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COURSE DESIGN ... ONLINE: HELPING STUDENTS PERFORM IN THE DIGITAL AGE

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COURSE DESIGN…ONLINE: HELPING STUDENTS PERFORM IN THE DIGITAL AGE

A Dissertation

Submitted to the Graduate Faculty of the Louisiana State University and Agricultural and Mechanical College in partial fulfillment of the requirements for the degree of Doctor of Philosophy in The Department of Human Resource Education & Workforce Development

by

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Abstract

The current study sought to test the relationship between course design, as described by the rubric produced by Quality Matters, and online university student performance. Due to the link between student motivation and active learning behaviors, and thus performance, it was predicted that the better-designed courses would facilitate student motivation. It was also predicted that goal orientation would moderate this relationship. While a significant relationship was observed between student motivation and course performance, no relationship was observed between course quality, as measured by the QM Rubric, and motivation, or performance. Only slight evidence was found for a moderating effect of goal orientation.
Chapter 1. Introduction

1.1. Background

For more than a decade, there has been an increasing demand for higher education, (Hurwitz & Kumar, 2015). This need has been met, in part, by offering higher education courses and degree programs online. In the 1990s, colleges and universities in the United States tripled the number of courses they offered online (Herbert, 2006). It is predicted that in the year 2017, the total financial capital invested in developing and providing online higher education will exceed $250 billion (“Edtech Digest Market Predictions,” 2013).

There are, however, substantive differences between online higher education and traditional face-to-face courses. Several studies have found that online students demonstrate poorer learning outcomes than their traditional counterparts (Emerson & MacKay, 2011; J. D. Morgan, 2015; Mottarella, Fritzsche, & Parrish, 2005; Wang & Newlin, 2000; Waschull, 2001). These lagging learning outcomes must be better understood and addressed in order for online learning to adequately meet the soaring demands for higher education.

While a number of factors are at play, there is one that is determined before a student takes his/her first test, decides whether to stay or withdraw, interacts with his/her instructor or even enrolls. This factor is how the course is designed. Course design has received a great deal of research attention, financial investment, time and energy because it is believed to be the most significant way that an instructor can maximize his/her students’ chances for academic success. The Quality Matters Rubric uses empirically-derived guidelines for online course design that aims to accomplish just that (Shattuck, 2007). Research touted and conducted by Quality Matters (QM) suggests that use of the Rubric is positively associated with academic performance (Bogle, Day, Matthews, & Swan, 2014; Dietz-Uhler, Fisher, & Han, 2007), but with little independent
scholarly research or theoretical explanation for how these positive outcomes are achieved. Whether and how the QM Rubric works to improve student outcomes are questions of some controversy. While nearly ten years old, relatively little peer-reviewed empirical research has been conducted on the Rubric’s efficacy. Research featured by QM suffers from methodological shortcomings, while other research fails to find an association between use of the Rubric and student outcomes (Aman, 2009). Given the role of QM as the dominant course design certification tool in the industry (Lowenthal & Hodges, 2015), and the influence that course design has on learner motivation and outcomes, it is important to understand how QM functions to shape the online learner experience by observing the student outcomes associated with QM. All of these points will be discussed in greater throughout this paper as it proposes a theoretical link between course design, the QM Rubric, and student outcomes.

Academic performance is commonly found to be the result of motivation (Boton & Gregory, 2015; Frankola, 2001; Kırmızı & Kirmizi, 2015; Morrow & Ackermann, 2012; O’Connor et al., 2003; Sansone, Smith, Thoman, & MacNamara, 2012; Visser, Plomp, Amirault, & Kuiper, 2002; Yurdugül & Menzi Çetin, 2015). Therefore, it is reasonable to explore the role of motivation in linking the application of the QM Rubric to academic outcomes. One of the predominant theories of motivation is Self-Determination Theory (SDT; Deci & Ryan, 2000). An advantage of applying SDT toward the exploration of the linkages is that the theory not only describes the relationship between motivation and academic success, but also the theoretical underpinnings that support motivation. To summarize SDT in a single sentence, people are most motivated when their innate needs are met. In practical terms, an instructor who wants to improve overall student motivation and performance could design their courses with these needs in mind and expect to meet with considerable success. Several studies describe the positive
association between student outcomes and course design characteristics that meet the needs described by SDT (Beachboard, Beachboard, Li, & Adkison, 2011; Black & Deci, 2000; Niemiec & Ryan, 2009).

Therefore, given the link between motivation and student performance, the relationship between need satisfaction and motivation, and the positive effects that courses designed to meet these needs have on student outcomes, it follows that any effort to improve student outcomes through course design will ultimately result in a course that satisfies the needs described by SDT. It could be argued at this point that course design may support student outcomes through means completely independent of motivation. This is a valid challenge and will be met in detail further in this chapter. For the moment, it is predicted that the best-designed courses (as reflected by QM standards) will demonstrate higher-than-average student performance, as well as meet the criteria specified by Self-Determination Theory to the greatest degree.
1.2. Research Aims

This study will explore the role of course design quality as defined by the popular QM Rubric as a means to motivate online learners toward successful academic performance and intention to remain in their program. This study will seek to replicate the predictions of the predominant theory of motivation in an online learning setting and will propose and test a hypothetical relationship between two major constructs in the motivation literature (i.e., intrinsic motivation and goal orientation), the outcome of which may have significant implications for motivation research.
1.3. The Role of Quality Matters in the Context of this Study

This study will focus on graduate students enrolled in online graduate degree programs offered at a Tier 1 research institution in the southeastern U.S. These online courses are organized and offered through a subsidiary institutional department which, to maintain anonymity, will be referred to throughout by a pseudonym: Valkyrie University (VU). The QM Rubric has been utilized by VU for a number of years, but largely in an unofficial capacity. Instructors are advised to ensure that their courses meet the standards outlined in the Rubric, but no formal review is done, and the courses have not been officially certified by QM. VU administrators have thus far been skeptical of the benefits of official, paid, QM certification over and above the Rubric’s unofficial use. This skepticism is due, in part, to questions of the Rubric as a guarantor of course quality.

The QM Rubric (Shattuck, 2007) is a practical model of course quality that has been developed from empirical evidence and is a higher education industry leader in online course design. Given this, it will also be used to conceptually define course design quality. Support for the relationship between the QM Rubric and student learning is minimal, and this relative lack of research makes it difficult to ascertain the Rubric’s validity and utility for affecting actual course outcomes. At present, a methodologically rigorous examination of the link between the Rubric and learner outcomes has not yet been conducted, though that is a goal of the current study. What follows will be a review of the QM Rubric and research concerning its utility. Based on this review, and a consideration of factors that have been empirically linked to student learning, this study will seek to explore the extent to which the QM Rubric reflects course design quality and has bearing on online learner motivation and performance.
To date, nearly 1,000 institutions have subscribed to QM, 4,500 online courses have been reviewed by QM, and 40,000 online instructors have received training in the application of the QM Rubric (Adair & Shattuck, 2015). The QM Rubric was initially developed by consolidating the best practices for distance learning described by Chickering and Gamson (1987), and The American Council on Education (Sullivan & Rocco, 1996) among others. The Rubric is periodically updated based on findings from current research and feedback from users (Shattuck, Zimmerman, & Adair, 2014).

The current version of the Rubric contains eight general standards that courses must meet: course overview and introduction, learning objectives, assessment and measurement, resources and materials, learner engagement, course technology, learner support, and accessibility. Each of the eight general standards is composed of a number of specific standards (43 in total) on which the course will be graded. Each specific standard is assigned a point value denoting its relative worth: “essential” (3 points), “necessary” (2 points), and “important” (1 point) (Shattuck, 2007). Points are awarded on a pass/no-pass basis by QM course reviewers who determine whether each particular standard has been met. A course must earn 85% of the available points (84 of 99) in order to become certified.

Regarding published research on the QM Rubric, the current state of the literature could best be described as incomplete. There are a number of crucial questions that stakeholders and researchers would likely care about, but which have not yet been answered. For example, the criterion-related validity of the QM Rubric has yet to be demonstrated. The discriminant validity of the eight general standards of the Rubric have also not been tested. The validity of the weighting system of the specific standards has also not been tested. In other words, the “essential”, “necessary” and “important” standards are worth three, two and one points
respectively, while there is currently no empirical evidence that an “essential” standard is three times as critical for course design as an “important” one. It is unclear how this weighting system was initially devised. Based on research it may be, but there is a desperate need for research on the QM Rubric itself.

Of critical interest to this study, there is little independent empirical evidence of the QM Rubric’s effectiveness for improving the quality of online courses. Arguing for the efficacy of the Rubric, Adair and Shattuck (2015) cite numerous studies showing the positive effects of QM standards on student experience and learning. Each such study will be briefly described below. Unfortunately, a number of these studies are either unpublished (Mott, 2006; Swan, Matthews, Bogle, Boles, & Day, 2011), or were presented at conferences whose minutes are unavailable online (Bowen & Bartoletti, 2009; Iyengar, 2006; Rutland & Diomede, 2011). These conferences were organized by the Maryland Distance Learning Association and QM, and few are peer-reviewed. Fortunately, the majority of cited studies remain available for review.

Simunich, Robins and Kelly (2015) sought to relate student online course satisfaction with findability (the extent to which an object on a course website is easy to find). Findability was treated as analogous to QM standard 6.3: “navigation throughout the online components of the course is logical, consistent, and efficient.” They found that courses with high findability were rated better on measures of experience than courses that were low in findability. Furthermore, findability was found to be positively related to motivation and self-efficacy.

Some studies appear to demonstrate the positive effects of the Rubric but stop short of providing actual evidence. For example, Legon and Runyon (2007) presented the findings of an unpublished manuscript (Runyon, 2006); in which changes made to an online course based on two general QM standards (4 & 5) resulted in increased student engagement. Methodological
procedures including statistical analyses were not reported, thus compromising the potential for scrutiny or replicability. Research conducted by Hall (2010) appears to be more promising, as she describes the effects of the QM standards on increased depth of processing among students, teacher presence, student satisfaction and grades on individual assignments. This research however is unpublished and exists currently as a PowerPoint presentation given at the 2nd Annual QM Conference. All other minutes are unavailable. Finally, Bogle, Day, Matthews, and Swan (2014) also report significant improvements in final exam and overall course grades after redesigning an online course to adhere to QM guidelines. This last citation raises something of a discrepancy that merits further explanation, as it implies a direct, causal relationship between use of the QM Rubric and improved student grades. The work by Bogle and colleagues (2014), as cited by Adair and Shattuck (2015), is a chapter written for a book (Shattuck, 2014). In this chapter, the authors reference yet an earlier study (Swan, Matthews, Bogle, Boles, & Day, 2012) in which the effects of course redesign on student grades are examined. The authors specifically explored two types of course redesign, one based on the QM Rubric, and one based on the Community of Inquiry Framework (CoI; Garrison, Anderson, & Archer, 1999). Swan and colleagues (2012) explicitly report that student grades before and after QM redesign were not significantly different. Over the following three semesters, they implemented course redesign based on CoI, their rationale being that CoI could leverage the design improvements made by QM. They then report a significant increase in final exam and overall course grades over a four-semester period, ultimately concluding that the joint application of QM and CoI resulted in increased student performance. The independent contribution of QM to this increase was not assessed and cannot be inferred, although the effect of QM in isolation on student grades was non-significant across two semesters. Whether QM and CoI jointly increased student
performance over four semesters, or CoI was responsible for most or all of the observed change, use of the QM Rubric alone was not responsible for the increase in student grades, contrary to implications to that effect (Adair & Shattuck, 2015).

Bogle, Cook, Day, and Swan (2009) proposed theoretical links between the various QM standards and the types of presence described by Garrison, Anderson and Archer (1999) for online learning: social, teaching, and cognitive. Arguments are presented for the theoretical compatibility between individual QM standards and the types of presence described, but no empirical demonstrations are presented.

Harkness (2015) describes a 20% increase in passing grades, a 67% reduction in failing grades, and a 24% reduction in attrition among online courses campus-wide over a five-year-period during which the QM framework was implemented. This period also saw an aggressively-implemented strategic initiative developed by the university’s Committee for Online Learning, so the isolated effects of QM cannot be determined.

Dietz-Uhler, Fisher and Han (2007) describe two online courses and the extent to which they adhere to QM standards. Both courses have an average retention rate of 95% over a minimum of six semesters, but no statistical analyses or methodological rigor allow for an attribution to QM standards. Any relation between QM and retention in this case is purely hypothetical.

Aman (2009) reported that students were significantly more satisfied in courses that were QM reviewed. However, careful reading of the results section of this study will reveal that satisfaction scores reported by students enrolled in online courses that were QM-reviewed vs. not QM-reviewed were not significantly different. The significant difference to which the author referred was between students on a secondary index of student satisfaction. This index was the
grand mean of a student’s rating of the extent to which his/her course met certain QM standards. The differences on this measure of student satisfaction between QM-reviewed courses and non-QM-reviewed courses were marginally significant: t(552) = 1.54, p= .06. It should also be noted that this was a one-tail t-test and that significance was set at p< .10. In short, these findings should be considered with a healthy degree of skepticism as the development of a satisfaction measure based on the QM Rubric for the purpose of determining whether QM reviewed courses yield greater student satisfaction is, at best, circular reasoning.

Finally, Geiger, Morris, Suboez, Shattuck, and Viterito (2014) sought to identify the student-related factors contributing to academic success. Factors external to the student were held constant (instructor experience, course quality, and learning management system) to determine the relative impact of individual factors (motivation, life factors, reading comprehension, reading rate, reading recall, general knowledge, typing accuracy, and typing speed) on online academic success. Only typing speed and accuracy and reading rate and recall significantly predicted academic performance. While these findings are interesting, especially considering that motivation and knowledge were not significant determinants of academic success, they do not support the premise that the QM Rubric enhances course quality.

According to the former Executive Director of QM, the most common question asked by educators before adopting the QM Rubric over the last ten years is whether they can demonstrate that the Rubric actually improves learner outcomes such as grades (Legon, 2015). In a recent article in *The American Journal of Distance Education* (Adair & Shattuck, 2015), both the Director and the Chief Planning Officer of QM describe how it is a practice based on research, and the research resulting from its practice. They take this second heading as an opportunity to address their most commonly-received question and present all of the above-described studies,
and no others, as evidence of QM’s positive impact on online learner performance. Given a period of ten years since QM’s development (Shattuck, 2007) and the adoption of the Rubric by nearly 1,000 institutions and 40,000 educators worldwide (Adair & Shattuck, 2015), it would appear that the answer to their most frequently asked question is “no”. Despite its widespread use, there is little other research to be found on the effects of the QM Rubric on student learning.

In summary, the QM Rubric was developed and continues to be updated based on current empirical research. It is the most popular tool of its kind for online course design. Yet for its pedigree and popularity, it suffers from a lack of research demonstrating what its clients are most concerned with: demonstrable positive effects on student outcomes. Research that ostensibly demonstrates the value of the Rubric in this area are often methodologically unsound, insufficiently rigorous, or simply unavailable for independent review. The current study seeks to fill this research gap.
1.4. Theory Framing the Research

The main theories framing this study will be Self-Determination Theory (SDT; Deci & Ryan, 1985), and the Social-Cognitive theory of motivation (Dweck & Leggett, 1988). The following discussions will focus on the development and components of these theories, and a body of empirical research that will be expanded upon in the next chapter.

1.4.1. Self-Determination Theory

Self-Determination Theory (SDT; Deci & Ryan, 1985) has its roots in the early days of empirical psychology. The idea of intrinsically motivated behavior was discussed by William James (James, 1890) and first theorized by Woodworth (1918). A recurring theme will be Woodworth’s portentous argument that behaviors are most effective when they are undertaken for their own sake. Relatively little attention was given to this organismic approach to human behavior research at the time, in favor of the mechanistic theories proposed by Thorndike (1913) and Watson (1913), and what would ultimately become known as Drive Theory (Hull, 1943). A central tenet of Drive Theory is that all behavior is an attempt to satisfy a particular drive, whether to mate, eat, drink or protect one’s body. While generally supported by research on humans and animals, Drive Theory fails to explain exploratory behaviors, or those associated with curiosity. The annals of psychological research are replete with findings of animal subjects forgoing food or enduring pain in order to explore a novelty in their environment (see Deci & Ryan, 1985 for a review).

Dissatisfaction with a passive and mechanistic view of human behavior ultimately supported the development of an active, purposeful and cognitive view wherein humans act because they enjoy doing so. Rather than beings that merely act to fulfill some biological purpose, White (1959), and others proposed that humans are motivated to act by various
psychological needs. It is these needs on which SDT is based: namely competence, autonomy and relatedness. The need for competence was described by Woodworth (1918) and White (1959), who proposed that utilizing and developing one’s abilities was inherently satisfying. A need for autonomy was proposed by DeCharms (1968), who wrote that a sense of personal causation was necessary for intrinsic motivation. The need for relatedness refers to the need to be accepted and cared for by fellow humans, based on the work of Bowlby (1958) and Harlow (1958). SDT holds that people will naturally seek to develop and improve their abilities to the extent to which their environment is supportive of these three needs.

Within the context of traditional academic settings, the extent to which these needs are met has been shown to reduce attrition (Buvoltz, Powell, Solan, & Longbotham, 2008; Vallerand & Blssonnette, 1992) and increase student performance (Black & Deci, 2000; Niemiec & Ryan, 2009). Evidence that need satisfaction supports learning in online settings will be presented in Chapter 2.

In addition to the necessity for autonomy, competence and relatedness for intrinsically motivated behavior, SDT proposes a spectrum of self-determined motivation describing the degree to which one is motivated by external and internal factors. This spectrum is generally considered to contain six distinct levels (Deci & Ryan, 1985b). The first level is amotivation, in which one is not motivated to act at all, whether extrinsically or intrinsically. The next four levels describe extrinsic forms of motivation, but with increasing levels of internal attribution. The first of these is external regulation, where one acts simply as a result of expected punishments or rewards associated with the act. The second is introjection, in which one acts according to social pressures, whether to avoid guilt or increase status. The third level is identification, wherein one acts because they believe that doing so will benefit them in the future.
This is the classic “I don’t want to, but I know that it’s important, so I’ll do it anyway” motivation, commonly seen in students. The fourth, and most internal, level of extrinsic motivation is integrated regulation. This occurs after a process of self-examination in which one integrates an external pressure to act with their own internal needs and values. Returning to the student example, this student has a personal need to excel and will study, read, write, make flashcards and do whatever else is necessary to achieve their goal. This is not yet true intrinsic motivation because action motivated by integrated regulation is still performed for its instrumental value that is unrelated to the activity itself (Ryan & Deci, 2000). A student thus motivated would not feverishly study a particular subject if they were not taking that class. They work as hard as they do for the grade, not for love of the work. Those who do love the work are motivated by the sixth level of motivation: intrinsic motivation. An intrinsically motivated individual acts simply because they enjoy the action.

Use of the term “self-determined motivation” for the rest of this paper will refer to the higher levels of extrinsic motivation as well as intrinsic motivation. Research in traditional academic settings on self-determined motivation, both intrinsic motivation and more internally-attributed forms of extrinsic motivation, generally find a positive relation with student performance (Gottfried, 1985; Miserandino, 1996; Simons, Dewitte, & Lens, 2004; Vansteenkiste, Lens, & Deci, 2006).

1.4.2. Social-Cognitive Theory of Motivation

While a great variety of individual difference constructs are described in the motivation literature, goal orientation is perhaps the most predominant. The concept of goal orientation was developed following the recognition that learning and performance are not solely determined by ability. Researchers of child education have described performance on cognitive skill
assessments varying not according to their intellectual ability, but on how the children approach the assessments (Dweck & Elliott, 1983; Nicholls, 1984). Children who view the assessments as opportunities to increase their competence or develop a new skill are said to have a learning goal, while children who see assessments as a way to show off their skills have a performance goal (Dweck & Elliott, 1983). Over time, children who demonstrate a general tendency toward adopting learning or performance goals are said to have either a learning goal orientation (LGO) or a performance goal orientation (PGO). It is these goal orientations that distinguish between high- and low-performing children with the same intellectual abilities. Children with an LGO were found to enjoy challenges, persist longer when faced with an obstacle, and exert more effort, with consequent effects on performance. Children with a PGO respond to obstacles with anxiety and negative self-assessments, resulting in poorer performance (Ames, 1984; Diener & Dweck, 1978, 1980; Dweck & Reppucci, 1973; Nicholls, 1975).

It should be clarified that the construct of goal orientation does not belong to any particular theory exclusively, so different language is sometimes used to describe contrasting motivational processes. Research conducted by Carol Dweck and colleagues describes the distinction between a learning goal orientation and a performance goal orientation (Dweck, 1986; Dweck & Leggett, 1988; Elliott & Dweck, 1988). This distinction is analogous to the difference between task- and ego-involvement described by Nicholls (1984), and between mastery and performance goals (Ames, 1992; Ames & Archer, 1987). The use of different labels for the same constructs is due to the differences in conceptualization of their originating processes.

Under the social-cognitive model proposed by Dweck (1986), one’s goal orientation is a function of their personal theory of intelligence. Under this framework, one can either view
intelligence as being fixed or malleable. If one sees intelligence as being a fixed entity, they do not believe that it can be changed. When subscribing to this entity theory, one tends to adopt a PGO and a desire to demonstrate their skills, as long as they believe that the current task is within their abilities. If they perceive that the current task is beyond them, they will likely try to avoid the task or persist only as long as necessary to confirm that they can’t do it. By contrast, those who see intelligence as malleable will see challenges as opportunities to increase their skill, and thus adopt an incremental theory of intelligence. Such individuals approach tasks that they can use to develop their skills or acquire new skills with enthusiasm and are not daunted by initial failure.

In contrast to the incremental/entity theory of intelligence explanation of goal orientations, Ames’ conceptualization centers on one’s definition of success and reasons for engaging in a particular activity (Ames, 1992). If one’s motivation for engaging in a task is to increase their mastery and considers their engagement a success if they perceive that their skills have increased as a result, they are said to have a mastery goal. If one engages in an activity to demonstrate their abilities to themselves or others and considers their effort successful if they think that they performed the task to an appropriate standard, one is said to have a performance goal.

Finally, Nichols proposes a similar conceptualization based on how a student believes that success is achieved (Nicholls, 1989). If one believes that success comes from hard work, active effort to understand new ideas, and collaboration with others, they are said to have a task orientation. If a student believes that success comes through superior ability and utilizing it to surpass others, they are said to have an ego orientation. After more than two decades of comparative research, the constructs of learning goal orientation, mastery goal orientation and
task orientation are generally acknowledged to be analogous, as are performance goal orientation and ego orientation. For the remainder of this paper, Dweck’s social-cognitive framework will be adopted and her terminology of learning and performance goal orientation will be used. This is due to the tendency for this model to predominate in the contemporary literature, as well as an important addition to goal orientation theory using the same language.

Early conceptualizations (proposed by Dweck, Ames, Nicholls and others) of what amounts to a performance goal orientation describe a desire to gain favorable judgements and avoid negative judgements of one’s ability. Building on this framework, VandeWalle (1997) proposed that these are separate goals, and thus conceptualized two performance goal orientations: prove and avoid. The prove performance goal orientation (hereafter PGOp) describes the desire to prove one’s competence and gain favorable judgements about it. The avoid performance goal orientation (PGOa) describes the desire to avoid disproving one’s competence, and thus receiving negative judgements about it. This binary conceptualization has been rigorously assessed and is the prevailing view of the PGO (Janke et al., 2016; Latham & Pinder, 2005). Proposals for describing the learning goal orientation similarly have been made (Elliot, 1999) but have yet to be adopted by the majority of motivation researchers, so a tripartite model of goal orientation including a unitary LGO, PGOp and PGOa remains the standard and will be used throughout this paper.
1.5. Study Contribution and Significance

This study has the potential to provide significant contributions to higher education research, and online learning research. First, the body of literature concerning online education is still in its infancy. The current codex of best practices was formed by more than a century of trial and error in face-to-face education. The optimal way to design and deliver instruction in an online environment has not yet been fully realized. This study seeks to test the efficacy of one of the most prominent models for doing so: the QM Rubric. This and similar future studies are critical primarily because the field of online education is set to expand so rapidly in the coming years. Increasing numbers of students are seeking their education through online channels. Concurrently, differing models of online pedagogy will be tried, tested and refined. The tendency over time will be for online courses to accrete towards adequacy, with countless online students having received instruction of widely varying quality. The results will be better in the short term for students, and better in the long term for researchers, practitioners and students, if researchers identify the mechanism that links course quality to student outcomes. Better still will be the identification of simple and easily-implemented guidelines for course design that activate that mechanism. From a practical standpoint, this will be the first assessment of the QM Rubric as a means of improving online student performance. It will demonstrate, among other findings, whether QM Certified courses provide better outcomes than other courses for online learners. This may be of immediate interest to users of the Rubric, as it either supports or challenges the view that it promotes learning outcomes. In the event that some areas of the Rubric are found to be more useful in that regard than others, this study has the potential to suggest changes that practitioners can immediately apply to their use of the Rubric. Future versions of the Rubric can even benefit from assessing the real-world results of practitioners’ modified use. Regardless of
the outcome, insight into the utility of the Rubric will be a valuable basis for future iterations. In other words, if student outcomes are of interest to QM, a description of which areas of the Rubric are most supportive of performance outcomes, for instance, will be valuable for developing the next version of the Rubric. These performance-supportive standards can be given higher priority. The functional mechanisms by which they support performance can even be explored in an effort to extend them to other areas of the Rubric that are less supportive.

This study also has the potential to make meaningful contributions to the research and practice of traditional education. As noted earlier, the QM Rubric was developed from various guidelines for face-to-face course design. It is therefore reasonable to suppose that a traditional course would also benefit from being designed according to QM standards, though there appears to be no published description of such a study. If the current study is able to successfully demonstrate a relationship between online course quality, student motivation and performance, it will provide a solid foundation for bridging the gap between online and traditional education research. A recent study (Copeland & Levesque-Bristol, 2011) explored the relationship between the need satisfaction of traditional students and their motivation as a result of their learning climate. This was a subjective measure of perceived autonomy support, and it was indeed found that autonomy-supportive teaching facilitated students’ need satisfaction, which then supported self-determined motivation. Given that a well-designed course should be more likely to facilitate students’ motivation than a poorly-designed course, the results of the current study will be applicable to future research on traditional course quality and student motivation and performance.

From a scientific perspective, this study will make meaningful contributions to the motivation literature. SDT was almost exclusively developed and tested in the context of face-to-
face interactions. The trend among this body of research is the general support for SDT and its use in any number of applications. SDT has also found widespread use and support in online settings, particularly online education. The typical finding from such studies is that autonomy, competence and relatedness support self-determined motivation, which supports learning, performance or any other positive outcome, as SDT would predict. However, in a relatively recent study, Chen and Jang (2010) tested a model of SDT that assessed the effect of need support on learners’ perceived need satisfaction, the effect of need satisfaction on learners’ self-determined motivation, and finally the effect of self-determined motivation on final grade, time spent studying and frequency of logging in to the course website. The authors found that need support and need satisfaction performed as expected, but self-determined motivation had no significant effect on final grade, time spent studying, or frequency of visiting the course website. Instead, need satisfaction predicted these outcome variables (except final grade, which nothing predicted). The authors suggest that the nature of the online learning environment causes need satisfaction to become more salient, though no functional mechanism is proposed. While this finding has yet to be replicated, it has major implications for possibly establishing the boundaries of SDT’s validity. The current study will approximately replicate the methods used by Chen and Jang (2010), while expanding on their theoretical model, in the hopes of either replicating their findings, or explaining them. Whether such findings are supported in this case is immaterial. Self-Determination Theory has been cited in thousands of peer-reviewed publications and used in nearly every motivational context. It has already made inroads in the field of online education, but important research has yet to be done. This study’s primary contribution to the motivation literature will be the provision of additional support, or the basis for future improvements, to SDT.
The final major contribution of this study to motivation research is its exploration of goal orientation as a moderating variable in the relationship between perceived psychological needs and self-determined motivation. Despite the extensive research on goal orientation and SDT, they are rarely considered in the same study. Goal orientation suffers from multiple conceptualizations (Ames & Archer, 1987; Dweck & Leggett, 1988; Nicholls, 1984), and incredible variety in operational definitions (Payne, Youngcourt, & Beaubien, 2007). The result of which is no clear consensus on what it is. Self-Determination Theory, meanwhile, is in need of a viable individual-differences variable to explain the variety of motivation experienced by individuals in the same settings; SDT’s own individual difference variable having found little acceptance by researchers (Koestner & Zuckerman, 1994). By integrating goal orientation theory and SDT, several long-standing questions and criticisms can be addressed.
1.6. Definition of Terms

The following terms are listed and defined for the purpose of this study.

- **Online Learning**: Learning that takes place partially or entirely over the Internet (Means, Toyama, Murphy, Bakia, & Jones, 2009).

- **Autonomy**: the organismic desire to self-organize experience and behavior and to have activity be concordant with one’s integrated sense of self (Deci & Ryan, 2000).

- **Competence**: the desire to interact effectively with one’s environment (White, 1959).

- **Relatedness**: the desire to feel connected to others—to love and care, and to be loved and cared for (Deci & Ryan, 2000).

- **Self-Determined Motivation**: motivation to act originating from an internal source, and regulated by internal processes (Deci & Ryan, 1985a)
1.7. Summary and Organization of Report

Chapter one introduces the background of the study, as well as its aims, context, the major theories framing the research, this study’s contributions and a definition of terms. There is an increasing demand for quality higher education services online, but current online courses produce students who under-perform and withdraw at a higher rate than their traditional counterparts. The QM Rubric is the most popular quality-assurance tool for the design of online courses, yet there is little convincing evidence linking use of the Rubric to improved learner outcomes. Because of the link between motivation and academic performance, this study will assess the QM Rubric through the lens of SDT.

Under SDT, all purposeful behavior is preceded by motivation, and the higher the quality of motivation, the better the outcomes of the behavior will be. Motivation is enhanced by satisfying the basic needs for autonomy, competence and relatedness, and research in traditional academic settings indicates that doing so has positive effects on student performance.

Goal orientations are also discussed. These are the reasons for why individuals perform achievement-related behaviors; whether to improve current abilities/develop new abilities, or to demonstrate the level of their abilities.

This study makes a number of practical and scientific contributions to the field. First, it will assess the utility of a tool of online course development and identify possible means for improving it. Second, it will test the predictions of SDT in an online environment. The model has received incremental support from past studies of online learning, but the current study is one of the first to test the complete model with online learners. Finally, this study seeks to integrate the goal orientation construct into SDT.
The following chapter provides an in-depth literature review of online course quality, and the satisfaction of basic psychological needs, the relationship between need satisfaction and self-determined motivation, goal orientation as a possible mediator of this relationship, and the effects of self-determined motivation on online learner performance. The Methodology chapter describes how the study was conducted, including the sample population, data collection procedures, measures, and data analysis plan.
Chapter 2. Review of Literature and Statement of Hypotheses

The purpose of this study is to explore the motivating potential of online courses as it relates to student outcomes. Motivating potential will be assessed through the lens of Self-Determination Theory (Deci & Ryan, 2000) and its conceptualization of basic psychological needs and levels of self-determined motivation. Finally, this study will attempt to address a gap in the literature by testing the proposal that goal orientation moderates the relationship between the satisfaction of learners’ psychological needs and the level of self-determined motivation that they demonstrate.

2.1. The Role of Course Quality and its association with Basic Psychological Needs

Online course design is thought to be an important facilitator of learner motivation (Hartnett, 2016; Keller & Deimann, 2008). Characteristics from the learning environment can be identified, evaluated and compared against course quality standards such as the QM Rubric. The extent to which a given course displays the necessary characteristics should be indicative of its ability to facilitate learner motivation, and thus its quality.

A study with particular bearing on the question of whether online course design facilitates learner motivation was recently published (Hartnett, 2016). In this study, quantitative measures of self-determined motivation were collected, as well as qualitative assessments of the aspects of the course that learners found to be supportive of the basic psychological needs described by SDT. The following sections will describe the findings of this study and others relating to each basic psychological need (autonomy, competence and relatedness) and their respective relationships with course quality.

2.1.1. Autonomy
Hartnett identified several factors of the online learning environment that were supportive of autonomy: relevance, interest, active learning, autonomy support from lecturers, and perceptions of choice (Hartnett, 2016). Under SDT, one’s sense of autonomy is a function of the degree to which they feel free to act, and to choose how to act (Deci & Ryan, 2000), and each of the above factors ultimately support the learners’ perception of choice. Hartnett (2016) found that providing learners with opportunities to make meaningful choices, such as the topics covered in future assignments, resulted in higher perceived autonomy scores, and subsequently higher levels of self-determined motivation. Other research supports the positive relationship between choice and motivation (Van Etten, Pressley, McInerney, & Liem, 2008).

Autonomy is not supported merely by the overt provision of choice, but also by whether one’s ability to choose is implicitly supported. For example, how instructors communicate with students can influence perceptions of autonomy. Instructors can communicate in ways that seem controlling or in ways that are informational in nature, with an emphasis on helping students improve themselves. Hartnett (2016) reports that learners felt a greater sense of autonomy when instructors used language that was less controlling in tone. This is corroborated by research from Reeve and colleagues (Reeve, 2009; Reeve, Ryan, Deci, & Jang, 2008), who identify a number of features of autonomy-supportive teachers. One such feature is the ability to clearly describe what is required of a student without seeming to control the student’s behavior. Autonomy-supportive teachers are those who can help students identify and utilize their own strengths to solve a problem, rather than constrain them to solve it in a prescribed manner.

Even when choices are not explicitly given, students are more likely to feel that they are acting autonomously when their activities correspond with their personal interests and goals, rather than simply acting at their instructor’s direction. In other words, learners feel more
autonomous when the activity closely resembles the activity that they would have chosen, had they been given a choice. This is referred to as situational interest (Hidi & Ainley, 2008), and can be facilitated by linking course material to students’ interests, or providing material that deals directly with these interests. When instructors do this, learners experience increased autonomy and self-determined motivation (Hartnett, 2016).

Situational interest has also been shown to promote perceptions of personal relevance (Hidi & Renninger, 2006) and utility (Hidi, 2000). Viewing the activities that one engages in as personally relevant and useful is characteristic of higher levels of self-determined motivation (Ryan & Deci, 2000). The finding that the relevance of an activity to an online learner’s future goals promotes a sense of autonomy and self-determined motivation (Hartnett, 2016) replicates previous research (Artino, 2008; Blumenfeld, Kempler, & Krajcik, 2006; Rentroia-Bonito, Jorge, & Ghaoui, 2006; Yukselturk & Bulut, 2007).

Active learning also promotes learners’ perception of autonomy. Active learning refers to the application of knowledge in an authentic context. Students involved in this type of learning report greater satisfaction of their need for autonomy (Hartnett, 2016). These results expand upon past findings that active learning enhances student motivation (Van Etten et al., 2008), performance (Yoder & Hochevar, 2005), engagement (Zapke, Leach, & Butler, 2009), and deeper levels of understanding (Brophy, 2013).

When considering the QM Rubric as a measure of course quality, it does not initially appear to have much bearing on autonomy. Choice is never explicitly mentioned in the Rubric, nor is interest, nor relevance. QM maintains a searchable database of published research that has contributed to the current version of the Rubric. A search in the QM Research Library for the
word “autonomy” yields ten (10) published studies which have reportedly contributed to the
development of the Rubric.

The majority of these studies are not relevant to motivation; describing autonomous use
of online resources, validating measures of autonomy, or making single use of the word (Al
Zumor, 2015; Armstrong & Thornton, 2012; Benton, Li, Gross, Pallett, & Webster, 2013;
Huang, Chandra, DePaolo, Cribbs, & Simmons, 2015; Lakhal, Khechine, & Pascot, 2013; L.
Morgan, 2011; Seyedmonir, Barry, & Seyedmonir, 2014; Smith & Craig, 2013). One study that
does consider autonomy in a motivational context tested whether a number of variables were
predictive of student engagement in an online learning game (Eseryel, Law, Ifenthaler, Ge, &
Miller, 2014). Autonomy was not predictive of engagement in this study. Another relevant study
was conducted by Hartnett (2015), in which she described a number of factors that undermined
online learners’ autonomy. These factors were high workload, salience of assessment, lack of
relevance, course expectations & language perceived as controlling, time constraints, technology
constraints, limited choice, workload inequity, and limited input in group discussion and tasks.
The extent to which this or any of the above studies were used in the development of the QM
Rubric is currently unknown.

In summary, there is considerable evidence that a number of aspects of course design
bear on student autonomy. On this basis, it is hypothesized that course quality will significantly
predict online learners’ perceptions of autonomy.

_Hypothesis 1: Course Quality will be positively associated with autonomy._

**2.1.2. Competence**

Hartnett (2016) also considered online learning environment features that were
supportive of competence. This section will describe her findings, additional research on course
quality and competence, and the hypothesized relationship between course quality and competence in this study. Before discussing previous research, it may be prudent to reiterate the meaning of competence in this context; it refers to one’s capacity to interact effectively with one’s environment (White, 1959). This is distinct from confidence in one’s abilities, or self-efficacy, as it describes the interaction between one’s abilities and the structure of their environment. In the case of education, this structure is largely provided by the instructor; the quality of which has the potential to support or undermine a learner’s sense of competence.

The provision of structure in education has been shown to facilitate both self-determined motivation and feelings of competence (Connell & Wellborn, 1991; Deci & Moller, 2005; Reeve, Deci, & Ryan, 2004; Reeve et al., 2008). Hartnett (2016) identifies several course characteristics relevant to learners’ perceptions of their competence: ongoing guidance and supportive feedback from lecturers; perceptions of clear guidelines and expectations; responsiveness of the lecturers; positive efficacy judgements; helpful and supportive peers; perceptions of useful course resources; and perceptions of the activity as optimally challenging. Feedback that is framed in terms of how a student can improve in the future, rather than what they did wrong in the past, has been shown to have positive effects on feelings of competence (Deci & Moller, 2005), as well as self-determined motivation (Reeve, 2006).

The use of clear guidelines for assignments and expectations for completed work also contributes to feelings of competence. Returning to the necessity of structure for learners to feel competent, the clarity of guidelines and instructor expectations facilitates the navigation of that structure. By knowing what is expected of them, students are able to use appropriate strategies and take appropriate measures to perform to the necessary standard. Failure to perform at this
standard, whether as a result of insufficient abilities or a flawed understanding of the criteria used to judge their performance, undermines learners’ sense of competence (Hartnett, 2016).

Responsiveness, the availability and general presence of the instructor in the learning environment, may not readily appear to have much bearing on competence. However, keeping in mind that competence refers to the quality of the structure in one’s environment, the availability and approachability of one’s instructor has a dramatic influence on a learner’s ability to effectively use that structure. Hartnett (2016) explains this finding in terms of the instructor being available to support learners as they develop their understanding. Taking a given course is an exercise in increasing one’s understanding of the material. Students are likely to have questions during this process or perceive that they have reached the limit of their ability to understand, and so reach to the instructor for clarification, or guidance. The availability of the instructor, their receptiveness to questions, and the timeliness and quality of their response can all then facilitate a student’s progress. This is supported by other studies of online learning (Artino, 2007; Bekele, 2010; Xie, DeBacker, & Ferguson, 2006).

Participants also reported higher perceptions of their competence depending on how relevant and useful they considered their learning resources to be. When participants saw learning materials presented in class as helpful for increasing their understanding, or as useful templates for future work, they tended to report a greater sense of competence (Hartnett, 2016). This finding is similar to that of Martens and Kirschner (2004), who reported a positive relationship between the perceived usefulness of learning materials and intrinsic motivation of students.

Optimal challenge was also supportive of competence. Students who felt that their assignments were neither too hard nor too easy reported the highest perceived competence
(Hartnett, 2016). When a task is easy, it is not seen as a meaningful test of one’s abilities, while if a task is too difficult, it can undermine one’s perception of their abilities. This finding is consistent with prior research (Csikszentmihalyi, 1985; Shroff, Vogel, & Coombes, 2008).

The QM research library has eight studies containing the word “competence” which were used in the development of the current version of the Rubric. Six of these studies are unrelated to motivation, using competence as a synonym of ability (Al Zumor, 2015; Cowley, Fantato, Jennett, Ruskov, & Ravaja, 2014; Danaher, Danaher, & Moriarty, 2007; Greer, Rice, & Dykman, 2014; Peterson, 2012; Somyürek & Coşkun, 2013). The remaining two studies are those discussed in the previous section on autonomy. Eseryel and colleagues (2014) found that student perceptions of competence were significantly and negatively predictive of engagement in an online context. The second study conducted by Hartnett (2015) indicated that a number of factors undermined online learners’ competence, including unclear and complicated instructions, insufficient guidance and feedback from the lecturer, judgements of low self-efficacy, reduction of lecturer input, perceived lack of useful resources, and challenges that were beyond one’s perceived capabilities.

To summarize, several course characteristics have been found to have a positive effect on student competence. It is therefore expected that course quality will have a positive relationship with student competence.

*Hypothesis 2: Course Quality will be positively associated with student competence.*

2.1.3. Relatedness

While there is comparatively little in an online environment to support a student’s need for relatedness, Hartnett (2016) identifies a few characteristics that support this need. They are a
sociable and considerate lecturer, use of self-disclosure by the lecturer, inclusivity and respect modeled by the lecturer.

Calling a lecturer sociable and considerate in this case refers to their level of involvement with the class, the time and care they take when interacting with students, and their general presence in the course overall. Hartnett found these factors to support perceptions of relatedness and intrinsic motivation (2016), as have other researchers (Brophy, 2013; Reeve, 2006; Rentroia-Bonito et al., 2006; Xie et al., 2006).

The use of appropriate self-disclosure by the lecturer was also found to increase students’ perceptions of relatedness and self-determined motivation (Hartnett, 2016), although specific examples are not provided. References to self-disclosure in this context are quite rare in the literature, yet Rourke and colleagues (2001) identify it as a means of facilitating social presence, which in turn has been shown to have positive effects on student learning (Richardson & Swan, 2003), and online learner satisfaction (Wise, Chang, Duffy, & Del Valle, 2004) and motivation (Baker, 2010).

Finally, the demonstration of inclusivity and respect towards students also supports a sense of relatedness (Hartnett, 2016). Inclusivity has been identified as necessary for fostering feelings of connectedness (Rovai, 2007). Both respect and inclusivity are also considered to be necessary for supporting motivation among culturally-diverse students (Ginsberg, 2005; Ginsberg & Wlodkowski, 2000), and the basis on which subsequent motivation techniques are successful (Brophy, 2013).

As in previous sections, the database of publications that were used to develop the current version of the QM Rubric was searched for studies pertaining to relatedness. The search yielded two studies, both of which have already been referenced (Eseryel et al., 2014; Hartnett, 2015).
Hartnett describes two factors found to undermine student relatedness: communication issues and disagreements, and lack of opportunity to interact with classmates (Hartnett, 2015). In their study of factors that contribute to engagement among online learners, Eseryel and colleagues found that relatedness did not significantly predict engagement (2014).

While fewer course characteristics have been found to relate to learner relatedness, there is still considerable evidence from a number of sources supporting this point. For this reason, it is predicted that course quality will support students’ perceptions of relatedness.

*Hypothesis 3: Course Quality will be positively associated with student relatedness.*
2.2. Basic Psychological Needs as they relate to Motivation among Online Learners

The relationship between the satisfaction of basic psychological needs and one’s subsequent motivation is a pillar of SDT and, as such, need not be discussed in any great length. A great number of studies demonstrate this relationship (Brophy, 2013; Connell & Wellborn, 1991; Csikszentmihalyi, 1985; Deci & Moller, 2005; Ginsberg & Wlodkowski, 2000; Guay, Vallerand, & Blanchard, 2000; Katz & Assor, 2007; Patall, Cooper, & Robinson, 2008; Reeve, 2009; Reeve et al., 2008; Ryan & Deci, 2000; Van Etten et al., 2008). One such study was conducted by Chen and Jang (2010) who assessed the supportiveness of a given online learning environment, the extent to which students perceived that their needs for autonomy, competence and relatedness were met, and the students’ levels of self-determined motivation. They then used structural equation modeling to test the relationships described by SDT. Just as would be expected from SDT, support from the learning environment fostered need satisfaction among students, which then promoted higher levels of self-determined motivation. One of the goals of the current study will be to replicate these results. On the basis of decades of supporting evidence, it is expected that a positive relationship will be found between basic psychological need satisfaction and online learner motivation in this study as well.

Hypothesis 4a: Perceptions of autonomy will be positively associated with self-determined motivation.

Hypothesis 4b: Perceptions of competence will be positively associated with self-determined motivation.

Hypothesis 4c: Perceptions of relatedness will be positively associated with self-determined motivation.
2.3. The Moderating Influence of Goal Orientation on Motivation

The role of individual differences in SDT has often been overlooked and is briefly if ever considered in academic motivation research. One of the first proposals for the consideration of individual differences in online education was made by Hartnett, St. George and Dron (2011), who reported a wide range of self-determined motivation from students who were all in the same learning environment. Assuming equal treatment, the only other explanation for this variance in motivation is on the level of individual differences. The following is an argument that goal orientation moderates the effect of the environment on self-determined motivation.

Unfortunately, this question does not yet appear to have been tested empirically, but the existing literature provides a suitable foundation for exploration.

First, we must return to SDT. Deci and Ryan (1985b) describe an individual-level construct that refers to one’s tendency to perceive a particular context as supportive or undermining of their self-determined motivation: their causality orientation. Different people may perceive the same environment to be more or less controlling of their behavior depending on which of three causality orientations predominate: autonomy, control, or impersonal. Someone with an autonomy orientation generally sees environments as supportive of their autonomy and thus feels that they are self-determined in their actions. Someone who is control oriented tends to see their environment as controlling and view their actions as a result of this external control. Finally, an impersonal orientation refers to the tendency to not be motivated.

Given that SDT already includes a construct at the individual level, the necessity for incorporating goal orientation into the model may well be challenged. The benefits are twofold. In the first place, causality orientation is a relative novelty in the literature. A Google Scholar search for the article in which Deci and Ryan first describe their conceptualization of causality
orientations (Deci & Ryan, 1985b) indicates that it has been cited approximately 1900 times. The same search engine indicates that a review of the current state of SDT published 15 years later (Ryan & Deci, 2000) has been cited approximately ten times as much. A possible explanation for this lack of acceptance in the literature is a general confusion on what causality orientations are. A fixture of the theory is that one’s causality orientation bears on one’s perceived locus of causality. This refers to whether one believes that they are acting because they chose to, or because they are being compelled to act from an external influence. An autonomy orientation facilitates the belief that external sources are not controlling but informative, and the individual can use this information to act more effectively. A control orientation is just the reverse, in which one tends to see external stimuli as controlling of one’s behavior, whether they were intended to control or not. A student with a control orientation is more likely to take feedback from a professor on how they can improve in the future as a command on what they are expected to do in the future. A common mistake that researchers make is to equate “locus of causality” with “locus of control” (Sheldon, Turban, Brown, Barrick, & Judge, 2003). For whatever reason, causality orientation has not been as widely accepted in the literature as the other dimensions of SDT. Goal orientation on the other hand has been extensively studied in its role within motivation. Incorporating goal orientation into SDT would only require demonstrating that the goal orientation construct is functionally comparable to causality orientation.

At first, causality orientations appear to be completely dissimilar to LGO and the PGOs, and unfortunately these descriptions of individual difference rarely appear in the literature together. Yet comparisons can be made on the basis of common processes. For example, both models describe similar reactions to failure. Individuals with an LGO/autonomous orientation are both likely to respond to failure with renewed perseverance, while those with a PGOa/impersonal
orientation respond to failure with self-deprecation and feelings of incompetence (Deci & Ryan, 1985b; Dweck & Leggett, 1988; Koestner & Zuckerman, 1994). The models also describe the similar ways in which individuals regulate their behavior. People with an LGO/autonomous orientation both tend to behave according to intrinsic cues, while those with a PGOp/controlled orientation are more likely to regulate their achievement behavior according to external cues.

The expectation of conceptual similarity between goal orientation and causality orientation has received support from a number of studies. For instance, Koestner and Zuckerman (1994) found a significant degree of covariation between causality orientations and goal orientations such that an autonomy orientation was associated with an LGO, and control and impersonal orientations were associated with PGO. Additionally, the researchers included measures of confidence in one’s abilities. A control orientation was thus associated with PGO and high confidence in one’s abilities, and an impersonal orientation was associated with PGO and low confidence in one’s abilities. These combinations functionally describe PGOp and PGOa, respectively. Clearly Deci and Ryan were on the right track, as they appear to have described the tripartite model of goal orientation more than a decade before VandeWalle operationalized it (1997). The same pattern of associations between goal orientations and causality orientations was also found in a later study (Lee, Sheldon, & Turban, 2003).

Next, if goal orientation can functionally take the place of causality orientation in SDT, it is necessary to demonstrate that goal orientation moderates the relationship between one’s environment and their level of motivation. Before proceeding, it is necessary to explore an issue relevant to the integration of goal orientation into SDT. An aspect of SDT is that it is a macro theory, broadly concerned with when people will be motivated and when they will not. Most of its sub-theories have already been discussed, if not named. The importance of basic
psychological needs is described in Basic Psychological Need Theory (BPNT; R. M. Ryan, 1995), the levels of self-determined motivation are described by Organismic Integration Theory (OIT; Deci & Ryan, 1985a), and causality orientations in Causality Orientation Theory (COT; Deci & Ryan, 1985a). While each of the sub-theories are consistent with SDT in themselves, they have not yet been fully integrated with each other. This lack of integration is relevant to the current study because it raises questions for potential hypotheses. If goal orientation can functionally take the place of causality orientation in SDT, it is necessary to demonstrate that goal orientation moderates the relationship between one’s environment and their level of motivation. However, it is not yet known whether goal orientation would do this by moderating the relationship between the environment and need satisfaction, or between need satisfaction and motivation. At present, there is evidence for both possibilities.

Evidence that goal orientation moderates the effect of the environment on basic psychological needs comes from a study of the undermining effect of external rewards (Hagger & Chatzisarantis, 2011). The proposal that providing someone with a reward in exchange for their performance of a task results in diminished motivation to perform that task is made by another of SDT’s sub-theories; Cognitive Evaluation Theory (CET; Deci, 1975). CET describes the role of perception on need satisfaction and motivation. Broadly, external stimuli are not inherently supporting or undermining of one’s BPN but become so based on how one perceives them. Performance-contingent rewards have the effect of focusing the recipient’s attention on the reward as the cause of their action, thus prompting an external perceived locus of causality, and diminished self-determined motivation. The functional mechanism for this effect is the diminished satisfaction of the need for autonomy. If someone performs a task because they enjoy it, or know that they should, then they feel that they are performing that task on their own
initiative. If they are paid to perform the same task, they will then feel that they are doing it for the money, because someone else wants them to. Thus, external rewards undermine motivation by undermining autonomy (Deci, Koestner, & Ryan, 1999). In their study, Hagger and Chatzisarantis (2011) had participants perform puzzle tasks in conditions with and without performance-contingent rewards. No effect of condition was found for LGO participants, but the external reward did undermine the motivation of PGOp participants. These findings not only demonstrate that goal orientation moderates the effect of external influences on motivation but do so by moderating the relationship between external influences on need satisfaction. Because rewards undermine motivation by undermining autonomy, participants with an LGO must have been protected from this effect, else their motivation would have been different between groups. These results replicate those of another study that demonstrated the protective effects of an LGO on autonomy-undermining stimuli (Whinghter et al., 2008). Given that PGOp is associated with a control orientation (Koestner & Zuckerman, 1994), it is reasonable to hypothesize that any perceived attempt to facilitate competence and relatedness in an online learning environment would result in diminished satisfaction of those needs as well. And on the assumption that a course of high quality would be designed to facilitate those needs, it is therefore hypothesized that goal orientation will moderate the effect of course quality on psychological need satisfaction.
Hypothesis 5: Goal orientation will moderate the relationship between course quality and psychological need satisfaction.

Hypothesis 5a: PGOp will moderate the relationship between course quality and psychological need satisfaction such that the strength of the relationship will diminish as PGOp increases.

Hypothesis 5b: PGOa will moderate the relationship between course quality and psychological need satisfaction such that the strength of the relationship will increase as PGOa increases.

Hypothesis 5c: The moderating effects of PGOp and PGOa on the relationship between course quality and psychological need satisfaction will be significantly different.

Evidence that goal orientation moderates the effect of need satisfaction on motivation comes from a study by Koestner and Zuckerman (1994). Participants were given an interesting puzzle task to perform under conditions of repeated failure or success, with the intention of undermining or supporting their intrinsic motivation. To perform in conditions of repeated success has been shown to support one’s sense of competence (Ryan, Koestner, & Deci, 1991). LGO participants demonstrated no effect of condition on their ultimate motivation, but PGOp participants were much less motivated in the success condition and more motivated in the failure condition. In this case, need-supportive conditions had an undermining effect on motivation. Having received repeated confirmation of their competence on the puzzle task, PGOp participants had much less motivation to perform it, having already achieved their desired goal. For PGOa participants, repeated success raised competence and motivation ratings. This study suggests that goal orientation moderates the relationship between need satisfaction and motivation, such that competence undermines motivation for PGOp individuals. Other
researchers report similar results of goal orientation moderating the effects of motivation-undermining stimuli (Hagger & Chatzisarantis, 2011; Rawsthorne & Elliot, 1999; Whitingter, Cunningham, Wang, & Burnfield, 2008). These results were also replicated by a meta-analysis conducted by Rawsthorne and Elliot (1999) who found that competence support only undermined the motivation of participants with a PGO orientation.

Despite the relative lack of research on causality orientation, and even less that also addresses goal orientation, there is some evidence of a conceptual and functional similarity. There is also evidence of two trends. The first is that the supportive or undermining effects of the environment are diminished or nullified among LGO participants. Second, the relationship between the environment and participants’ motivation is significantly different, often inverted, for PGOp and PGOa participants. On this basis, it is hypothesized that goal orientation will moderate the relationship between need satisfaction and self-determined motivation.

Hypothesis 6: Goal orientation will moderate the effect of psychological need satisfaction on self-determined motivation.

Hypothesis 6a: PGOp will moderate the relationship between each of the basic psychological needs and self-determined motivation such that the strength of the relationship will diminish as PGOp increases.

Hypothesis 6b: PGOa will moderate the relationship between each of the basic psychological needs and self-determined motivation such that the strength of the relationship will increase as PGOp increases.

Hypothesis 6c: The moderating effect of PGOp and PGOa on the relationship between relatedness and self-determined motivation will be significantly different.
2.4. The Role of Motivation in Predicting Academic Performance

Before discussing the effects of self-determined motivation on online-learning, a brief review of the literature from traditional education settings will be made. The general consensus within the literature is that higher levels of self-determined motivation are positively associated with academic achievement, as demonstrated by a recent meta-analysis (Taylor et al., 2014). Intrinsic motivation and identified regulation were found to have a strong and positive association with academic performance, while introjection and external regulation had negative effects, and amotivation had a strong negative relationship with achievement. Additional studies replicate these findings (Amabile, 1996; Black & Deci, 2000; Cerasoli & Ford, 2014; Grolnick & Ryan, 1987; Miserandino, 1996; Utman, 1997).

Due to the relatively recent emergence of online learning, it is understandable that the body of research on motivation and performance is not yet so complete, though there have been a number of studies exploring the relationship between motivation and online learning performance. For example, higher levels of self-determined motivation have been found to result in higher performance on an online course’s final exam (Giesbers, Rienties, Tempelaar, & Gijselaers, 2013). Although not necessarily tied to performance, Xie, Durrington and Yen (2011) found that intrinsic motivation was positively associated with the frequency of participation in online course discussions. Interestingly, Black and Deci (2000) found that autonomous motivation at the start of a course did not predict performance, but increases in motivation over time did. This suggests that performance is associated with factors in the learning environment that were supportive of self-determined motivation over time.

In another study of online students, autonomy, competence and relatedness were all positively correlated with intrinsic motivation and perceived academic success (Butz &
Stupnisky, 2016). Unfortunately, objective measures of academic performance were not collected, and causal relationships were not tested, as these were not the focus of the study.

In a significant departure from expectations, Chen and Jang (2010) found no effect of self-determined motivation on final grade in an online course. The authors suggest that this may signify the diminished importance of self-determination in online learning and the increased necessity of environmental support for learners’ psychological needs. They point out that, while self-determination was not significantly associated with learning outcomes, the satisfaction of psychological needs was positively associated with hours spent studying, frequency of logging into the online classroom, expected grade and perceived learning, while the perception of a supportive environment was associated with course satisfaction, and that these variables contributed to students’ final grades. Unfortunately, this hypothesis was not tested. Ultimately, none of the independent variables assessed in this study were found to be related to exam grade. Given past evidence of a strong relationship between need satisfaction and motivation on student performance, another possible explanation is that the final grades were not sufficiently variable, owing to a ceiling effect. At present this study has not been replicated, but the present study is sufficiently similar in design to potentially explain the findings reported by Chen and Jang (2010). Despite these particular findings, the trend in the literature for both traditional and online learning environments is that self-determined motivation has a positive effect on academic performance. It is therefore safe to predict a positive effect of self-determined motivation on online learning performance in this study as well.

**Hypothesis 7:** Self-determined motivation will positively predict online learner performance.
2.5. Summary

This chapter began with a discussion of the relationship between course quality and the basic psychological needs described by SDT. It was found that the course characteristics that support autonomy, competence and relatedness are also often cited as features of well-designed courses.

The relationship between the satisfaction of basic psychological needs and self-determined motivation was also discussed. This relationship is well-supported in the motivational literature, and was demonstrated outright among online learners by Chen and Jang (2010).

Next, it was argued that goal orientation moderated the relationship between course quality and student motivation. Parallels were drawn between the goal orientations described by Dweck and Leggett (1988) and the causality orientations described by Deci and Ryan (1985b). Predictions were made on the findings that would be expected if goal orientation moderated the relationship between course quality and need satisfaction, as well as the relationship between need satisfaction and self-determined motivation.

Finally, the effects of self-determined motivation on learner performance were discussed. The consensus within the literature is that self-determined motivation has a positive effect on student performance. See Appendix C for a diagram that illustrates the proposed relationships between the constructs described in this section, and which the results of this study are expected to support.
Chapter 3. Methodology

The primary purpose of this study is to determine whether online course quality, as measured by the QM Rubric, is supportive of intrinsic motivation and subsequent performance. A secondary purpose is to explore whether goal orientation moderates this relationship. This section describes the sample population, data collection procedures, measures, and data analysis plan used in the study.

3.1. Population Sample

The sample for this study consisted of students enrolled in at least one course taught through the online education arm of VU during the either of the Summer or Fall modules of 2017, who responded to the invitation to participate in the online study and completed both surveys (n = 245). Due to the ability for students to be enrolled in more than one course, and thus contribute more than one observation to the data set, the number of total observations was greater than the number of students (n = 397). In terms of missingness, 229 observations have no missing data, and the remaining 168 observations are missing data on one variable; either Course Quality (n = 125) or Final Grade (n = 43). Of the observations missing Course Quality, this was a result of an instructor withholding permission to evaluate their course, but whose students still participated in the survey. Of the observations missing Final Grade, this was because some students did not have numerical grades for a given course for such reasons as withdrawing or taking a course on a pass/fail basis.
3.2. Procedures

Courses offered by VU are offered in a series of seven modules per year, each approximately seven weeks long. In any given module, approximately 100 courses are offered with 660 students enrolled. Data were collected across multiple modules in order to achieve a sufficient sample size. The target sample size was 400 observations in a minimum of 50 classes, with a minimum of five students in each class. Support and justification for these estimates is presented in section 3.4.

In order to generate support for this study from instructors, and facilitate their recommendation of it to their students, they were approached through online communication. It was explained that one of the goals of this study is to assess whether standard measures of course quality actually reflect a measurable benefit to student performance. It was also made clear that this was not an investigation of the quality of instructors or their methods, but of the course design guidelines. All that was needed from the instructors was access to their course at the student level on VU’s learning management system (LMS). This research was conducted with the support of a top VU administrator, meaning that instructors did not need to provide the data of interest such as QM score and students’ final grades. Student surveys were also distributed and collected electronically by the researcher. Students were invited to participate through email.

To facilitate participation from the students, each set of surveys that they completed entered them to win a selection of VU branded items, such as shirts, wall pennants, mugs, etc. Participants were only allowed to complete one set of surveys per course, but if they took multiple courses concurrently, they were allowed to complete one set of surveys for each of them. Aside from the benefit of gaining research experience, students who did not win the drawing did not stand to benefit from participating in the study directly. To the best of the
author’s knowledge, instructors did not offer extra credit to students to encourage their participation. It is also conceivable that any improvements to course quality measures will not be implemented until after they graduate. However, the interested participant may benefit from further investigation into the question of motivation and performance. While a course’s characteristics can satisfy or fail to satisfy a learner’s needs for autonomy and so on, there are a number of things that individuals can do in a learning setting to satisfy these needs and boost their motivation. Introspection is commonly associated with higher levels of motivation and performance and understanding one’s mental processes and using that knowledge for practical purposes imbues one with a sense of power and control over their lives. One might even say “self-determination”.

All survey materials were distributed electronically. Initial data were collected in the first week of the module to capture goal orientation data. The second wave of data collection took place one week before the module ended. On the assumption that course design can support or undermine students’ basic psychological needs, and thus motivation, this strategy was used to allow the effect of course design to impact students over time. The second wave of data collection captured motivation levels after a long experience in the course. Survey data are anonymous, linked to the student with a randomized number.

Final grade data provided by VU’s Registrar’s Office. The rating of courses according to the QM Rubric was done by two reviewers who were trained in its use. With access to the course’s online presence and syllabus, the reviewers determined whether the course met each of the 43 specific standards and awarded points accordingly. Each standard has a specific point value (1, 2 or 3) which is awarded on a pass/fail basis. Partial credit cannot be awarded for partially meeting a given standard. In the event of a disagreement on whether a course met a
particular standard, the course was re-reviewed according to that standard and discussed between the reviewers. This resulted in agreement on all standards which had been questioned. The course’s overall QM score is the sum of all points attached to successfully met standards out of 99.

Courses in this study were also assessed according to the Quality Scorecard (QSC) developed by the Online Learning Consortium (OLC). The QSC is similar to the QM Rubric in that it details specific “quality indicators” in a number of general categories. The primary difference between the two is that the QSC allows for points to be awarded by degree, meaning that a course may meet a particular indicator completely, partially, or not at all, and receive between zero and three (0-3) points per indicator. The QSC contains 75 such indicators in nine categories, and courses are therefore capable of scoring up to 225 points. As with the QM Rubric, courses in this study were assessed by two independent reviewers. As before, disagreements between reviewers were discussed and the items were re-reviewed. This usually resulted in consensus. For one indicator on which both reviewers still disagreed after discussion whether two or three points should be awarded, the scores from both reviewers were averaged.
3.3. Instrumentation & Variables

Course Quality

Course Quality ultimately refers to the extent to which a course’s design characteristics support or undermine learners’ basic psychological needs. Such characteristics as clear expectations of students’ performance, the linking of course activities to student goals and the demonstration of continual presence from the instructor are not only descriptive of a well-designed course but are also supportive of learners’ basic needs. Indeed, it can be argued that courses are not well designed because their characteristics facilitate student learning, but because their characteristics facilitate higher levels of motivation, which then facilitate learning.

In this study, course quality was measured in two ways: with the QM Rubric, and with the OLC Quality Scorecard. Course quality is operationally defined as the course’s QM score out of 99 (M=87.57, SD=6.52).

As discussed in Chapter 1, the QM Rubric contains eight general standards. These are Course Overview and Introduction, Accessibility and Usability, Learner Support, Course Technology, Course Activities and Learner Interaction, Instructional Materials, Assessment and Measurement, and Learning Objectives. Each of these general standards contain a number of specific standards against which a course is ultimately evaluated.

Course quality was also measured with the OLC Quality Scorecard. The QSC presents 75 quality indicators under nine general categories. These are Institutional Support, Technology Support, Course Development and Instructional Design, Course Structure, Teaching and Learning, Social and Student Engagement, Faculty Support, Student Support, and Evaluation and Assessment. Only the category Course Development and Instructional Design was used to evaluate courses in this study, as the other categories addressed topics beyond the scope of
course design, such as delivery and factors that are beyond an instructor’s ability to control. This category contains eight quality indicators. Points are awarded on a scale of zero to three (0-3) depending on the degree to which the course demonstrates each indicator. This means that a maximum of 24 points can be awarded to a given course (M = 20.64, SD = 3.38). Examples of point values appropriate for each level of indicator are provided in the QSC handbook. For example, three points should be awarded if “the administrator has found that the quality standard is being fully implemented, can be fully substantiated, and there is little to no need for improvement in this area.”

**Basic Psychological Need Satisfaction**

Need satisfaction refers to the extent to which learners’ needs for autonomy, competence and relatedness are met. The satisfaction of these needs was assessed with the Basic Needs Satisfaction in Class Scale (Copeland & Levesque-Bristol, 2011) (BNS; Deci et al., 2001). This is a 21-item, self-report measure on a 1-7 Likert scale. Seven items in the scale measure autonomy (α = .79), six measure competence (α = .73), and eight measure relatedness (α = .84). In the current sample, the average autonomy, competence and relatedness scores were (M=31.68, SD=4.66), (M=28.45, SD=4.22) and (M=38.28, SD=8.07) respectively.

**Self-Determined Motivation**

Self-determined motivation refers to the extent to which one perceives their motivation to act as coming from an internal source, and that their continuation to act is regulated by internal processes. As with the basic needs, this is a completely subjective assessment requiring a self-report measure. In this study, self-determined motivation was assessed with the Situational Intrinsic Motivation Scale (SIMS; Guay, Vallerand, & Blanchard, 2000). This scale measures respondents’ intrinsic motivation (α = .86), identified regulation (α = .65), external regulation (α
= .73), and amotivation (α = .62), each with four self-report 1-7 Likert scale items. The average scores were (M=18.29 SD=5.68), (M=19.19 SD=5.54), (M=17.34 SD=5.39) and (M=10.28 SD=4.83) respectively.

To represent the continuum of self-determined motivation, a single index of self-determination was computed. In past studies utilizing the SIMS, it is common practice to weight and pool each participant’s scores on its sub-scales. This is done by multiplying the amotivation score by negative two (-2), the external regulation score by negative one (-1), identified regulation by positive one (1), and intrinsic motivation by positive two (2), and adding the resulting products. The result is a self-determination index score (SDI) on a scale from negative seventy-two (-72) to positive seventy-two (72) (M=17.88 SD=26.23).

**Goal Orientation**

Goal orientation refers to one’s internal belief about whether ability is fixed or malleable, and their consequent goal when they undertake an achievement task. A belief that ability is fixed orients learners to demonstrate their ability if they think that they are capable of the task (PGOp), or to attempt to disguise their lack of ability if they think that the task is beyond their ability (PGOa). A belief that ability is malleable orients learners to approach tasks as opportunities to maintain or develop their ability (LGO). This conceptualization of goal orientation is also completely subjective. Therefore, goal orientation was assessed with the measure developed by VandeWalle (1997). This is a 16-item self-report measure on a 1-6 Likert scale. Six items assess LGO (α = .89), five assess PGOp (α = .85), and five assess PGOa (α = .88). The average scores were (M= 29.61 SD=4.34), (M= 15.78 SD=5.07) and (M= 12.42 SD=4.82) respectively. It had originally been planned to categorize students according to their predominating goal orientation, but in the current study all three measures of goal orientation were considered, as the software
used to estimate the research model cannot accommodate categorical variables. This model also allows for greater accuracy, as goal orientations do not exist in all individuals to the same degree. Rather, all individuals can be seen to demonstrate each goal orientation to varying degrees.

Compared to the need satisfaction and SIMS survey items, the items in the goal orientation survey were inverted (larger numbers indicate less agreement with an item). To reduce cognitive burden on the participants, and thus potentially improve reliability, the scale presented to participants was reversed and thus consistent with the scales of other measures in the survey.

**Performance**

Performance serves as a conceptual indicator for learning. Because learning is a process that takes place internally, it cannot be measured directly. How well a student performs on a test of material covered in class is often used as an indicator of how much that student has learned in that class. The studies cited in this paper thus far tend to measure class performance in one of two ways: final exam grade, and final grade in the course. These measures should produce similar results but are conceptually distinct. A student’s final exam grade represents their performance on one learning assessment, presumably their last learning assessment, in a given class. It might be assumed that performance on this exam is more representative of overall learning than performance on other exams because it is the final assessment of what the student knows. However, final exams can vary greatly between classes. They can be cumulative, non-cumulative, harder, easier, formatted the same or differently from previous assessments, and different in any number of other ways. The only thing that a detached researcher can infer from a student’s final exam grade is how well they performed on their final exam. Conceptually, performance on a single assessment is too far removed from one’s learning over the course of a
semester. For that reason, students’ final exam scores were not used as a measure of learning in this study. Because final grades are contributed to by all assignments and exams over the course of the semester, they describe something of a midpoint in a student’s performance across time and assessment type. Therefore, in this study, student performance was measured by that student’s final course grade on a percentage scale (M=93.31 SD=5.65).

**Control Variables**

Demographic variables such as students’ age, number of previously-taken online courses, and the size of individual courses were used as control variables in the current study as these have been found to relate to need satisfaction and performance in online learning.

**Age**

Participants’ ages were calculated by subtracting their reported date of birth from the recorded date that they completed the first survey, rounded down to the nearest whole number of years. (M=33.69 SD= 7.68).

**Course Experience**

Course experience refers to the number of online courses that a participant has completed at their current university prior to participating in the survey (M=4.73 SD= 4.32).

**Course Load**

Course load refers to the number of online courses that a participant is enrolled in at the time of their participation in the study (M=1.55 SD= 0.89).

**Course Size**

Course size refers to the number of students who remain enrolled in a course until the end (M=48.65 SD=24.18).
3.4. Data Analysis Strategy

Univariate and Bivariate Analyses

Descriptive statistics were calculated for each variable to identify their overall distribution, and bivariate correlation analyses were conducted to determine which variables are interrelated. These analyses were analyzed using SPSS Version 24 (IBM Corporation, 2016).

Multivariate Analyses

As mentioned in section 3.2, participants completed a survey for each course in which they were enrolled per module. This approach introduces a violation of sample independence. Fortunately, this problem has frequently been encountered in educational research and statistical analyses have been developed to address it: The Cross-Classified Multilevel Model (CCMM; Goldstein & Sammons, 1997). This is an extension of typical multilevel models in which, for instance, students are nested in schools. Individuals at level 1 are nested in groups at level 2, and group effects are expected to apply equally to all individuals nested in it. It may be the case however that individuals can be classified into more than one group, or that a researcher was interested in the effects of two types of groups, to put it another way. Subjects are no longer considered “nested” because a single individual is now a member of more than one group. These subjects are now “cross-classified” or classified as members of multiple groups at the same level. This was the case for one of the first uses of a CCMM, in which the researchers were interested in the effects of both secondary and junior school attendance (high school and junior high school in the colonies) on GCSE performance (Commonwealth equivalent of the ACT). More than 700 students were sampled from nearly 50 high schools, with each student having come from one of more than 100 junior high schools previously. The aim of that study was to determine whether the choice of junior high school that a student attended still had any effect on how well they
performed on a major exam at the end of high school. Use of a CCMM allowed researchers to estimate the independent effects of two groups on performance at the individual level.

In CCMM, individuals need not be restricted to Level-1. Individuals can also be specified at Level-2. Consider the example of course evaluations at a high school or university. Each student is likely taking more than one class and will therefore submit multiple evaluations. After the evaluations are collected and placed in a single pile they can be sorted according to which course they pertain to, or the student who filled them in. Likewise, each evaluation that a course receives is a function of both the course (a good course will presumably receive a higher score than a bad course) and of the evaluating student (inclined to be more or less harsh for whatever reason). A flaw in this course-evaluating method is that the characteristics of the individual are often not considered, so the average rating for each course is assumed to be indicative only of the course’s quality. Given the opportunity to collect relevant data on the students, a CCMM could be used to identify the proportions of variance in the overall course rating attributable to the course and to the students.

Specifying groups and individuals at level 2 to identify their effects on a variable at level 1 has been done numerous times in the literature. In two separate studies, Spooren and colleagues (Spooren, 2010; Brockx, Spooren & Mortelmans, 2011) did so in real-life versions of the example above, and Jayasinghe, Marsh and Bond (2003) to test the effects of researcher and reviewer characteristics on grant proposal evaluations. In all of these studies the DVs were contributed to by the same individuals across groups, meaning that a single student evaluated multiple courses and a single reviewer evaluated multiple grant proposals. This is similar to the design for the current study in which a single student will evaluate the extent to which multiple courses satisfy their basic psychological needs.
A number of statistical software packages are capable of performing CCMM analyses and the steps involved are broadly similar across platforms. CCMM analyses in the current study were carried out in M-Plus (Muthén & Muthén, 2005). It is worthwhile to note that when conducting cross-classified analyses in M-Plus, the software will always use Bayesian Estimation rather than Maximum Likelihood Estimation for estimating parameter values. This will become relevant when discussing model fit in Chapter 4 as many indices of model fit rely on ML estimation, such as the Akaike Information Criterion (AIC).

Regarding the sample size necessary to test a CCMM, there appears to be no consensus on general guidelines or a priori power calculations. The question of sample size is largely absent from the literature on this analysis. In their study of traditional nested models, Maas and Hox (2005) suggest a minimum sample size of 50 at the group level for multilevel models. Spooren’s (2010) analyses were conducted with 1025 responses collected from 566 students in 87 courses, and Brockx, Spooren and Mortelmans’ (2011) with 1244 evaluations from 531 students in 56 courses. A recent study (Vassallo, Durrant, & Smith, 2017) examined the impact of varying group size and group number on power in a CCMM using simulated data. As in the current study, the researchers specified a two-level model with individuals and groups at the second level. In order to achieve a power of .80 or greater for both the group effects and individual effects, a minimum of 60 individuals and 30 groups were needed, with each individual a member of three groups. Increases in group size, group number, and the total group membership of each individual each had the effect of increasing power, often to ceiling. Past research supports this estimate. In the case of Spooren (2010), 1025 evaluations were collected from 566 students. The author states that 315 of these students only submitted one evaluation. That leaves 251 students who evaluated two or more courses to supply the remaining 710 evaluations, an average of 2.83
evaluations/courses each. If the 315 students who only submitted one evaluation were divided evenly across the 87 courses sampled in that study, an average of 3.62 of these students were in each course. Therefore, for every three courses (rounding up from 2.83), a single student evaluated all three of them, and either three or four unique students evaluated each of them. In short, each course in that study was likely evaluated by only four or five students. Given that this group size is so near the empirically-derived minimum reported by Vassallo, Durrant and Smith (2017), a minimum group size of five was sought in the current study as well. Also given that the average number of groups from the studies discussed hovers around 50; a minimum of 30 proposed by Vassallo, Durrant and Smith (2017), a minimum of 50 proposed by Maas and Hox (2005), 56 used by Brockx, Spooren and Mortelmans (2011) and 87 by Spooren (2010), 50 seems a reasonable target for courses to sample from.

When estimating CCMM, Raudenbush and Bryk (2002) recommend testing multiple models of increasing complexity and comparing their fit. The model with the best fit will then be used to address the research questions. Following the model-building process described by Raudenbush and Bryk (2002), six models were tested in order of complexity, beginning with the least complex model with no predictors and ending with the most complex interaction model. Descriptions of how each model was structured will be presented, followed by a discussion of how the models were evaluated. The first model was fully unconditional with no predictors (Model 1). At Level-1, the model is

\[ Y_{i(j1j2)} = \pi_{intercept (j1j2)} + \epsilon_{i(j1j2)} \]  

(1)
where $Y_{i(j_1j_2)}$ represents the performance outcome associated with survey response $i$ attached to student $j_1$ and course $j_2$. The intercept, $\pi_{\text{intercept} \ (j_1j_2)}$, represents the predicted performance of student $j_1$ in course $j_2$. The residual, $e_{i(j_1j_2)}$, represents the deviation of the performance outcome associated with a particular survey response from the predicted intercept value based on the student from whom the response came and the course to which it refers.

At level-2, the level-1 intercept, $\pi_{\text{intercept} \ (j_1j_2)}$, is modeled as a random effect in the fully unconditional model (Equation 2).

$$\pi_{\text{intercept} \ (j_1j_2)} = \Theta_{\text{intercept}} + b_{0j10} + c_{00j2}$$ (2)

The overall intercept, $\Theta_{\text{intercept}}$, represents the grand mean student performance score. The student residual, $b_{0j10}$, represents the student effect for student $j_1$ averaged across courses. The course residual, $c_{00j2}$, represents the course effect for course $j_2$ averaged across students.

Next, a level-1 model (Model 2) examines the extent to which student performance varies according to autonomy, competence, relatedness and motivation (Equation 3).

$$Y_{i(j_1j_2)} = \pi_{\text{intercept} \ (j_1j_2)} + \pi_{\text{autonomy} (j_1j_2) \text{autonomy}_{i(j_1j_2)}} +$$

$$\pi_{\text{competence} (j_1j_2) \text{competence}_{i(j_1j_2)}} + \pi_{\text{relatedness} (j_1j_2) \text{relatedness}_{i(j_1j_2)}} +$$

$$\pi_{\text{motivation} (j_1j_2) \text{motivation}_{i(j_1j_2)}} + e_{i(j_1j_2)}$$ (3)

At level-1, $Y_{i(j_1j_2)}$, still represents the performance associated with response $i$ from student $j_1$ in course $j_2$. The intercept, $\pi_{\text{intercept} \ (j_1j_2)}$, represents expected performance when all predictors are set to zero. $\pi_{\text{autonomy} (j_1j_2)}$ represents the expected change in performance associated with a
response from student j1 in course j2 for every change of one standard deviation in autonomy while controlling for all other predictors. $\Pi_{\text{competence}(j1j2)}$ represents the expected change in performance associated with a response from student j1 in course j2 for every change of one standard deviation in competence while controlling for all other predictors. $\Pi_{\text{relatedness}(j1j2)}$ represents the expected change in performance associated with a response from student j1 in course j2 for every change of one standard deviation in relatedness while controlling for all other predictors. $\Pi_{\text{motivation}(j1j2)}$ represents the expected change in performance associated with a response from student j1 in course j2 for every change of one standard deviation in motivation while controlling for all other predictors.

At level-2, the level-1 intercept, $\pi_{\text{intercept}}(j1j2)$, was modeled as a random effect in the level-1 model (Equation 4).

$$\pi_{\text{intercept}}(j1j2) = \Theta_{\text{intercept}} + b_{0j10} + c_{0j10} + d_{0j10} + e_{00j2}$$

$$\pi_{\text{autonomy}}(j1j2) = \Theta_{\text{autonomy}}$$

$$\pi_{\text{competence}}(j1j2) = \Theta_{\text{competence}}$$

$$\pi_{\text{relatedness}}(j1j2) = \Theta_{\text{relatedness}}$$

$$\pi_{\text{motivation}}(j1j2) = \Theta_{\text{motivation}}$$

The overall intercept, $\Theta_{\text{intercept}}$, represents the grand mean of performance when all Level-1 predictors are set to zero. In other words, the average performance score expected from a survey response reporting average need satisfaction and average motivation. The residuals $b_{0j10}$, $c_{0j10}$ and $d_{0j10}$ represent the effects of autonomy, competence and relatedness for value $j1$ averaged across motivation values, and $e_{00j2}$ represents the motivation effect for value $j2$. 

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averaged across need satisfaction values. $\theta_{\text{autonomy}}, \theta_{\text{competence}}, \theta_{\text{relatedness}}$ and $\theta_{\text{motivation}}$ represent the fixed effects of autonomy, competence, relatedness and motivation. The level 1 equation of Model 2 (Equation 3), will serve as the level 1 equation for all remaining models.

Next, a level-2 model (Model 3) examined the extent to which performance varied according to student-level variables: goal orientation, age, experience and course load, while controlling for autonomy, competence, relatedness and motivation differences at Level 1 (Equation 5).

$$\pi_{\text{intercept}}(j1j2) = \theta_{\text{intercept}} + \gamma_{\text{LGO}} LGO_{j1} + \gamma_{\text{PGO}_p} PGO_{p_j1} + \gamma_{\text{PGO}_a} PGO_{a_j1}$$
$$+ \gamma_{\text{age}} \text{age}_{j1} + \gamma_{\text{experience}} \text{experience}_{j1} + \gamma_{\text{course load}} \text{course load}_{j1} +$$
$$\gamma_{\text{major}} \text{major}_{j1} + b_{0j10} + c_{0j10} + d_{0j10} + e_{00j2}$$

$$\pi_{\text{autonomy}}(j1j2) = \theta_{\text{autonomy}}$$
$$\pi_{\text{competence}}(j1j2) = \theta_{\text{competence}}$$
$$\pi_{\text{relatedness}}(j1j2) = \theta_{\text{relatedness}}$$
$$\pi_{\text{motivation}}(j1j2) = \theta_{\text{motivation}}$$

The intercept, $\theta_{\text{intercept}}$, now refers to the expected performance score (adjusted for Level-1 predictors) when all Level 2 predictors are set to zero, or a student with average goal orientation values, of average age, with average experience and an average course load. Each $\gamma_x$ represents the fixed effects of variable X across students. The residual terms as well as $\pi_x$ and $\theta_x$ terms still represent the values described in Equations 3 and 4.
Next a complimentary level-2 model (Model 4) examined the extent to which performance varied according to course-level variables: quality and course size, while controlling for need satisfaction and motivation differences at Level 1 (Equation 6).

\[
\pi_{\text{intercept}}(j1j2) = \Theta_{\text{intercept}} + \gamma_{\text{Quality}} \cdot \text{Quality}_{j2} + \gamma_{\text{size}} \cdot \text{size}_{j2} + b_{0j10} + c_{0j10} + d_{0j10} + e_{00j2}
\]

\[
\pi_{\text{autonomy}}(j1j2) = \Theta_{\text{autonomy}}
\]

\[
\pi_{\text{competence}}(j1j2) = \Theta_{\text{competence}}
\]

\[
\pi_{\text{relatedness}}(j1j2) = \Theta_{\text{relatedness}}
\]

\[
\pi_{\text{motivation}}(j1j2) = \Theta_{\text{motivation}}
\]

The intercept, \( \Theta_{\text{intercept}} \), now refers to the expected performance score (adjusted for Level-1 predictors) when all Level 2 predictors are set to zero, or a course of average quality and size. Each \( \gamma_{x} \) represents the fixed effects of variable \( X \) across courses. The residual terms as well as \( \pi_{e} \) and \( \Theta_{e} \) terms still represent the values described in Equations 3 and 4.

Next, a level-2 model (Model 5) examined the extent to which performance varied according to both individual- and course-level variables, while controlling for need satisfaction and motivation differences at Level 1 (Equation 7).
\[ \pi_{\text{intercept}}(j_1j_2) = \theta_{\text{intercept}} + \gamma_{\text{LGO}}LGO_{j_1} + \gamma_{\text{PGO}}PGO_{j_1} + \]
\[ \gamma_{\text{GO}}PGO_{a_1} + \gamma_{\text{age}}age_{j_1} + \gamma_{\text{experience}}experience_{j_1} + \]
\[ \gamma_{\text{course_load}}course\_load_{j_1} + \gamma_{\text{major}}major_{j_1} + \]
\[ \gamma_{\text{Quality}}Quality_{j_2} + \gamma_{\text{size}}size_{j_2} + b_{0j_{10}} + c_{0j_{10}} + d_{0j_{10}} + e_{00j_2} \]
\[ \pi_{\text{autonomy}}(j_1j_2) = \theta_{\text{autonomy}} \]
\[ \pi_{\text{competence}}(j_1j_2) = \theta_{\text{competence}} \]
\[ \pi_{\text{relatedness}}(j_1j_2) = \theta_{\text{relatedness}} \]
\[ \pi_{\text{motivation}}(j_1j_2) = \theta_{\text{motivation}} \]

(7)

The intercept, \( \theta_{\text{intercept}} \), now refers to the expected performance score (adjusted for Level-1 predictors) when all Level 2 predictors are set to zero, or a student with average goal orientation values, of average age, with average experience and an average course load in a course of average quality and size. Each \( \gamma \) represents the fixed effects of variable X across students and courses. The residual terms as well as \( \pi \) and \( \theta \) terms still represent the values described in Equations 3 and 4.

Finally, a level-2 model (model 6) examined the extent to which performance varied according to both individual- and course-level variables, as well as an interaction between the individual variables goal orientation and the course variable quality (Equation 8).
The intercept, $\Theta_{intercept}$, now refers to the expected performance score (adjusted for Level-1 predictors) when all Level 2 predictors are set to zero, or a student with average goal orientation values, of average age, with average experience and an average course load in a course of average quality and size. Each $\gamma_x$ represents the fixed effects of variable X across students and courses. The interactions $\gamma_{LGO*Quality}$, $\gamma_{PGOp*Quality}$ and $\gamma_{PGOa*Quality}$ represent the moderating effects of goal orientation on course quality. The residual terms as well as $\pi_x$ and $\Theta_x$ terms still represent the values described in Equations 3 and 4.

Intraclass correlation coefficients (ICCs) were calculated to determine the degree to which performance varied among students, among courses, and among students and courses. Equations 9, 10 and 11 were used to calculate ICCs based on the results from the unconditional model (Model 1).
Student ICC = $\frac{\tau_{b00}}{\tau_{b00} + \tau_{c00} + \sigma^2}$ \hspace{1cm} (9)

Course ICC = $\frac{\tau_{c00}}{\tau_{b00} + \tau_{c00} + \sigma^2}$ \hspace{1cm} (10)

Student and Course ICC = $\frac{\tau_{b00} + \tau_{c00}}{\tau_{b00} + \tau_{c00} + \sigma^2}$ \hspace{1cm} (11)

In the above equations, $\tau_{b00}$ refers to the student variance, $\tau_{c00}$ refers to the course variance, and $\sigma^2$ refers to the variance at Level-1. The total proportion of variance attributable to Students is .250 or 25%. The total proportion of variance attributable to courses is .407 or 40.7%. The total proportion of variance attributable to both students and courses is .343 or 34.3%.

As a basis for comparison, pseudo-$R^2$ values were calculated for Models 2 through 6. These pseudo-$R^2$ values describe the difference in Level-2 residuals between a given model and the null model in a coefficient of partial determination. See Equations 12 through 16 for descriptions of how each of these pseudo-$R^2$ values were calculated.

$$\frac{[[\tau_{b00} + \tau_{c00}]_{\text{Model 1}} - [[\tau_{b00} + \tau_{c00}]_{\text{Model 2}}]}{[[\tau_{b00} + \tau_{c00}]_{\text{Model 1}}}} \hspace{1cm} (12)$$

$$\frac{[[\tau_{b00} + \tau_{c00}]_{\text{Model 1}} - [[\tau_{b00} + \tau_{c00}]_{\text{Model 3}}]}{[[\tau_{b00} + \tau_{c00}]_{\text{Model 1}}}} \hspace{1cm} (13)$$

$$\frac{[[\tau_{b00} + \tau_{c00}]_{\text{Model 1}} - [[\tau_{b00} + \tau_{c00}]_{\text{Model 4}}]}{[[\tau_{b00} + \tau_{c00}]_{\text{Model 1}}}} \hspace{1cm} (14)$$

$$\frac{[[\tau_{b00} + \tau_{c00}]_{\text{Model 1}} - [[\tau_{b00} + \tau_{c00}]_{\text{Model 5}}]}{[[\tau_{b00} + \tau_{c00}]_{\text{Model 1}}}} \hspace{1cm} (15)$$

$$\frac{[[\tau_{b00} + \tau_{c00}]_{\text{Model 1}} - [[\tau_{b00} + \tau_{c00}]_{\text{Model 6}}]}{[[\tau_{b00} + \tau_{c00}]_{\text{Model 1}}}} \hspace{1cm} (16)$$

Identifying the best model to address the research questions is not as simple as comparing $R^2$ values to determine which model provides the greatest improvement over the null model. Each model is different, containing different variables and fundamentally answering different questions, and therefore cannot be compared directly. One model may explain more variance
than another, but it may also contain more variables. In order to conclude that one model is better than another, the difference in the variances explained must be significant not only in themselves, but in the context of the difference in the number of variables. This is the virtue of specifying multiple models of increasing complexity: it is possible to determine whether each model explains significantly more variance than the model before, while also identifying the most parsimonious model. To compare two models in this way requires a comparison of their overall deviance; that is the difference between its observed and expected parameters expressed as a $\chi^2$ statistic. The difference between these values is significant when it exceeds a critical $\chi^2$ value with degrees of freedom being the difference between the number of predictor variables in each model. If the difference between $\chi^2$ values is significant, the difference in pseudo-$R^2$ values will be shown to be significant as well.
Chapter 4. Results

4.1. Preliminary Analysis

Before tests of hypotheses can be conducted, several conditions must be established to ensure the data quality meet standards for a rigorous test of measurement validly and modeling fit. Univariate, bivariate and multivariate analyses were conducted to explore the sufficiency of these conditions.

4.1.1. Univariate and Bivariate Analyses

Descriptive statistics were calculated for each variable, as well as correlation coefficients between pairs of variables to determine whether and which pairs share significant relationships. Given that all variables were standardized for analysis, descriptive and correlational statistics describe the variables before standardization. See Table 1 for the results of these analyses.
Table 1.

*Descriptive and correlational statistics of unstandardized Level-1, Individual- and Course-Level variables*

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>SD</th>
<th>Age</th>
<th>Experience</th>
<th>Load</th>
<th>LGO</th>
<th>PGOp</th>
<th>PGOa</th>
<th>Autonomy</th>
<th>Competence</th>
<th>Relatedness</th>
<th>Motivation</th>
<th>Grade</th>
<th>Size</th>
<th>QM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>33.69</td>
<td>7.68</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Experience</td>
<td>4.73</td>
<td>4.32</td>
<td>.116*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Load</td>
<td>1.55</td>
<td>0.89</td>
<td>-.160**</td>
<td>-.111*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>LGO</td>
<td>29.61</td>
<td>4.34</td>
<td>.273**</td>
<td>-.164**</td>
<td>-.041</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PGOp</td>
<td>15.78</td>
<td>5.07</td>
<td></td>
<td></td>
<td>-.254**</td>
<td>-.079</td>
<td>.054</td>
<td>.03</td>
<td>(   .81)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PGOa</td>
<td>12.42</td>
<td>4.82</td>
<td>-.350**</td>
<td>.028</td>
<td>.062</td>
<td>-.432**</td>
<td>-.408**</td>
<td>(.87)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Autonomy</td>
<td>31.68</td>
<td>4.66</td>
<td>.079</td>
<td>-.109*</td>
<td>.021</td>
<td>.184**</td>
<td>-.115*</td>
<td>-.254**</td>
<td>(.80)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Competence</td>
<td>28.45</td>
<td>4.22</td>
<td>.106*</td>
<td>-.062</td>
<td>.070</td>
<td>.250**</td>
<td>.025</td>
<td>-.189**</td>
<td>.373**</td>
<td>(.81)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Relatedness</td>
<td>38.28</td>
<td>8.07</td>
<td>.054</td>
<td>.167**</td>
<td>-.016</td>
<td>.310**</td>
<td>-.114*</td>
<td>-.191**</td>
<td>.294**</td>
<td>.366**</td>
<td>(.75)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Motivation</td>
<td>17.88</td>
<td>26.23</td>
<td>.051</td>
<td>-.075</td>
<td>.006</td>
<td>.313**</td>
<td>-.042</td>
<td>-.256**</td>
<td>.364**</td>
<td>.533**</td>
<td>.442**</td>
<td>(.89)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Grade</td>
<td>93.31</td>
<td>5.65</td>
<td>-.023</td>
<td>.070</td>
<td>.129**</td>
<td>.042</td>
<td>-.007</td>
<td>.061</td>
<td>.018</td>
<td>.003</td>
<td>.025</td>
<td>.063</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Size</td>
<td>48.65</td>
<td>24.18</td>
<td>.176**</td>
<td>-.273**</td>
<td>.118*</td>
<td>.121*</td>
<td>-.042</td>
<td>-.187**</td>
<td>-.009</td>
<td>.076</td>
<td>.010</td>
<td>.072</td>
<td>-.118*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>QM</td>
<td>87.57</td>
<td>6.52</td>
<td>.066</td>
<td>-.022</td>
<td>.004</td>
<td>.025</td>
<td>.082</td>
<td>-.006</td>
<td>-.052</td>
<td>.102*</td>
<td>.036</td>
<td>.104*</td>
<td>-.025</td>
<td>.202**</td>
<td>(.85)</td>
</tr>
</tbody>
</table>

* = p < .05
** = p < .01

The results of this correlational analysis indicate that the three goal orientations all share significant relationships. LGO and PGOp share a relationship presumably on their shared tendency to perform well in a classroom setting, though for different reasons. PGOp and PGOa share a very strong significant relationship presumably due to their shared preoccupation with their performance in the eyes of others. And as expected LGO and PGOa share a significant negative relationship as they reflect mutually exclusive goals: either to learn with no concern for others’ perceptions, or principally to avoid being seen as a poor performer in others’ eyes.

Autonomy shared significant relationships with all three goal orientations, namely positive with LGO and negative with PGOp and PGOa. This may reflect an increased perception of freedom in
one’s actions on the part of the LGO student, and for PGO students a self-imposed constraint on one’s activities to those which will give the desired impression to others. An LGO also had positive associations with competence, relatedness and motivation in accordance with past research. Likewise, a PGO orientation has significant negative relationships with all three psychological needs as well as motivation. Each of the psychological needs also shared significant relationships with one another and motivation, as would be expected. Interestingly, student performance was not correlated with any of the psychological needs or motivation. Another finding of interest is that course quality significantly correlated with student competence and self-determined motivation.

4.1.2. Multivariate Analyses

Before testing the CCMM, data were evaluated for violations of multivariate assumptions, these being normality, linearity, multicollinearity and homoscedasticity. The normality of Level-1, Course and Student residuals were assessed through Q-Q plots. All plots appeared normal (See Appendix G). Multicollinearity was assessed by examining the tolerance and Variance Inflation Factor (VIF) values from four multiple regression models (Berry, 1993). These models pertained to the Level-1 predictor variables, Student predictor variables, Course predictor variables, and both Student and Course predictor variables. Critical tolerance values were considered below .10, and critical VIF values were considered greater than 10. In all four models, tolerance values were acceptable (.58-.99), as were VIF values (1.01-1.73). See Appendix G for results of multicollinearity tests. Homoscedasticity was assessed with scatterplots of residuals. There was no evidence of heteroscedasticity (See Appendix G). Finally, before estimating the multilevel models, all variables were standardized to account for the considerable variance in their ranges.
Finally, in order to determine which statistical model to use in hypothesis testing, pairs of models were compared on the basis of their deviance, beginning with the two most complex models: Model 5 and Model 6. When comparing Model 6 against Model 5 the difference in the proportion of variance that they each explained was quite small (.005), however this became significant as the observed parameters in Model 6 were closer to their expected values than those in Model 5. The addition of relatively few predictor variables (df = 3) resulted in a low critical value to meet ($\chi^2 = 7.815$). Model 6 was then compared to the remaining models with similar results. See Table 2 for the results of these likelihood ratio tests. Model 6 predicted significantly more variance in student performance than any other model and was therefore used to test individual hypotheses.

Table 2.

*Model Comparisons*

<table>
<thead>
<tr>
<th></th>
<th>Model 6 to Model 5</th>
<th>Model 6 to Model 4</th>
<th>Model 6 to Model 3</th>
<th>Model 6 to Model 2</th>
<th>Model 6 to Model 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta$ pseudo-R²</td>
<td>.005*</td>
<td>.012*</td>
<td>.041*</td>
<td>.018*</td>
<td>.123*</td>
</tr>
<tr>
<td>$\Delta$ $\chi^2$</td>
<td>39.278</td>
<td>65.298</td>
<td>33.635</td>
<td>19.892</td>
<td>30.84</td>
</tr>
<tr>
<td>$\Delta$ Predictor Variables</td>
<td>3</td>
<td>9</td>
<td>5</td>
<td>11</td>
<td>15</td>
</tr>
</tbody>
</table>

4.2. Hypothesis Testing

**Hypothesis 1: Course quality will be positively associated with autonomy.**

Based on the results of CCMM analysis, course quality does not predict student autonomy in this sample ($- .05, p > .05$). Statistical power was calculated through a Monte Carlo study in which sample data were generated based on the parameters of the current model. In this study 100 samples were generated, and their estimates and standard deviations were averaged.
Power was defined as the proportion of samples for which a given parameter is significant at the .05 level. In this instance, course quality significantly predicted autonomy seven times in 100 replications, resulting in a power of .07. In other words, the probability that the null hypothesis was correctly rejected in this instance on a scale of 0 to 1 is .07.

At this point an estimate of effect size is calculated to determine whether the observed power was the result of the size of the effect of course quality on autonomy or too small a sample size to detect a significant effect. Unfortunately, a measure of effect size has not yet been agreed upon for specific parameters within a cross-classified model. However, there are alternatives that can provide an approximation. First, while Mplus is not able to calculate an effect size for individual parameters, it does calculate an \( R^2 \) value for each dependent variable at each level. For the effect of Course level variation on autonomy, Mplus reports an effect size of .14 (\( p < .05 \)). It should be noted that this is not only the combined effect of the variables on the Course level on autonomy, namely quality and course size, but also the unexplained variance within the Course level. On the subject of residual variance, the second method of approximating the effect of quality on autonomy involves an analysis of autonomy’s residual variance at each level of the model. In addition to parameter estimates, Mplus also provides the proportion of residual variance for each dependent variable at each level. With autonomy as an example, .602 of its variance remains unexplained at Level-1, an additional .267 of its variance remains unexplained at the Student level, and .092 of its variance is unexplained at the Course level. In other words, 96.1% of autonomy’s observed variance is unexplained by the model. The remaining 3.9% of variance is explained to a greater or lesser degree by the model’s twenty independent variables, two of which explain a statistically significant amount. On this basis, and without an empirical
effect size measure compatible with the current model, it is reasonable to conclude that the effect
of course quality on autonomy is negligible and this hypothesis is not supported.

**Hypothesis 2: Course quality will be positively associated with competence.**

Based on the results of the CCMM analysis, course quality does not predict student competence in this sample (.07, p > .05). The power for this parameter was estimated in the same Monte Carlo study described above and was found to be .1. The R² value for competence at the Course level is .11, which reflects the effect of both explained and unexplained variance at the Course level on competence. Considering the proportion of observed variance in competence that remains unexplained at Level-1 and the Student and Course levels, the values are .688, .18 and .07 respectively, indicating that 93.8% of competence’s variance is unexplained. This leaves 6.2% of the variance to be explained by the independent variables, two of which significantly predict competence. On this basis, it is likely that course quality does not affect student competence to a meaningful degree, meaning that this hypothesis is not supported.

**Hypothesis 3: Course quality will be positively associated with relatedness.**

Based on the results of the CCMM analysis, course quality does not predict student relatedness in this sample (.00, p > .05). The power for this parameter was estimated in the same Monte Carlo study described above and was found to be .06. The R² value for relatedness at the Course level is .04, which reflects the effect of both explained and unexplained variance at the Course level on relatedness. Considering the proportion of observed variance in relatedness that remains unexplained at Level-1 and the Student and Course levels, the values are .333, .449 and .119 respectively, indicating that 90.1% of relatedness’s variance is unexplained. This leaves 9.9% of the variance to be explained by the independent variables, four of which significantly
predict relatedness. On this basis, it is likely that course quality does not affect student relatedness to a meaningful degree, meaning that this hypothesis is not supported.

**Hypothesis 4: Perceptions of autonomy competence and relatedness will significantly relate to student motivation.**

Based on the results of the CCMM analysis, autonomy (.12, p < .05), competence (.33, p < .001) and relatedness (.33, p < .001) all significantly predict student motivation. The power for these parameters was estimated in the same Monte Carlo study described above and were found to be .6, 1.00 and 1.00 respectively. The R² value for motivation at Level-1 is .35, which reflects the effect of both explained and unexplained variance at Level-1. Considering the proportion of observed variance in motivation that remains unexplained at Level-1 and the Student and Course levels, the values are .307, .327 and .126 respectively, indicating that 76% of motivation’s variance is unexplained. This leaves 24% of the variance to be explained by the independent variables, none of which aside from autonomy, competence and relatedness significantly predict motivation. A note on the Student and Course level variances for motivation before proceeding: these were not residual variances, as motivation was not modeled to vary as a function of any variable on these levels directly. These values reflect variance in motivation between courses, and students, independent of other sources of variance. On the basis of significant parameter estimates, a moderate effect size at Level-1 and a lack of additional significant predictors, it is likely that autonomy, competence and relatedness all affect student motivation to a meaningful degree. The hypothesis that need satisfaction significantly relates to student motivation is supported.

**Hypothesis 5: Goal orientation will moderate the relationship between course quality and psychological need satisfaction.**
Hypothesis 5a: PGOp will moderate the relationship between course quality and psychological need satisfaction such that the strength of the relationship will diminish as PGOp increases.

Hypothesis 5b: PGOa will moderate the relationship between course quality and psychological need satisfaction such that the strength of the relationship will increase as PGOa increases.

Hypothesis 5c: The moderating effects of PGOp and PGOa on the relationship between course quality and psychological need satisfaction will be significantly different.

Based on the results of the CCMM analysis, there is only minor support for the hypothesis that goal orientation moderates the relationship between course quality and psychological need satisfaction. Specifically, it was found that PGOp significantly moderates the relationship between course quality and competence (-.10, p < .05). In other words, as one’s PGOp increases, the effect of course quality on one’s sense of competence trends in the negative direction. To illustrate, the median PGOp score is .04, with 193 observations below .04, and 204 observations at .04 or above. For the half below the median, course quality and competence are significantly and positively correlated (.19, p < .01), while this relationship is nearly nonexistent in the half above the median (.01, p > .05). Given that there was no support for Hypothesis 5b, Hypothesis 5c was not tested.

The power for the significant parameter was estimated in the same Monte Carlo study described above and was found to be .46, while the highest power value among the nonsignificant parameters was .11. This is further evidence that the lack of power found in these analyses is a result of effect size, rather than sample size, as the current sample was sufficient to detect a significant effect even at 46% power.
Hypothesis 6: Goal orientation will moderate the effect of psychological need satisfaction on self-determined motivation.

*Hypothesis 6a: PGOp will moderate the relationship between each of the basic psychological needs and self-determined motivation such that the strength of the relationship will diminish as PGOp increases.*

*Hypothesis 6b: PGOa will moderate the relationship between each of the basic psychological needs and self-determined motivation such that the strength of the relationship will increase as PGOp increases.*

*Hypothesis 6c: The moderating effect of PGOp and PGOa on the relationship between relatedness and self-determined motivation will be significantly different.*

Based on the results of the CCMM analysis, goal orientation did not moderate the effect of any psychological needs on motivation. Of the nine combinations of goal orientation and psychological needs in the model, the parameter estimates connected to motivation range from -.07 to .09, and the range of power estimates was between .08 and .42. This finding also supports the possibility that the observed power is a function of effect size rather than sample size. If the sample size were insufficient to detect significant effects in this analysis, it would be expected that power would be consistently low across all estimations, rather than varying between 8% and 42%. On the contrary, a correlation analysis demonstrates that the absolute values of parameter estimates and their corresponding powers are significantly correlated (.97, p < .01). Because power varies so closely with the estimates, it is most likely that effect size is the limiting factor for power rather than sample size. As above, because of the lack of evidence for Hypotheses 6a and 6b, Hypothesis 6c was not tested.
Hypothesis 7: Self-determined motivation will be positively associated with student performance.

Based on the results of the CCMM analysis, student performance is predicted by self-determined motivation in this sample. Specifically, motivation significantly and positively predicts student performance (.24, p < .001) such that as motivation increases, performance increases as well. The power for this parameter was estimated in the same Monte Carlo study described above and was found to be 1.00. The $R^2$ value for performance at Level-1 is .07, which reflects the effect of both explained and unexplained variance at Level-1. Variance at the student level was .24, while variance at the course level was .37. In other words, 37% of the variance in student performance was due to differences between courses. Despite the relatively small proportion of variance explained, motivation has been shown to significantly predict student performance. The hypothesis that self-determined motivation is positively associated with student performance is supported.
Chapter 5. Discussion

The purpose of the current study was to test the effectiveness of online course design as a means of improving student motivation and performance in the context of SDT. In order to address relevant gaps in the literature, seven hypotheses were tested (See Appendix B).

5.1. Summary of Findings

The findings overall support SDT in an online education context. Bivariate correlation analyses revealed patterns similar to those that would be expected from previous research. The expected relationships were observed between goal orientations, between the psychological needs as well as between the needs and motivation. Of interest is the fact that student grade was not associated with anything aside from course load, with which it shared a positive relationship. After a number of models were computed and compared, from the simplest with no predictors, to the most complex with all predictors and hypothesized relationships. This final model was found to explain the greatest relative proportion of variance in student grade and was used to test the individual hypotheses. The psychological needs described by SDT were all found to predict self-determined motivation among online learners, which in turn predicted their performance.

Support was not found for the role of goal orientation as a moderating variable in this process. This is not particularly surprising as Deci and Ryan (2000) clearly explain the nature of their proposed moderating variable as distinct from goal orientation. It was however reasonable to test goal orientation in this role as past research has demonstrated a moderating effect of goal orientation on performance in the context of SDT.

Support was also lacking for a relationship between course quality and psychological need satisfaction. Based on Hartnett’s work (2016), among others, there is strong evidence to suggest that course design can have positive or negative effects on student motivation and
learning. Unfortunately, course quality as described by QM had no effect in this study. It should be noted that QM do not claim that building courses to their standards is not all that is necessary to maximize students’ outcomes, and that a number of other considerations can affect a learner’s overall experience, such as how the course is actually taught and how prepared the student is to learn.

Despite the finding that course quality shared significant positive correlations with student competence and self-determined motivation, course quality did not predict competence in the current model, and a relationship between course quality was neither hypothesized nor modeled as no support for such a model was found in the literature. Out of interest, a modified version of Model 6 was also tested which included a direct relationship between course quality and self-determined motivation. This relationship was not significant.

5.2. Limitations of the Study

The present study suffers from a number of limitations. Principally, the study did not meet with overwhelming support from instructors. Despite the head of VU’s online education office promoting the study to all acting instructors, relatively few instructors were willing to allow their courses to be assessed or to encourage their students to participate in the online survey. As a result, relatively few courses compared to those that were available were included.

The use of final grade as the sole indicator of student outcome is also a shortcoming. Final grades in a course may be affected by a number of variables independent from the course’s quality including student preparedness, prior knowledge, and other factors beyond the instructor’s control. As such, a student’s final grade is not necessarily a reliable indicator of how much they learned in a given class. Perhaps pre- and post-course evaluations of student knowledge could address this question in future studies.
The current study sampled students from only six departments, with the result that its findings may not be generalizable across an entire college or university. Those departments sampled from were those which offered dedicated courses through Valkyrie Online, and while they represent a range from Social Work to Construction Management to Business, the sample is not representative of a complete cross-section of learners. Future studies should make an effort to address this by including a broader range of courses and departments across academic disciplines.

Another shortcoming was the lack of a measure of causality orientation. The significance of causality orientation to the current study was based on evidence that it may moderate the effects of external support on a learner’s perceived need satisfaction, and thus motivation. However, due to causality orientation’s relative obscurity in the literature, a measure of goal orientation was substituted in the current study. This decision was based on evidence of common processes and significant correlations between goal orientations and their corresponding causality orientations. However, based on the current study’s failure to demonstrate a moderating role of goal orientation comparable to what would be expected of causality orientation, it is possible that goal orientation does not always function similarly to causality orientation. Future studies can be improved by measuring both orientations within learners and potentially identify their distinguishing characteristics.

Another potential limitation is one of instrument reliability. Specifically the amotivation and identified regulation subscales of the SIMS (Guay, Vallerand, & Blanchard, 2000) have somewhat low reported reliability: $\alpha = .62$ & $.65$ respectively. Reliability values calculated from the current sample were found to be somewhat stronger for both amotivation ($\alpha = .72$) and identified regulation ($\alpha = .75$), if not as strong as would be desired.
While it was beyond the scope of the current study, it is likely that other factors relevant to student performance were neglected. In addition to course design, other considerations such as the content and delivery of the course, the degree of institutional support given to online courses, student preparedness and the learning management system through which the course is provided can all impact a student’s experience and learning outcomes. While the focus of the current study was the role of course quality in student learning, the other considerations presented undoubtedly played a role as well. By failing to account for them in the model, their impact on student motivation and performance are effectively contributing to the error variance.

Finally, a limitation shared with similarly designed studies is in the area of power. Following the assessment of the multilevel model, power analyses were conducted to determine whether the sample size of the current study was sufficient to detect significant effects. Power was calculated in Mplus based on the results of 100 randomly generated models. These models in turn were based on the parameter values from Model 6. By calculating power for each of these models and taking their average, a close estimation of Model 6’s true power can be calculated. The resulting analysis identifies the power for each relationship specified in the model, rather than the model as a whole. See Tables 3, 4 and 5 for the results of these power analyses at the within level, the between student level, and the between course level respectively.
Table 3.

Post Hoc power for Model 6 Paths at the Within Level

<table>
<thead>
<tr>
<th>Path</th>
<th>Estimate</th>
<th>Power</th>
</tr>
</thead>
<tbody>
<tr>
<td>Motivation -&gt; Performance</td>
<td>0.238</td>
<td>1.00</td>
</tr>
<tr>
<td>Autonomy -&gt; Motivation</td>
<td>0.124</td>
<td>0.60</td>
</tr>
<tr>
<td>Competence -&gt; Motivation</td>
<td>0.335</td>
<td>1.00</td>
</tr>
<tr>
<td>Relatedness -&gt; Motivation</td>
<td>0.333</td>
<td>1.00</td>
</tr>
<tr>
<td>LGO*Autonomy -&gt; Motivation</td>
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</tr>
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</tr>
<tr>
<td>LGO*Relatedness -&gt; Motivation</td>
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<td>0.09</td>
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<tr>
<td>PGOp*Autonomy -&gt; Motivation</td>
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<td>0.28</td>
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<tr>
<td>PGOp*Competence -&gt; Motivation</td>
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<td>0.08</td>
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<tr>
<td>PGOp*Relatedness -&gt; Motivation</td>
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<td>0.42</td>
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<tr>
<td>PGOa*Autonomy -&gt; Motivation</td>
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<td>0.13</td>
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<tr>
<td>PGOa*Competence -&gt; Motivation</td>
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<td>0.41</td>
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<tr>
<td>PGOa*Relatedness -&gt; Motivation</td>
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<tr>
<td>QM*LGO -&gt; Autonomy</td>
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<tr>
<td>QM*PGOa -&gt; Autonomy</td>
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<tr>
<td>QM*LGO -&gt; Competence</td>
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<tr>
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<td>QM*PGOp -&gt; Relatedness</td>
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<tr>
<td>QM*PGOa -&gt; Relatedness</td>
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<td>0.06</td>
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Table 4.

*Post Hoc power for Model 6 Paths at the Between Students Level*

<table>
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<tr>
<th>Path</th>
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<th>Power</th>
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</thead>
<tbody>
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<td>LGO -&gt; Autonomy</td>
<td>0.095</td>
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<td>PGOp -&gt; Autonomy</td>
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<td>PGOa -&gt; Autonomy</td>
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<td>0.00</td>
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<td>Age -&gt; Autonomy</td>
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<td>0.00</td>
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<td>Experience -&gt; Autonomy</td>
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<td>0.01</td>
</tr>
<tr>
<td>Load -&gt; Autonomy</td>
<td>0.037</td>
<td>0.00</td>
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<td>0.00</td>
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<tr>
<td>PGOp -&gt; Competence</td>
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<td>0.01</td>
</tr>
<tr>
<td>PGOa -&gt; Competence</td>
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<td>0.03</td>
</tr>
<tr>
<td>Age -&gt; Competence</td>
<td>0.089</td>
<td>0.00</td>
</tr>
<tr>
<td>Experience -&gt; Competence</td>
<td>-0.065</td>
<td>0.00</td>
</tr>
<tr>
<td>Load -&gt; Competence</td>
<td>0.063</td>
<td>0.01</td>
</tr>
<tr>
<td>LGO -&gt; Relatedness</td>
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<tr>
<td>PGOp -&gt; Relatedness</td>
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</tr>
<tr>
<td>PGOa -&gt; Relatedness</td>
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<td>0.02</td>
</tr>
<tr>
<td>Age -&gt; Relatedness</td>
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</tr>
<tr>
<td>Experience -&gt; Relatedness</td>
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</tr>
<tr>
<td>Load -&gt; Relatedness</td>
<td>-0.057</td>
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</table>

Table 5.

*Post Hoc power for Model 6 Paths at the Between Courses Level*

<table>
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<tr>
<th>Between Courses</th>
<th>Estimate</th>
<th>Power</th>
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</thead>
<tbody>
<tr>
<td>Size -&gt; Autonomy</td>
<td>-0.084</td>
<td>0.08</td>
</tr>
<tr>
<td>Quality -&gt; Autonomy</td>
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<td>0.06</td>
</tr>
<tr>
<td>Size -&gt; Competence</td>
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<td>0.04</td>
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<tr>
<td>Quality -&gt; Competence</td>
<td>0.072</td>
<td>0.10</td>
</tr>
<tr>
<td>Size -&gt; Relatedness</td>
<td>0.009</td>
<td>0.04</td>
</tr>
<tr>
<td>Quality -&gt; Relatedness</td>
<td>-0.001</td>
<td>0.06</td>
</tr>
</tbody>
</table>

Based on these results, there is a range of power estimates for the model. At the within level, power ranges from 1.00 to .03. At the Student level, power ranges from .03 to 0.00. At the Course level, power ranges from .1 to .04. Careful examination of the table shows that those paths with the highest power are also those that were found to be significant. In other words,
their estimates were the furthest from zero. A shortcoming of the post-hoc power analysis is that power describes a model’s ability to identify parameters that are significantly different from zero. The further a parameter is from zero, the smaller the sample that is necessary to identify its significance. When a parameter is very close to zero, a much larger sample is needed to establish significance. This is helpful when conducting a priori power analyses and the relationship between two variables is known to be very small as it allows researchers to identify beforehand the sample size they are likely to need to achieve their desired power. However, when a new model is tested, and past research suggests a strong relationship between variables, low power only shows that a larger sample was needed to make that relationship significant. But if no meaningful relationship exists, one can still be created with a sufficiently large sample size. As this relates to the current study, it cannot be said definitively whether the sample size or the non-significant effects were too small. Future studies would benefit from a Bayesian analogue to effect sizes, as well as empirically derived guidelines for sample size in cross-classified models.

5.3. Implications for the Field

The current study has a number of implications for the field, first among them is its research design. The vast majority of educational research has necessarily constrained itself to examining the effects of relatively few variables due to computational limitations. More sophisticated software has allowed the testing of more complex models and among multiple levels, but simultaneously testing the effects of distinct clusters of variables on the same level, on multiple mediating variables on another level has largely been possible only for a very few researchers. As a result, relative consensus has been achieved on the effects of one class of variables on another, but when multiple classes of variables are thought to provide simultaneous and independent effects, there has been less agreement on how to effectively test such models.
As was just discussed, a number of considerations can impact a student’s learning outcomes whether they are characteristics of the students themselves, or of a course, its instructor or the institution as a whole. To simultaneously explore the effects of each of these factors, whether direct, indirect or interactive, on student learning in the past would have been prohibitively difficult. But with increased use of and familiarity with such cross-classified designs and the power they provide to answer more complex questions, the functional relationships between the factors that influence online learning can be more accurately understood.

Another significant contribution of the current study is the continued exploration of course design guidelines, specifically the framework provided by QM. As has been described, the body of empirical and peer-reviewed research on the QM Rubric is quite light, despite its adoption by more than 1,000 institutions in the last ten years. As such, there is relatively little evidence that the QM Rubric has a positive effect on student learning. Even if such an effect had been found, there are so many other considerations that can impact a student’s learning that the optimization of course design can be considered the first of a long line of necessary steps before consistent improvement in the quality of students’ experiences are seen.

The current study also supports Self-Determination Theory in an online setting. This had been a subject of some dispute, particularly in the context of online education, as Chen and Jang (2010) had found evidence suggesting that motivation was less important among online students in terms of pro-learning behaviors or final grade. While those findings still pose important questions, the current study provides nearly spot-on support for SDT in online education.

It was also hoped that the current study could make a significant contribution to future research by establishing goal orientation as an analog for SDT’s individual differences variable: causality orientation. Despite some evidence for conceptual and functional similarity, it appears
that goal orientation does not adequately reflect an individual’s tendency to perceive their behavior as having an internal or external origin.

5.4. Directions for Future Research

Perhaps the most critical direction for future research is in validating course quality guidelines. As has been discussed at great length above, Hartnett (2016) and others have identified several dimensions of course design that have significant impacts on student motivation and, by extension, learning and performance. And while the QM Rubric appears to demonstrate sufficient content validity, being built on the most current research and being continually vetted and refined by experts in their field, there is little if any evidence of criterion validity. As has been shown in this study, QM-defined course quality has no bearing on student motivation or performance. After an extensive review of the QM Rubric and the literature surrounding it, the word “quality” appears not yet to have been operationally defined. The purpose for having a course designed to the highest standard has not been made clear. As QM themselves have acknowledged, the most frequently asked question received from institutions and educators is whether the Rubric will help their students to learn. QM go to great pains to not answer this question, arguing that the answer isn’t so easy, or that the value of QM isn’t in the Rubric but the process of continual improvement. This is a mistake. In traditional higher education, the features that distinguish a well-designed course from a poorly-designed course are minutely understood such that a completely inexperienced instructor can design their course according to guidelines that have been empirically demonstrated to create the best environment for a student to learn. This is what online instructors need as well. The next great advancement in online education will be the identification of quantifiable design factors that not only promote student learning but are accessible to all online instructors.
References.


Aman, R. R. (2009). *Improving Student Satisfaction and Retention with Online Instruction through Systematic Faculty Peer Review of Courses*.


Kırmızı, Ö., & Kirmızı, Ö. (2015). The Influence of Learner Readiness on Student Satisfaction and Academic Achievement in an Online Program at Higher Education. *Turkish Online Journal of Educational Technology-TOJET, 14*(1), 133–142.


Reeve, J. (2009). Why teachers adopt a controlling motivating style toward students and how they can become more autonomy supportive. Educational Psychologist, 44(3), 159–175. https://doi.org/10.1080/00461520903028990


Appendix A. Institutional Review Board Approval

ACTION ON PROTOCOL APPROVAL REQUEST

TO: Tracey Rizzuto
SHREWD

FROM: Dennis Landin
Chair, Institutional Review Board

DATE: March 10, 2017

RE: IRB# 3853

TITLE: Course design online: Helping students perform in the digital age


Review type: Full ___ Expedited _X__ Review date: 3/9/2017

Risk Factor: Minimal ___ X ___ Uncertain _______ Greater Than Minimal _______

Approved _____ X _____ Disapproved __________

Approval Date: 3/9/2017 Approval Expiration Date: 3/8/2018

Re-review frequency: (annual unless otherwise stated)

Number of subjects approved: 400

LSU Proposal Number (if applicable):

Protocol Matches Scope of Work in Grant proposal: (if applicable)

By: Dennis Landin, Chairman

PRINCIPAL INVESTIGATOR: PLEASE READ THE FOLLOWING –
Continuing approval is CONDITIONAL on:

1. Adherence to the approved protocol, familiarity with, and adherence to the ethical standards of the Belmont Report, and LSU’s Assurance of Compliance with DHHS regulations for the protection of human subjects* 
2. Prior approval of a change in protocol, including revision of the consent documents or an increase in the number of subjects over that approved.
3. Obtaining renewed approval (or submittal of a termination report), prior to the approval expiration date, upon request by the IRB office (irrespective of when the project actually begins); notification of project termination.
4. Retention of documentation of informed consent and study records for at least 3 years after the study ends.
5. Continuing attention to the physical and psychological well-being and informed consent of the individual participants, including notification of new information that might affect consent.
6. A prompt report to the IRB of any adverse event affecting a participant potentially arising from the study.
8. SPECIAL NOTE: When emailing more than one recipient, make sure you use bcc.

*All investigators and support staff have access to copies of the Belmont Report, LSU's Assurance with DHHS, DHHS (45 CFR 46) and FDA regulations governing use of human subjects, and other relevant documents in print in this office or on our World Wide Web site at http://www.lsu.edu/irb
Appendix B. Hypotheses

1. Course quality will be positively associated with autonomy
2. Course quality will be positively associated with competence
3. Course quality will be positively associated with relatedness
4. Perceptions of autonomy competence and relatedness will significantly relate to student motivation
5. Goal orientation will moderate the relationship between course quality and psychological need satisfaction.
   a. PGOp will moderate the relationship between course quality and psychological need satisfaction such that the strength of the relationship will diminish as PGOp increases.
   b. PGOa will moderate the relationship between course quality and psychological need satisfaction such that the strength of the relationship will increase as PGOa increases.
   c. The moderating effects of PGOp and PGOa on the relationship between course quality and psychological need satisfaction will be significantly different.
6. Goal orientation will moderate the effect of psychological need satisfaction on self-determined motivation.
   a. PGOp will moderate the relationship between each of the basic psychological needs and self-determined motivation such that the strength of the relationship will diminish as PGOp increases.
   b. PGOa will moderate the relationship between each of the basic psychological needs and self-determined motivation such that the strength of the relationship will increase as PGOa increases.
   c. The moderating effect of PGOp and PGOa on the relationship between relatedness and self-determined motivation will be significantly different.
7. Self-determined motivation will be positively associated with online learner performance
Appendix C. Theoretical Model.
Appendix D. Tests of Assumptions

Normal Q-Q Plot of Age

Normal Q-Q Plot of Course Experience_1
**Level-1 Collinearity**

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**Course Collinearity**

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### Interaction Collinearity

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Vita

Joseph Wayland Harris was born in Fort Worth, Texas and received his bachelor’s degree from Saint Edward’s University. After earning his master’s degree from Louisiana State University, he began pursuing his doctoral degree in Human Resource Education and Workforce Development, gaining practical and research experience in instructional design. Upon completion of his doctoral degree, he plans to pursue a career in instructional design in online higher education.