment, gender, and age differentiate university academic performance. *British Journal of Educational Psychology*, *79*(1), 189–204.

Shulruf, B., Hattie, J., & Tumen, S. (2008). The predictability of enrolment and first-year university results from secondary school performance: the New Zealand National Certificate of Educational Achievement. *Studies in Higher Education*, *33*(6), 685-698.

Spatariu, A., Hartley, K., Schraw, G., Bendixen, L. D., & Quinn, L. F. (2007). The influence of the discussion leader procedure on the quality of arguments in online discussions. *Journal of Educational Computing Research*, *37*(1), 83–103.

Stipek, D. J. (1993). *Motivation to learn: From theory to practice*. Needham Heights, MA: Allyn & Bacon

Stowell, J. R., & Bennett, D. (2010). Effects of online testing on student exam performance and test anxiety. *Journal of Educational Computing Research*, *42*(2), 161–171.

Stupnisky, R. H., Renaud, R. D., Daniels, L. M., Haynes, T. L., & Perry, R. P. (2008). The interrelation of first-year college students' critical thinking disposition, perceived academic control, and academic achievement. *Research in Higher Education*, *49*(6), 513-530.

Tempelaar, D. T., Rienties, B., Giesbers, B., & Gijselaers, W. H. (2015). The pivotal role of effort beliefs in mediating implicit theories of intelligence and achievement goals and academic motivations. *Social Psychology of Education*, *18*(1), 101–120.

Villavicencio, F. T. (2011). Critical thinking, negative academic emotions, and achievement: A mediational analysis. *The Asia-Pacific Education Researcher*, *20*(1), 118–126.

Wampold, B. E., & Freund, R. D. (1987). Use of multiple regression in counseling psychology research: A flexible data-analytic strategy. *Journal of Counseling Psychology*, *34*(4), 372-382.

Wang, C.-H., Shannon, D. M., & Ross, M. E. (2013). Students' characteristics, self-regulated learning, technology self-efficacy, and course outcomes in online learning. *Distance Education*, *34*(3), 302–323.

Wilcox, R. R. (2011). *Introduction to robust estimation and hypothesis testing, 3rd edition*. San Diego, CA: Academic Press.

Wojciechowski, A., & Palmer, L. B. (2005). Individual student characteristics: Can any be predictors of success in online classes. *Online Journal of Distance Learning Administration*, *8*(2). Retrieved from https://www.westga.edu/~distance/ojdla/summer82/wojciechowski82.htm

Wood, R., & Bandura, A. (1989). Impact of conceptions of ability on self-regulatory mechanisms and complex decision making. *Journal of Personality and Social Psychology*, *56*(3), 407-415.

Wood, W. B., & Tanner, K. D. (2012). The role of the lecturer as tutor: doing what effective tutors do in a large lecture class. *CBE-Life Sciences Education*, *11*(1), 3-9.

Yeager, D. S., Romero, C., Paunesku, D., Hulleman, C. S., Schneider, B., Hinojosa, C., … others. (2016). Using design thinking to improve psychological interventions: The case of the growth mindset during the transition to high school. *Journal of Educational Psychology*, *108*(3), 374-391.

Zimmerman, W. A. (2017). Predicting Success in an Online Undergraduate-Level Introductory Statistics Course using Self-Efficacy, Values, and Typical Mode of Instruction. *International Journal of E-Learning & Distance Education*, *32*(1). Retrieved from http://ijede.ca/index.php/jde/article/viewFile/1011/1680

Zimmerman, W. A., & Kulikowich, J. M. (2016). Online learning self-efficacy in students with and without online learning experience. *American Journal of Distance Education*, *30*(3), 180–191.