Investigating Math Motivation and Math Anxiety in Undergraduate Students

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Abstract

Academic anxiety and motivation have been extensively studied as predictors of academic performance (e.g., Halat & Çimenci Ateş, 2016, Struthers et. al, 2000), and math anxiety and motivation have been studied as predictors of math performance (e.g., Chang & Beilock, 2016, Steinmayr & Spinath, 2009). However, little research has examined the relationship between these two foundational concepts directly. Following the self-determination theory framework (Deci et. al, 1991, Ryan & Deci, 2000), this study uses a two part-survey to examine the relationship between math motivation and math anxiety in undergraduate students at a large research university. Multiple linear regression analysis of survey results reveals a suggestive, but not definitive, relationship between the two variables. Based on these results and an extensive review of the literature, the researcher proposes a conceptual model which incorporates math performance as an intermediary variable between math anxiety and math motivation.

1. Introduction

Math anxiety has received an enormous amount of interest in recent years: the term yields almost 5,500 "hits" on Google Scholar for articles published between 2015 and 2019 alone. There seems to be a good reason for its popularity. A meta-analysis of 151 studies on math anxiety (Hembree, 1990) found it to negatively impact math performance and lead to future avoidance of the subject. Furthermore, Ashcraft (2002) hypothesized that this math avoidance behavior leads many students to avoid math-intensive career fields. However, not all experts believe that math anxiety and math performance follow a simple inverse relationship. For example, Wang. et. al (2015) found that the two variables have a U-shaped curvilinear relationship, suggesting that math anxiety is *beneficial* to performance up until a certain point, where it starts to have a negative effect. This finding is consistent with the Yerkes-Dodson Law, which relates arousal (stimulation) and performance in a similar U-shaped curvilinear fashion (Yerkes & Dodson, 1908). These findings are also consistent with a study done by Keeley et. al

(2008), which found that students with moderate levels of statistics anxiety performed the best on statistics examinations. Nonetheless, consensus does not exist, and research continues into this high-interest area.

Academic motivation has also been extensively studied as an important predictor of academic success (e.g., Turner et. al, 2009), and math motivation has been studied as a predictor of math performance (Steinmayr & Spinath, 2009). Given the demonstrated utility of math anxiety and math motivation as explanatory variables for math performance, it seems reasonable to conduct a study incorporating both predictive variables. Wang et. al (2015) used math motivation was used only as a blocking variable while the relationship between math anxiety and math performance was analyzed. This means that students were divided into groups according to their level of math motivation so that the relationship between math anxiety and math performance could be examined, with the idea that math motivation might be a confounding variable. This study seeks to take a step back and evaluate the relationship between math motivation and math anxiety directly, free from the consideration of their effect on performance. With an improved understanding of correlations between math motivation and math anxiety, educators might better be able to coordinate curricula and teaching actions that foster student success.

Therefore, this study seeks to determine whether students' scores on a math motivation assessment are predictive of their level of math anxiety. The researcher hypothesizes that math motivation is predictive of math anxiety, and furthermore that extrinsically-regulated motivation and amotivation will be positively correlated with math anxiety, while intrinsically-regulated motivation will be negatively correlated with math anxiety. Section 2 provides an explanation of math motivation, math anxiety, and the theoretical ideas that underlie both concepts.

2. Background

2.1 Math Motivation

There are many theories of motivation: expectancy theory (Vroom, 1995), Maslow's hierarchy of needs (Maslow, 1943), and McClelland's need theory (McClelland, 1985) are just three of the most prominent. However, this paper will follow the self-determination theory (SDT), developed initially by Richard Ryan and Edward Deci (Ryan et. al, 1985, Deci et. al, 1991, Ryan & Deci, 2000). Self-determination theory is concerned with “the investigation of people's inherent growth tendencies and innate psychological needs that are the basis for their self-motivation and personality integration, as well as for the conditions that foster those positive processes” (Ryan & Deci, 2000, p. 68). From this perspective, motivation doesn’t exist in isolation. On the contrary, it arises from innate psychological needs and external conditions and is what allows an individual to achieve personal growth.

SDT further acknowledges that motivation itself isn’t one simple construct—there are in fact three levels of motivation defined on a continuum: amotivation, extrinsic motivation, and intrinsic motivation. Amotivation refers to a lack of motivation, while extrinsic motivation refers to “the performance of an activity in order to obtain some separable outcome,” and intrinsic motivation refers to the performance of an activity “for the inherent satisfaction of the activity itself.” (Ryan & Deci, 2000, p. 71). These three motivational constructs are further broken down into different regulatory styles: external regulation, introjected regulation, identified regulation, and integrated regulation all correspond to extrinsic motivation, while non-regulation corresponds to amotivation and intrinsic regulation corresponds to intrinsic motivation (see Figure 1). Here, the term “regulation” concerns the ways in which people control or modify (“regulate”) their behavior, and the different regulatory styles are delineated by the degree to which societal standards are internalized (Ryan et. al, 1985). This further delineation of extrinsic motivation is what makes the SDT so useful for the study of academic motivation generally, and

The Self Determination Continuum

Motivation Type	Amotivation	Extrinsic Motivation	Extrinsic Motivation	Extrinsic Motivation	Extrinsic Motivation	Intrinsic Motivation
Regulatory Styles	Non-regulation	External Regulation	Introjected Regulation	Identified Regulation	Integrated Regulation	Intrinsic Regulation
Perceived Locus of Causality	Impersonal	External	Somewhat External	Somewhat Internal	Internal	Internal
Regulatory Processes	Nonintentional, Nonvaluing, Lack of Control	Compliance, External Rewards and Punishments	Self-control, Internal Rewards and Punishments	Personal Importance, Conscious Valuing	Congruence, Awareness, Synthesis with Self	Inherent Enjoyment, Satisfaction

Figure 1: The Self Determination Continuum, Adapted from Ryan & Deci (2000)

math motivation more specifically. After all, most students do not find all academic subjects intrinsically motivating (Ryan et. al, 1985). Other theories would be forced to lump all such students into the broad categories of “extrinsic motivation” or “amotivation.” SDT allows for a spectrum of regulatory styles under extrinsic motivation, recognizing that not all extrinsic motivation is the same.

For example, take two students, Student A and Student B. Student A performs his homework to avoid punishments he knows his parents will impose if he receives a failing grade on his next exam. Student B, on the other hand, performs her math homework because she recognizes that working hard now will prepare her for more difficult courses in college. Neither Student A nor Student B is exhibiting intrinsic motivation, because neither student is performing the homework out of inherent enjoyment and interest. However, an obvious difference exists between Student A and Student B—namely that Student B’s behavior is much more self-regulated than Student A’s. Accordingly, Student B would be said to be exhibiting identified regulation, while Student A more clearly exhibits external regulation. Therefore, Student B’s behavior is more self-determined than Student A’s, which places Student B to the right of Student A on the Self-Determination Continuum.

It is crucial to further note that, from the SDT perspective, motivation is activity-specific; an individual can be intrinsically motivated to perform one activity but not another. For example, a student may be intrinsically motivated to train her basketball skills, because she enjoys shooting baskets and practicing dribbling in her driveway. This same student may not be intrinsically motivated to study history, because reading her history textbook isn’t inherently satisfying for her as basketball is. The following two paragraphs and the Methods section will review the academic applications of SDT in the literature.

Turner et. al (2009) studied the relationship between parenting styles, achievement motivation, self-efficacy, and academic performance in college students. Using the SDT framework to conceptualize academic motivation, they found that intrinsic motivation was positively correlated with performance while amotivation was negatively correlated with performance. Black and Deci (2000) applied SDT to a university-level organic chemistry course. They hypothesized that higher autonomous (self-regulated) motivation would be associated with higher course grades. The results failed to support this conclusion. However, changes in autonomous motivation levels throughout the semester were predictive of final course performance. Furthermore, degree of autonomous motivation was correlated with course drop-out rates.

Fewer studies have applied SDT to math specifically. However, Ng et. al (2016) used SDT to examine math motivation and teacher support of student autonomy using a sample of secondary school students in Singapore. They found that students can be grouped into clusters based upon their degree of self-regulated motivation and that these clusters are predictive of math achievement. In another study, Areepattamannil (2014) used SDT to analyze math motivation and performance for two sample groups: one of Indian adolescent immigrants in Canada, and one of Indian adolescents in India. Areepattamannil found that levels of extrinsic and intrinsic motivation were correlated with math performance for the Indian immigrant students in Canada but weren't correlated for the Indian students living in India, suggesting that SDT may not be fully generalizable across cultures and geographic environments.

2.2 Math Anxiety

Many definitions for the term "math anxiety" exist in the literature (Halat & Çimenci Ateş, 2016). This paper will follow Ashcraft (2002), who defined the concept as "a feeling of tension, apprehension, or fear that interferes with math performance" (p. 181) and Chang & Beilock (2016), who added that "math anxiety is a separate phenomenon from general trait anxiety or test anxiety and is associated with specific impairments in processing math-related or number-related tasks" (p. 33).

Two key points come out of these definitions: first, math anxiety must, by definition, interfere with math performance; second, it must go beyond test anxiety to include anxiety surrounding the performance of mathematical tasks more generally. Most math anxiety questionnaires, including the widely-used Mathematics Anxiety Rating Scale (MARS) (Richardson & Suinn, 1972), don't directly address the first point, likely because math performance is commonly otherwise assessed in academic settings via homework, quizzes, and tests. However, almost all math anxiety questionnaires do address the second point by including non-examination-based mathematical tasks, such as reading a math textbook or observing a professor lecturing. This is the case for the math anxiety assessment used in this study, the Abbreviated Math Anxiety Scale (AMAS) (Hopko et. al, 2003), which includes specific subscales for both “learning math anxiety” and “math evaluation anxiety.” The “learning math anxiety” subscale addresses anxiety experienced while learning math, which includes watching a lecture, performing homework, or reading a textbook. “Math evaluation anxiety,” on the other hand, is associated with math assessments, such as quizzes or tests.

3. Methods

3.1 Survey Development and Administration

To assess math motivation and math anxiety, the researcher designed a two-part survey based on the Academic Motivation Scale-Chemistry (AMS-Chemistry) (Liu et. al, 2017) and the AMAS (Hopko et. al, 2003). For the purpose of this paper, the math version of the AMS-Chemistry will be referred to as the “AMS-Math.” The result was a 37-item Likert-style questionnaire (see Appendices A & B) that was administered to students enrolled in a College Algebra or Precalculus for Business, Life, and the Social Sciences course at a large university (n=56).

Liu and colleagues created the AMS-Chemistry based on the original Academic Motivation Scale (AMS) developed by Vallerand et al. (1992). The AMS assesses motivation on the SDT spectrum by asking the respondent “Why do you go to college?” followed by 28 Likert-style items where the respondent must select the degree to which each statement corresponds to their motivation for attending college. The AMS has been widely used and validated across a wide range of disciplines, including chemistry (Liu et. al., 2017), business (Smith et al., 2010), and physical education (Spittle et al., 2009). Liu and colleagues developed their chemistry-specific version of the AMS by composing 28 items which respond to the question “Why do you take chemistry courses?” The wording of these items was only subtly altered from the original AMS items to fit the chemistry-specific context. Liu and colleagues found this new scale to have a high degree of internal consistency and content validity based on their large sample of undergraduate chemistry students. The current study, with the permission of the authors, modified the AMS-Chemistry scale to instead examine math motivation. For most questions, this simply required substituting the word “chemistry” with the word “math.” However, the wording had to be modified slightly more for some items. For example, item 18 on the AMS-Chemistry answers the “Why do you take chemistry” question with “for the enjoyment I experience when I think about the world in terms of atoms and molecules.” Item 18 on the AMS-Math instead reads "for the enjoyment I experience when I think about the world in terms of numbers and equations." The subscales for both the AMS-Math and the AMS-Chemistry are derived from the regulatory styles of the SDT, with two exceptions. First, the non-regulation style is referred to by its parent motivation type (amotivation). Second, the intrinsic regulation style is split into three different subscales covering intrinsic motivation to know, to experience, and to accomplish.

Hopko and colleagues developed the AMAS to be a shorter, "more parsimonious and valid approach to assess mathematics anxiety" (p. 178). This work serves as an alternative to the widely used Math Anxiety Rating Scale (MARS) (Richardson & Suinn, 1972), and various abbreviated or revised versions of it (e.g., Plake & Parker, 1982, Suinn & Winston, 2003). Hopko and colleagues found the AMAS to be both valid and reliable, and it is reproduced exactly to assess the math anxiety construct for part two of this survey.

The completed survey was administered to students enrolled in a College Algebra or Precalculus course at a large research university in the Southwestern United States. For the two College Algebra sections studied, completion of the survey counted for an optional quiz grade. No incentive was provided to students in the three Precalculus sections studied. In both cases, respondents completed the survey outside of class via an online survey platform. Following administration, survey results were tabulated and analyzed using the R language and environment for statistical computing (R Core Team, 2017). Details regarding model selection are discussed in the next section.

3.2 Variable and Model Selection

The researcher decided to implement multiple linear regression to model the data, using the motivational subscales as explanatory variables and math anxiety as the response variable. Demographic data were not incorporated into the final model, for reasons dependent on the variable in question. Major was excluded from the analysis because students were spread across far too many individual majors to establish significant groups. Furthermore, there were many more STEM (Science, Technology, Engineering, and Math) majors than non-STEM majors, so dividing students into these two groups was largely unhelpful. Year in school was excluded because almost 77% of respondents were first-year students. Gender was initially included in the model, but it was removed because it was an insignificant predictor and because it is not the focus of this study. The researcher tested a stepwise linear regression model, which removed all motivational constructs except for amotivation, external regulation, and to experience. However, the researcher decided to employ a multiple linear regression model that includes all motivational constructs as predictive variables given the statistical bias that can come from using stepwise regression to remove variables when there is no theoretical argument for doing so (Derksen & Keselman, 1992). Furthermore, stepwise regression did not provide significantly better fit than traditional multiple linear regression, even after the traditional model was negatively adjusted for containing more explanatory variables (multiple R-squared of 0.378 vs. .348).

3.3 A Note on Likert-scales and Parametric Statistical Analysis

Much controversy exists regarding the use of parametric statistical analyses such as linear regression on Likert-style data. For example, Jameison (2004) notes how ordinal Likert-style data violates many of the assumptions of parametric analysis, while Sulivan and Artino (2013) argue that even when these assumptions are violated, parametric analysis usually results in robust and unbiased estimation. However, the present study avoids this controversy because parametric methods are more clearly valid when full Likert-scales (composite indices composed of individual Likert items) are the basis for analysis (Boone and Boone, 2012). This is the case for the math anxiety scores and motivational subscales used in this study.

4. Results

4.1 Survey Validation

Cronbach’s alpha was calculated for the seven subscales of the AMS-Math and for the AMAS. Alpha coefficients for the seven subscales were excellent and ranged between .87 (identified regulation) and .93 (introjected regulation). For the AMAS, alpha was .878 based on the present study’s survey results and .90 when originally calculated by Hopko et. al (2003). For reference, alpha levels of greater than .7 are traditionally considered acceptable (Murphy and Davidshofer, 2005).

4.2 Demographic Data

Among students who responded to demographic questions, slightly more identified as female than male (31 compared to 22). Most students were in their first year of college, although the range was 1-5+ years. Students had a diverse set of majors including Computer Science, Psychology, and Accounting. Gender was the only demographic category with large enough sample groups to conduct a reasonable comparative analysis. Contrary to the findings from several previous studies (e.g. Hembree, 1990, Hopko et. al, 2003) females were not found to experience significantly higher math anxiety levels than males (p-value for difference = .77).

4.3 Regression Assumptions and Results

The regression model satisfies key assumptions for linear regression, namely that the model residuals are homoscedastic and roughly normally distributed (Figure 2).

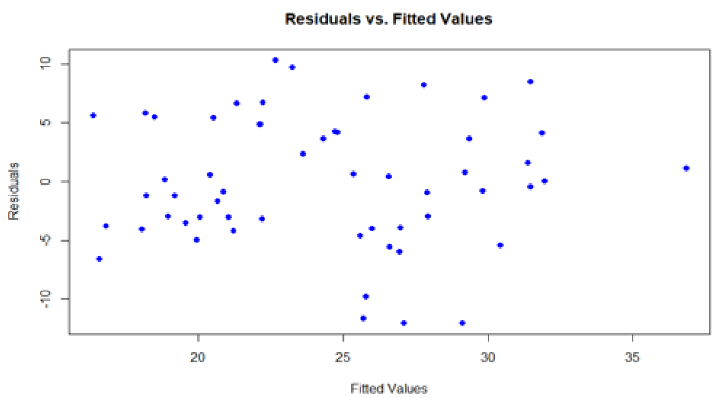

Figure 2a) Homoscedasticity

Random scatter observed on residual plot suggests that the fitted linear model is appropriate

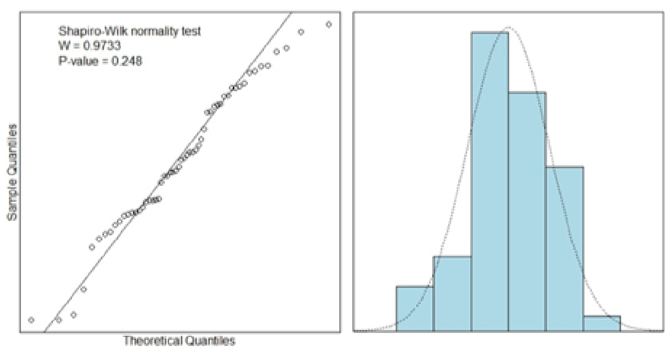

Figure 2b) Normal Distribution of Residuals

Shapiro-Wilk test provides insignificant evidence to reject the null hypothesis that the residuals are normally distributed

The model has an R-squared value of .431, meaning that approximately 43.1% of the variation in math anxiety can be explained by its linear relationship with the 7 motivational constructs. Amotivation is the only statistically significant predictor variable in the model (p-value of .007), and has a point estimate of 1.01, meaning that for every one-point increase in a student's amotivation score, we expect an approximately 1.01-point increase in that student's math anxiety score (see Figure 3). A 95% confidence interval estimate for amotivation is (0.288, 1.734), meaning that we are 95% confident that the true amotivation parameter falls between

.288 and 1.734 (anxiety points per amotivation point). For reference, the maximum number of anxiety points (maximum “anxiety score”) is 45, while the maximum number of amotivation points (maximum “amotivation score”) is 20. Although the other motivational constructs aren’t statistically significant, one may notice the sign (positive or negative) on their point estimates. Namely, external regulation and introjected regulation have positive estimates, while identified regulation, “to experience”, and “to know” have negative estimates. “To accomplish” has a positive estimate, making it the only regulatory style to not fit this trend. The potential meaning of these tentative results will be discussed in the next section.

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Coefficients:
                       Estimate Std. Error t value Pr(>|t|)
(Intercept)             17.6617     6.9081   2.557  0.01379 *
Amotivation              1.0108     0.3595   2.811  0.00712 **
External.Regulation      0.4853     0.3263   1.488  0.14340
Introjected.Regulation   0.1593     0.3249   0.490  0.62621
Identified.Regulation   -0.2348     0.4396  -0.534  0.59571
Experience              -0.5042     0.4568  -1.104  0.27517
Accomplish               0.4167     0.5142   0.810  0.42175
Know                    -0.5912     0.6368  -0.928  0.35781
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Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 5.877 on 48 degrees of freedom
Multiple R-squared:  0.4311,    Adjusted R-squared:  0.3481
F-statistic: 5.196 on 7 and 48 DF,  p-value: 0.0001863
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Figure 3: **Multiple Linear Regression Results**

5. Discussion

5.1 Initial Discussion

The strong positive relationship between math amotivation and math anxiety supports the researcher’s hypothesis that non-regulated or externally-regulated forms of motivation are correlated with more math anxiety, while more intrinsically-regulated forms of motivation are correlated with less math anxiety. The point estimates for the other motivational constructs fail to validate this hypothesis, as they are not statistically significant. Nonetheless, these constructs may be worthy of further study as the sign on their point estimates fits with the hypothesis. For example, the point estimates for external regulation and introjected regulation are positive, meaning that, according to the linear model, math anxiety increases as they increase. This fits with the researcher’s hypothesis because external regulation and introjected regulation are both on the left (more-externally regulated) half of the Self Determination Continuum. Meanwhile, identified regulation, “to experience,” and “to know” are all negatively correlated with math anxiety, meaning that as they increase, we expect math anxiety to decrease. This fits with the hypothesis because these types of motivation are all on the right (more intrinsically-regulated) half of the Self Determination Continuum. Introjected regulation, which is in the center of the Self Determination Continuum, has the smallest point estimate and the highest p-value, meaning it is the least statistically significant. This also seems to fit with the hypothesis, as introjected regulation doesn’t correspond strongly to either extrinsically-regulated or intrinsically-regulated behavior. Of course, these analyses of relationship direction are extremely tentative for all non-significant explanatory variables in the model. The discussion of these non-significant results serves only to provide inspiration for future research.

5.2 Towards a Conceptual Model

The observed relationship between amotivation and math anxiety is further supported by Hembree’s (1990) meta-analysis, which found a strong, -.64 average correlation between math motivation and math anxiety. Of course, these correlational data are alone not sufficient to establish causal relationships between math anxiety and math motivation. Furthermore, other variables, such as math performance and math self-efficacy, may have mediated the relationship between math anxiety and math motivation. Indeed, the following conceptual model (Figure 4) suggests that math performance mediates the relationship between math motivation and math

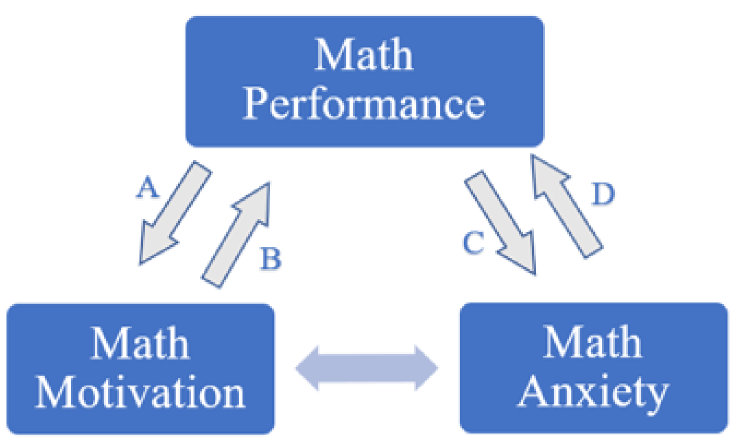

Figure 4: A Conceptual Model

anxiety because of its bidirectional relationships with both concepts. If relationships A, B, C, and D from this model can be validated, one can easily see how math anxiety and math motivation might interact with each other through the intermediate variable of math performance. The following section discusses how the literature supports these relationships.

5.2.1 Performance and Math Anxiety: Relationships C and D

The strongest evidence exists for relationship D. After all, math anxiety negatively affects math performance by definition (Ashcraft, 2002, Chang & Beilock, 2016). Researchers have debated the best model for this interaction. For example, some have found curvilinear relationships between the concepts (Wang et. al, 2015, Keeley et. al, 2008) while others suggest a simple inverse relationship (Hembree, 1990). However, in both cases, it is assumed that math anxiety exerts a causal influence on math performance. Regardless of what the best mathematical model is, there seems to be strong evidence that “math anxiety depresses performance” (Hembree, 1990, p. 44).

Hembree (1990) disputes relationship C, writing that “there is no compelling evidence that poor performance causes mathematics anxiety.” However, Ma & Xu (2004) argued to the contrary. The authors used data from the Longitudinal Study of American Youth (LSAY) to evaluate different causal relationship structures that are present in the literature. These include the “interferences model (high mathematics anxiety causes low mathematics achievement), the deficits model (low mathematics achievement causes high mathematics anxiety), and the reciprocal model (mathematics anxiety and mathematics achievement are reciprocally related)” (p. 176). They found strong evidence for the deficits model, because “prior low mathematics achievement significantly related to later high mathematics anxiety, but prior high mathematics anxiety hardly related to later low mathematics achievement” (p. 165). This supports relationship C in the present study’s structural model. It does somewhat question relationship D but does not provide enough evidence to remove it from the structural model. As discussed earlier, math anxiety is in fact defined by its ability to cause performance deficits, and one study is not enough to fully overturn a meta-analysis of 151 studies (Hembree, 1990).

5.2.2 Performance and Motivation: Relationships A and B

In a 1995 study of French-Canadian 9th graders, Fortier et. al (1995) found a strong relationship between academic motivation and academic performance (and math motivation and math performance specifically), leading them to conclude that “students who feel competent and self-determined in the school context develop an autonomous motivational profile towards education which in turn leads them to obtain higher school grades" (p. 268). This implies that motivation variables precede (and cause) performance results (i.e. higher grades), which fits with relationship B in the present study's proposed model. It is reasonable that the authors would view the causal relationship in this direction, given that they were employing the SDT framework—after all, while explicating the SDT conception of motivation, Ryan and Deci (2000) wrote that "in the real world, motivation is highly valued because of its consequences: motivation produces" (p. 69). From the SDT perspective, motivation is what drives performance. Maslow's popular humanistic theory of motivation (1943) also runs in this direction, positing that, when basic needs are satisfied, motivation to self-actualize helps people to reach their full potential. Here again, motivation is the driver of achievement.

Although motivation has implicitly and explicitly been conceptualized as the driver of performance, there is no theoretical reason why this relationship couldn't be bidirectional. Indeed, Fortier et. al (1995) acknowledged that one cannot be certain that the causal relationship doesn't also run from performance to motivation, because their study was not a controlled experiment or a longitudinal analysis. To the author's knowledge, no studies have used longitudinal analysis to better understand this relationship. Green et. al (2006) published a paper outlining suggested methods for such a study, but their suggested design has never been implemented, to the researcher's knowledge. However, Marsh & Yeung (1997) conducted a longitudinal analysis of self-concept and academic achievement in three subjects for 603 high school students over the course of three years. Notably, they concluded that self-concept and academic performance are reciprocally related, meaning that the causal relationship is likely bidirectional. Furthermore, "although there was support for this reciprocal effects model for all 3 school subjects, self-concept effects tended to be larger and more systematic for mathematics than for science and, particularly, English" (p. 41). Of course, self-concept isn't the same thing as motivation. However, it is often considered to be a subconstruct of motivation, or a "motivational variable" (Berg & Coetzee, 2014). Therefore, it is reasonable that motivation in general may satisfy a similar reciprocal effects model.

Cleary & Chen (2009) also commented on relationship A, although in a somewhat indirect way. They wrote that "when students evaluate their sense of competency based on peer performance and also experience a decreased sense of autonomy, they are more likely to exhibit maladaptive motivational behaviors, such as poor effort and persistence" (p. 294). While a student's poor performance isn't directly implicated in changes to motivational variables, unfavorable performance comparisons with other students are. This is of practical importance, as most students study math in the classroom setting, where many compare their performance on assignments and examinations with other students. Finally, support for relationship A can be practically observed in universities as many students will drop a course if they perform poorly on the first exam. For these students, poor initial performance is enough to decrease motivation for completing the course enough that dropping the course is perceived as the best option.

5.3 Study Limitations

This study's quantitative analysis has several key limitations. First, students were selected by a convenience sample based on their enrollment in a College Algebra or Precalculus course, so while the sample size is relatively large and the composition of respondents relatively diverse, results may not be fully generalizable. It is likely, for example, that students in more advanced math courses experience much lower levels of math amotivation and math anxiety overall. Therefore, it is unclear whether the relationship between amotivation and math anxiety would continue to hold in these students. The presence of response bias is a further study limitation, given that highly motivated students may have been more likely to take the survey than less motivated ones. Furthermore, survey respondents self-reported their experiences of math anxiety and their motivation for taking math courses. Therefore, although no identifying information was requested in the survey, responses still may have been influenced by the social desirability bias (Edwards, 1953). Finally, the survey was given to students only once during the semester because of time constraints. Liu et. al (2017) found that type and level of motivation changed over the course of a semester, so a future study could better clarify the present study's results by re-testing students over time.

6. Conclusion

This study demonstrates the use of a combined assessment for testing math anxiety and math motivation in undergraduate students. Furthermore, it provides strong evidence that amotivation is positively correlated with math anxiety, a finding potentially worthy of further research; it also establishes a tentative link between other SDT motivational constructs and math anxiety. Finally, it proposes a structural model that describes how math performance may mediate the relationship between math motivation and math anxiety. Future research might expand this model by examining how study habits mediate the relationship between motivation and performance (Ryals & Keene, 2017) or how self-efficacy (Bandura, 1997) influences student motivation, anxiety, and performance. With a more confident understanding of how these variables interact with each other, educators may better be able to foster enjoyment and success in math for many more students.

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Appendix A: AMS-Math

Adapted from AMS-Chemistry by Liu et. al (2017)

Why do you take math courses?

Using the scale provided, indicate to what extent each of the following items presently corresponds to one of the reasons why you take math courses.

	Not at all	A little	Moderately	A lot	Exactly

1. Because without having taken math I would not find a high-paying job later on.

2. Because I experience pleasure and satisfaction while learning new things.

3. Because I think that math courses will help me better prepare for the career I have chosen.

4. For the feelings I experience when I am communicating math ideas to others.

5. Honestly, I don't know; I really feel that I am wasting my time taking math courses.

6. For the satisfaction I experience while improving my understanding of math.

7. To prove to myself that I am capable of succeeding in math.

8. In order to obtain a better job later on.

9. For the pleasure I experience when I learn new things about math.

10. Because taking math will enable me to enter the job market in a field that I like.

11. For the pleasure that I experience when I perform math problems.

12. I once had good reasons for taking math courses; however, now I wonder whether I should continue.

13. For the satisfaction I experience while succeeding in math.

14. Because when I succeed in math I feel smart.

15. Because I want to have a well-paying career.

16. For the pleasure that I experience in broadening my knowledge about math.

17. Because taking math courses will help me make more informed choices about my career options.

18. For the enjoyment I experience when I think about the world in terms of numbers and equations.

19. I don't know why I take math courses, I couldn't care less about them.

20. For the satisfaction I feel as I work toward an understanding of math.

21. To show myself that I am an intelligent person.

22. In order to have a better salary later on.

23. Because studying math allows me to continue to learn about things that interest me.

24. Because I believe that math courses will improve my skills in my chosen career.

25. For the satisfaction I experience while learning about various math topics.

26. I don't know; I can't understand what I am doing taking math courses.

27. Because math courses allow me to experience satisfaction in my quest for knowledge.

28. Because I want to show myself that I can succeed in studying math.

Appendix B: Abbreviated Math Anxiety Scale (AMAS)

Reprinted from Hopko et. al (2003)

How much anxiety do you feel in the following situations? Please respond below according to the scale provided.

Not at all anxious	Slightly anxious	Moderately anxious	A lot anxious	Very much anxious

1. Having to use the tables in the back of a math book.

2. Thinking about an upcoming math test one day before.

3. Watching a teacher work an algebraic equation on the blackboard.

4. Taking an examination in a math course.

5. Being given a homework assignment of many difficult problems that is due the next class meeting.

6. Listening to a lecture in math class.

7. Listening to another student explain a math formula.

8. Being given a "pop" quiz in math class.

9. Starting a new chapter in a math book.