

Contents lists available at ScienceDirect

The International Journal of Management Education

journal homepage: www.elsevier.com/locate/ijme



Research notes

Improving students' performance in quantitative courses: The case of academic motivation and predictive analytics



Ahmad Rahal*, Mohamed Zainuba

College of Business, University of Arkansas, Fort Smith, 5210 Grand Avenue, Fort Smith, Arkansas 72913, USA

ARTICLE INFO

Article history: Received 14 November 2014 Received in revised form 15 May 2015 Accepted 25 November 2015 Available online xxx

Keywords:
Academic performance
Predictive analytics
Self-monitoring
Self-regulation academic engagement

ABSTRACT

This 5 years longitudinal study explores and tests the effect of the combined use of some principles from the motivation achievement theories of educational psychology and predictive analytics (pedagogical innovation) on enhancing students' academic selfmonitoring, engagement, and performance in a junior level quantitative business course. If and when unsatisfied with their class performance, or their predicted grade and likelihood of success of the pedagogical innovation, students in the post-innovation group were directed to either self-regulate their class engagement, and/or seek the intervention of the instructor for remedies to facilitate their success. Results show the post-innovation group outperforming the pre-innovation group with more As (+43%), Bs (+35%), with fewer Cs (-20%) supporting the hypothesis that the suggested innovation significantly improved students' performance. However, no significant improvement in the failure rate of the atrisk students (DFWs) was observed. While most students with high predicted probability of passing were able to self-regulate their academic engagement, only few of the at-risk students sought the intervention of the instructor, with the majority eventually succeeding in passing the course (some after several trials) due to their improved class engagement, and their perceptions of the instructor's positive role in facilitating their success.

© 2015 Elsevier Ltd. All rights reserved.

1. Introduction

Students' negative attitude and anxiety toward mathematics and their far reaching implications on their academic performance and career opportunities are well documented in the literature (Bessant, 1995; Meece, Wigfield, & Eccles, 1990; Wigfield & Meece, 1988). With only 26% of graduating high school students meeting the minimum ACT College Readiness Benchmark¹ in all testing subject matters, e.g., English, Algebra, Social Science, and Biology (ACT, 2013), higher education institutions have been prompted to develop interventions strategies to facilitate learning, and guide their students toward continually improving their academic performance (Handel, 2009).

^{*} Corresponding author.

E-mail addresses: ahmad.rahal@uafs.edu (A. Rahal), mohamed.zainuba@uafs.edu (M. Zainuba).

¹ The Benchmarks are scores on the ACT subject-area tests that represent the level of achievement required for students to have a 50% chance of obtaining a B or higher or about a 75% chance of obtaining a C or higher in corresponding credit-bearing first-year college courses. http://www.act.org/solutions/college-career-readiness/college-readiness-benchmarks/.

1.1. Literature review

Educational psychologists assert that most human actions are thought to be goal-directed toward either achieving desired outcomes or avoiding dreaded ones (Bandura, 1986). As such, this study posits that the combined use of motivation achievement theories and predictive analytics (pedagogical innovation), will facilitate students' academic self-monitoring and self-regulation, and assist in linking current actions to future goals for the purpose of improving their academic performance.

Although several definitions exist for academic engagement, this research adopts Kuh's and Hu's view which defines academic engagement as the "quality of effort students devote to educationally focused activities that contribute directly to desired outcomes" (Kuh & Hu, 2001). It is a multi-dimensional construct involving students' emotion, behavior, and cognition (Fredrick, Blumenfield, & Paris, 2004), and a robust predictor of students' learning, test scores, retention, and graduation (Appleton, Christenson, & Furlong, 2008; Patrick, Ryan, & Kaplan, 2007; Skinner & Pitzer, 2012). Students who were positively engaged in their course work and with instructors tend to be highly motivated (Ryan & Deci, 2009), are able to develop a better perspective about their academic progress and achievements (Finn & Zimmer, 2012; Fredricks et al., 2004), tend to score higher grades (Astin, 1993; Darling-Hammond, 1997; Kuh, 2003; Roderick & Engel, 2001), and experience lower dropout rates (Croninger & Lee, 2001; Mangum, Baugher, Winch, & Varanelli, 2005). In contrast, unmotivated and disengaged students are at risk of lower performance and dissatisfaction which might lead to academic failure (Curwin, 2010; Willingham, Pollack, & Lewis, 2002; Uekawa, Borman, & Lee, 2007), and students' dropout (Bridgeland, Dilulio, & Morision, 2006). Hence, educators are expected to motivate students to help them achieve their educational goals (Miller & Brickman, 2004), and to self-monitor and self-regulate their own progress (Ames, 1992; Brophy, 2010; Covington, 1992).

Self-monitoring is the act of observing and recording one's own behaviors (Hallahan, Kauffman, & Pullen, 2011). It is an effective behavioral intervention to actively engage students (Blick & Test, 1987), enhance their academic skills (Maag, Rutherford, & Digangi, 1992), improve their productivity and accuracy (Rock, 2005), and positively impact student—teacher relationship (Reid, 1996). Successful self-monitoring requires students to self-regulate their academic progress and meet stated academic goals or complete required tasks (Porter & Ronit, 2006), where self-regulation is defined as "self-generated thoughts, feelings, and behaviors that are planned and cyclically adapted based on performance feedback to attain self-set goals" (Zimmerman, 1990).

The mechanisms through which students' cognitively manage their academic learning and engagement level are primarily influenced by four sets of psychological variables such as competence, autonomy and control, values and goals, and relatedness (Bandura, 1997; Dweck, 2000; Pintrich, 2003; Ryan & Deci, 2000).

- 1.1.1 Competence refers to the individual's ability to complete a specific task (Elliot & Dweck, 2005; Harter, 1978) such as students' belief about their academic competence and how it relates to their engagement, learning, and academic performance (Bandura, 1997; Dweck, 2000; Harter, 1982; Skinner, 1996; Skinner, Zimmer & Connell, 1998). Competence is determined by previous performance, vicarious learning, verbal encouragement, and physiological reactions (Bandura, 1977, 1997). Competence is addressed in the self-efficacy theory (Bandura, 1977, 1997); self-concept and self-worth theories (Covington, 1992; Harter, 1982), where the vision of one's self of the future can motivate behavior (Garcia & Pintrich, 1994; Markus & Wurf, 1987).
- 1.1.2 Autonomy and control refers to the motivation and willingness of individuals to engage in a specific task when feeling in control and are able to link required actions to desired outcomes. Pioneered by Deci and Ryan, the Self-Determination Theory (SDT) argues that students with greater sense of autonomy show high levels of academic engagement, persistence, and achievement (Deci & Ryan, 2002; Grolnick & Ryan, 1987), and their reasons for engaging are fully internalized (Ryan & Deci, 2000). To that extent, a study of differently structured reward programs by Fryer (2011) determined that rewarding students to increase their test score did not produce better results, in part because students had no control over their test scores, while on the other hand rewarding students for performing specific tasks such as reading books and taking a corresponding quiz, which students knew how to control, produced excellent results that persisted well past the duration of the study. Furthermore, Connell and Wellborn (1991) linked control beliefs to competence needs by concluding that individuals who believe they control their achievement outcome should feel more competent.
- 1.1.3 Values and goals refer to students' motivations to perform some academic tasks that are influenced by their perceived value, and students' goals for performing these tasks. Eccles and Wigfield (1995) defined four motivational components of task value: attainment value, intrinsic value, utility value, and cost. Wigfield, Eccles, Schiefele, Roeser, and Davis-Kean (2007) defined attainment value as the importance of doing well in a task, while intrinsic value is the enjoyment achieved from performing a task. Extrinsic value is the desire to achieve because of a certain objective and not so much for the enjoyment of the activity, while utility value is defined by how well a task relates to current and future goals, and reasons for engaging in terms of the lost opportunities resulting from making one choice rather than another.

Achievement goals theorists have identified two different types of achievement goals: mastery goals, and performance achievement goals (Ames, 1992; Dweck, 1986). Bandura and Schunk (1981), Bandura (1997), and Schunk (1991) argued that specific proximal goals combined with somewhat challenging goals promoted both self-efficacy and improved performance.

Furthermore, it has been argued that Future Time Perspective (FTP) is essential for students' engagement in learning, and function as roadmaps for their strategic learning (Hilpert et al., 2012). Therefore, if students believe that current educational activities are useful in the long run, they are more likely to be positively motivated, self-regulated, and achieve higher grades (Husman & Lens, 1999; Kauffman & Husman, 2004; Lens, 1986). Furthermore, research about the motivational relevance of a task's instrumentality and its utility value, supports the positive influence of future goals in an academic context (De Volder & Lens, 1982; Eccles & Wigfield, 1995; Miller, DeBacker, & Greene, 1999; Rheinberg, Vollmeyer, & Rollett, 2000; Simons, Dewitte, & Lens, 2000, Simons, Dewitte & Lens, 2004; Wigfield & Eccles, 1992).

1.1.4 Relatedness refers to the desire to feel connected to others (Ryan, 1992), and has been linked to important academic outcomes including self-efficacy, engagement, academic achievement (Furrer & Skinner et al., 2003), and motivation (Appleton et al., 2008). Students' perceptions of relatedness to their teachers have shown to positively impact their behavioral engagement and academic outcomes (Connell & Wellborn, 1991; Furrer & Skinner et al., 2003; Goldstein, 1999; Ryan, Stiller, & Lynch, 1994; Ryan & Powelson, 1991). Research also indicates that student motivation can be influenced through classroom reward structure (Ames & Ames, 1984), classroom organization (Rosenholtz & Wilson, 1980), and curriculum (Renniger, Hidi, & Krapp, 1992).

Although the application of the Ordinary Least Square (OLS) in assessing and/or predicting students' performance in many business disciplines has been well-documented in the literature, such as accounting (Buckless, Lipe, & Ravenscroft, 1991; Danko, Duke, & Franz, 1992; Eikner & Montondon, 2006; Gracia & Jenkins, 2003; Hartnett, Römcke, & Yap, 2004; Kealey, Holland, & Watson, 2005; Koh & Koh, 1999; Naser & Peel, 1998; Turner, Holmes, & Wiggins, 1997), marketing (Borde, 1998), management science (D'Souza & Maheshwari, 2011), and operations management (Peters, Kethley, & Bullington, 2002), the logistic regression has been shown to be superior (to OLS) at predicting the probability of an attribute (Pohlmann & Leitner, 2003), such as students likelihood of success (Goldstein & Perin, 2008; Zhang, Patel, & Ewing, 2014), or in determining the drivers of students' performance (Estelami, 2014; Tseng, 2010).

It is worth noting that the literature review did neither reveal any research that actively involve the student in the prediction process, nor any combined use of the suggested predictive tools to assist students in both gaging the gap between their current academic performance and their future desired outcomes, and in quantifying their likelihood of success. Hence, this study aims at bridging this existing gap in the literature by drawing from the motivation achievement theories of educational psychology and the use of predictive analytics to provide the necessary tools to engage students in self-monitoring and self-regulating their own performance for the purpose of better outcome and continuous improvement.

1.2. Background

With many students showing apprehension, fear, and concern from the first day of class, this junior level quantitative business course requires statistics as a prerequisite, and is considered by many as one of the most demanding and difficult course in the business curricula. Although the students' first exam's historical average is quite acceptable (72.54% over the first four year period of the study), the grade distribution over the same period clearly substantiate the students' anxiety toward this course with about 38% scoring either D or F on their first exam as shown in Fig. 1. Inputs from students revealed that math anxiety and lack of perceptions of the utility of the course work were the main culprits.

Changes to the course design, management, and delivery and the adoption of a newer textbook did not result in any significant improvement in the students' performance or attitude toward the course over the initial 4 years of the study (pre-innovation group). Furthermore, the growing concern about the poor performance in the aforementioned quantitative business course prompted the need for a change to create a better course environment and an improved student engagement, hence the idea of combining the motivation achievement theories and predictive analytics to enhance the students' academic performance, and provide them with effective tools to assist them in linking their current actions to their future goal of passing the class.

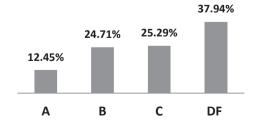


Fig. 1. First exam (E1) – grade distributions.

1.3. Proposed improvements

Applying the FTP theory (Husman & Lens, 1999; Kauffman & Husman, 2004; Lens, 1986) to relate current educational activities to future goals, e.g. passing the course, students were required to use a database of multiple graded activities of assignments, quizzes, exam scores, final scores, apply the (OLS) regression skills learned in this analytical course to develop a multiple regression model to predict their likely final grade. Furthermore, to alleviate self-doubts and assist the students in quantifying their likelihood of success in the aforementioned course, students were provided a logistic regression model where the probability of an event is determined using the regression or logit coefficients denoted as "b" as shown in the model below

$$P(\textit{event}) = \pi \textit{j} = 1 \Big/ \Big(1 + e^{-(\textit{b}0 + \textit{b}1X1 + \dots \textit{b}kXk)} \Big)$$

As described by Rahal and Rabelo (2006), "The binary logistic regression uses the iterative Maximum Likelihood Estimation (MLE) fitting procedure for predicting a probabilistic classification outcome by finding those coefficients that have the greatest likelihood of producing the pattern of the observed data. A trial estimate of the coefficients are initially proposed, tested, and then re-estimated until a convergence has been reached. The optimal solution is reached by maximizing the Log-Likelihood (LL) or minimizing the -2 Log-Likelihood (-2 LL) function which indicates how probable, how likely, or the odds on how to obtain the observed values of the dependent variable (outcome 0 or 1), given the observed values of the independent variables". Using the existing dataset, both predictive tools (the linear and the logistic regression) were modeled and tested with an accuracy rate exceeding 86% as early as the first exam as shown in Table 1 below.

A spreadsheet containing both predictive tools was then made available to students to be updated for continuous feedback throughout the duration of the course as shown in Fig. 2.

If and when unsatisfied with their class performances or the real time feedback of the predictive tools (predicted grade or likelihood of passing the course), students of the post innovation group were directed to either self-regulate their class engagement, and/or seek the intervention of their instructor to provide remedies to facilitate their success.

Achievement goals theorists argued that proximal goals combined with somewhat challenging goals promoted both self-efficacy and improved academic performance (Bandura, 1997; Bandura & Schunk, 1981; Schunk, 1991). As such, long and tedious assignments were divided into smaller ones with added complexity and multiple allowed attempts (non-multiple choice questions). Given the online assessments' immediate performance feedback capability and its positive association with perceived competence (Raska, 2014), students had the opportunity to react and self-regulate their class engagement and mastery skills, and and promote their self-efficacy and competence.

Stemming from self-determination theorists who argue that students with a greater sense of autonomy show high levels of academic engagement, persistence, and achievement (Deci & Ryan, 2002; Grolnick & Ryan, 1987), students were allowed the flexibility to submit quizzes and assignments (both performed online) on time for a full score or late for a preset penalty; hence, a lower perceived value. It is worth noticing that unlike the students who have taken the course over the initial four years of the 5-year longitudinal study (group 1, pre-innovation), students in the fifth year (group 2, post-innovation) worked diligently to submit their work prior to the due dates to avoid any penalty. On time assignments completion increased substantially.

Following other researchers lead which argues that students' perceptions of relatedness to their instructor have shown to positively impact their behavioral engagement and academic outcomes (Connell & Wellborn, 1991; Furrer & Skinner et al., 2003; Goldstein, 1999; Ryan et al., 1994; Ryan & Powelson, 1991), the instructor instituted an open door policy in which students could at will discuss their assignments or any of their concerns about the class.

2. Analysis and results

Motivated by all of these new changes, the research question in this study was to determine if the newly implemented innovation had any impact on students' performance.

2.1. Pre-innovation analysis

We initially posit that no difference exists between the two groups up to and including the first exam and prior to the implementation of the pedagogical innovation and students' use of predictive analytics. Hence,

Table 1 Predictive tools and accuracy rates.

Variables	Linear regression (OLS) pass/fail accuracy rate	Logistic regression pass/fail accuracy rate
After first exam (HW, Q, E1)	86.1%	88.9%
After the second exam (HW, Q, E1, E2)	87.9%	90.0%
After the third exam (HW, Q, E1, E2, E3)	88.5%	92.4%

Enter your Quiz Average	68.00		
Enter your Homework Average	71.00		
Enter your Exam#1 Score (when available)	70.00		
Enter your Exam#2 Score (when available)			
Enter your Exam#3 Score (when available)			
Given your current class performance, your predicted score and likelihood of passing are	Your Predicted Course Average	Your Likelihood of Passing this Course	Your Current Course Average
Your predicted score (Q, HW, E1)	67.50	72.06%	69.80
Your predicted score (Q, HW, E1) Your predicted score (Q, HW, E1, E2)	67.50	72.06%	69.80

Fig. 2. Predictive tools spreadsheet.

```
H0: \mu G1E1 - \mu G2E1 = 0 no difference between the 2 groups
```

 $H1: \mu G1E1 - \mu G2E1 \neq 0$ there is a difference between the 2 groups

where

- where μ G1E1 represents the mean score of the pre-innovation group (group 1) up to and including the scores of the first exam (E1), where group 1 consisted of 511 representing all student enrollees in years 1–4, and
- μ G2E1 represents the mean score of the post-innovation group (group 2) up to and including the scores of the first exam (E1), where group 2 consisted of 147 representing all student enrollees in year 5.

Analysis shows the means and the variances of the two groups were comparable as shown in Table 2.

Conditions of a two-sample t-test of independent samples of normal populations and equal population variances (difference between the variances was statistically insignificant with Levene's test of p-value of .36) were met as shown in Table 3, with no significant difference between the performance of the two groups up to and including the first exam (E1) at the 5% significant level (P-value of .0998).

This result was expected given the suggested innovation and the fact that predictive analytics tools would not be implemented until after the first exam's results were known, hence students were not yet able to assess and/or self-monitor their own progress, nor apply the predictive tools to make that connection between their current performance and their goal of passing the course.

2.2. Post-innovation analysis

Comparing the overall final performance score results of the two groups of students, we posit that the pedagogical innovation and the use of predictive analytics enhanced group 2 (post-innovation) performance compared to that of the pre-innovation group (group 1). Hence,

```
H0: \mu G1F - \mu G2F \ge 0

H1: \mu G1F - \mu G2F < 0
```

where

- μ G1F represents the course overall final score for the pre-innovation group (group 1), and
- μ G2F represents the course overall final score for the post-innovation group (group 2)

The means and the variances of the two groups are shown above in Table 4. Furthermore, the required conditions of a two-sample t-test of independent samples, normal populations, and equal population variances (Levene's test of p-value of .610) were met as shown in Table 5.

The statistical analysis of the two groups overall scores shows a P-value of .007 (Sig. 2 tailed/2) and a t-statistic of -2.461 (t-critical one tail of -1.647), hence rejecting the null hypothesis in favor of the alternative and concluding that the use of the pedagogical innovation was effective in enhancing the students' performance.

Despite the increased complexity of the covered subject matter over the duration of the semester, further analysis of the post-innovation group (group 2) performance showed an improvement of about 4.7 percentage points in the students' average final score when compared to their performance average by the first exam (see Table 6), with a t-statistics value of

Table 2Descriptive statistics- groups performance by Exam1.

	Groups	N	Mean	Std. deviation	Std. error mean
E1	Group 1	511	72.545	15.267	.6754
	Group 2	147	70.227	14.169	1.169

Table 3 t-Test: two-sample assuming equal variances.

	Levene' for equ varianc	ality of	t-Test for	r equality o	f means				
	F	Sig.	T	df	Sig. (2-tailed)	Mean difference	Std. error difference	95% confid interval of difference	the
								Lower	Upper
E1	.839	.360	1.648	656	.0998	2.318	1.407	4439	5.0802

Table 4 Descriptive statistics-course overall final score.

Group	N	Mean overall final score	Std. deviation	Std. error mean
G1F	511	72.153	12.2657	.5426
G1F G2F	147	74.923	11.1422	.91904

Table 5 t-Test: Course Overall Group Performance.

	Levene's test for equality of variances		t-Test for	t-Test for equality of means					
	F	Sig.	T	df	Sig. (2-tailed)	Mean difference	Std. error difference	95% confide interval of t difference	
								Lower	Upper
Overall score	.261	.610	-2.461	656	.014	-2.7699	1.1254	4.9795	5597

-6.685 and P-value of "0" (see Table 7) confirming the effectiveness of the use of motivation achievement theories of educational psychology and predictive analytics.

Comparing the grade distribution of the two groups (Fig. 3), it can be easily seen that the post-innovation group of students outperformed those in the pre-innovation group with 43% more As (from 6.58% to 9.40%), 35% more Bs (from 19.34% to 26.17%), and 20% fewer Cs (from 50.48% to 40.27%). Although the failure rate of the at-risk students (DFWs) stayed at about 24%, the majority of these students eventually succeeded in passing the course, thanks to their improved class engagement, and the instructor's proposed remedies to facilitate their success. Hence, further confirming the effectiveness of the use of motivation achievement theories of educational psychology and predictive analytics.

Comparing the post-innovation group grade distributions, Fig. 4 clearly shows a significantly improved performance by the end of the course compared to that by the first exam with 27% more As, 22% more Bs, 62% more Cs, with almost 48% of atrisk students (DFWs) being remedied.

To further validate the efficacy and sustainability of the proposed innovation, data for 79 students in the first semester of year six (group 3) and a one way Analysis of Variance (ANOVA) was performed for all the three groups concluding that the data provides substantial evidence of at least one significant difference in the final score performance of the three groups. Tuckey's Honestly Significant Difference Test (HSD) confirmed a significant difference between group 1 and groups 2 and 3 with no significant difference existing between groups 2 and 3 (see Tables 8 and 9).

 Table 6

 Descriptive statistics post-innovation group. Exam1 & course final average.

		Mean	N	Std. deviation	Std. error mean
Post-innovation group 2	G2E1	70.22721	147	14.169495	1.168680
	G2F	74.92271	147	11.142209	.918994

Table 7Paired t-test post-innovation group exam1 & course final average.

	0 1								
		Paired differences						df	Sig. (2-tailed)
		Mean	Std. deviation	Std. error mean	95% C. I. of difference				
					Lower	Upper			
Post-innovation group 2	G2E1-G2F	-4.6955	8.5165	.7024	-6.0838	-3.3073	-6.685	146	.000

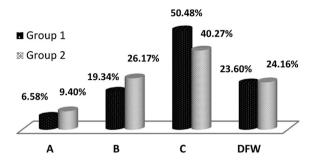


Fig. 3. Pre-innovation group (1) vs. post-innovation group (2) final grade distributions.

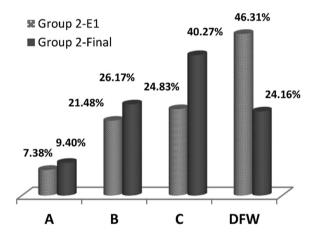


Fig. 4. Post-innovation group (2) grade distributions as of exam1 vs.-final grades.

Table 8 ANOVA-Final course performance score-all groups.

	Sum of squares	df	Mean square	F	Sig.
Between groups	2915.950	2	1457.975	10.017	.000
Within groups	106835.983	734	145.553		
Total	109751.933	736			

Table 9Multiple comparisons- Tukey's HSD- dependent variable: Final course average.

(I) group	(J) group	Mean difference (I-J)	Std. error	Sig.	95% confidence interval		
					Lower bound	Upper bound	
Pre-innovation (group 1)	2	-2.769584 ^a	1.129158	.038	-5.42138	11779	
	3	-5.997122^{a}	1.458521	.000	-9.42242	-2.57182	
Post-innovation (group 2)	1	2.769584 ^a	1.129158	.038	.11779	5.42138	
, ,	3	-3.227538	1.683033	.134	-7.18010	.72502	
Group 3	1	5.997122 ^a	1.458521	.000	2.57182	9.42242	
-	2	3.227538	1.683033	.134	72502	7.18010	

^a The mean difference is significant at the .05 level.

3. Results and conclusion

This study provides statistical evidence to support the hypothesis that combining motivation achievement theories of educational psychology and predictive analytics can positively influence the academic performance of students in quantitative business courses. Unlike existing research, this study required students to play an active role in the development of the predictive tools and the prediction process, and provided them the capability to capture real-time performance feedback enabling them to relate their current educational activities to future goals, hence providing them the opportunity to react and self-regulate their class engagement. This positive learning environment promoted self-efficacy and competence, improved students' self-confidence, and led to higher levels of class engagement, relatedness, and improved mastery skills, as illustrated in Fig. 3, making the course more enjoyable to both students and instructors.

Given the vast and challenging endeavor of student academic performance, this study also sought to show an approach that transcends classical learning goals to include experiential learning, and provide a process that educators and practitioners may find useful to facilitate a student-based active learning environment. Furthermore, the authors believe that this study can be replicated across many courses and disciplines, and may provide a continuous improvement tool to enhance students' academic engagement, and provide them the opportunity to see the likely outcome of their current class performance. It should be noted that this study is limited to the motivation achievement theories the authors deemed appropriate for their specific use and does not in any way claim to be applicable under all circumstances.

References

ACT Profile Report. (2013). National ACT profile report – graduating class 2013. Retrieved from https://www.act.org/research/policymakers/cccr13/index.

Ames, C. (1992). Classrooms: goals, structures, and student motivation. *Journal of Educational Psychology*, 84(3), 261–271. http://dx.doi.org/10.1037/0022-0663.84.3.261.

Ames, C., & Ames, R. (1984). Systems of student and teacher motivation: toward a qualitative definition. *Journal of Educational Psychology*, 76(4), 535–556. http://dx.doi.org/10.1037/0022-0663.76.4.535.

Appleton, J. J., Christenson, S. L., & Furlong, M. J. (2008). Student engagement with school: critical conceptual and methodological issues of the construct. *Psychology in the Schools*, 45(5), 369–386. http://dx.doi.org/10.1002/pits.20303.

Astin, A. W. (1993). What matters in college? Four critical years revisited (Vol. xxi). San Francisco, CA, US: Jossey-Bass.

Bandura, A. (1977). Self-efficacy: toward a unifying theory of behavioral change. Psychological Review, 84(2), 191-215.

Bandura, A. (1986). Social foundations of thought and action: A social cognitive theory. Prentice-Hall.

Bandura, A. (1997). Self-efficacy: The exercise of control. Macmillan.

Bandura, A., & Schunk, D. H. (1981). Cultivating competence, self-efficacy, and intrinsic interest through proximal self-motivation. *Journal of Personality and Social Psychology*, 41(3), 586–598. http://dx.doi.org/10.1037/0022-3514.41.3.586.

Bessant, K. C. (1995). Factors associated with types of mathematics anxiety in college students. *Journal for Research in Mathematics Education*, 26(4), 327–345. http://dx.doi.org/10.2307/749478.

Blick, D. W., & Test, D. W. (1987). Effects of self-recording on high-school students' on-task behavior. *Learning Disability Quarterly*, 10(3), 203–213. http://dx.doi.org/10.2307/1510493.

Borde, S. F. (1998). Predictors of student academic performance in the introductory marketing course. *Journal of Education for Business*, 73(5), 302–306. http://dx.doi.org/10.1080/08832329809601649.

Bridgeland, J. M., Dilulio, J. J., Morision, K. B., LLC, C. E., Associates, P. D. H. R., et al. (2006). The silent epidemic: Perspectives of high school dropouts. Civic Enterprises. LLC.

Brophy, J. E. (2010). Motivating students to learn (3 ed.). New York: Routledge.

Buckless, F., Lipe, M., & Ravenscroft, sue (1991). Do gender effects on accounting course performance persist after controlling for general academic aptitude. *Issues in Accounting Education*, 6(2), 248–261.

Connell, J. P., & Wellborn, J. G. (1991). Competence, autonomy, and relatedness: a motivational analysis of self-system processes. In M. R. Gunnar, & L. A. Sroufe (Eds.), Self processes and development (pp. 43–77). Hillsdale, NJ: England: Lawrence Erlbaum Associates, Inc.

Covington, M. V. (1992). Making the grade: A self-worth perspective on motivation and school reform. Cambridge University Press.

Croninger, R. G., & Lee, V. E. (2001). Social capital and dropping out of high school: benefits to at-risk students of teachers' support and guidance. *Teachers College Record*, 103(4), 548–581.

Curwin, R. L. (2010). Meeting students where they live motivation in urban schools. Alexandria: Va.: ASCD.

Danko, K., Duke, J. C., & Franz, D. P. (1992). Predicting student performance in accounting classes. *Journal of Education for Business*, 67(5), 270.

Darling-Hammond, L. (1997). The right to learn: A blueprint for creating schools that work. San Francisco: Jossey-Bass.

De Volder, M., & Lens, W. (1982). Academic achievement and future time perspective as a cognitive—motivational concept. *Journal of Personality and Social Psychology*, 42(3), 566–571. http://dx.doi.org/10.1037/0022-3514.42.3.566.

Deci, E. L., & Ryan, R. M. (2002). Handbook of self-determination research. University Rochester Press.

Dweck, C. S. (1986). Motivational processes affecting learning. *American Psychologist*, 41(10), 1040–1048. http://dx.doi.org/10.1037/0003-066X.41.10.1040. Dweck, C. S. (2000). *Self-theories: Their role in motivation, personality, and development*. Psychology Press.

D'Souza, K. A., & Maheshwari, S. K. (2011). Predicting and monitoring student performance in the introductory management science course. *Academy of Educational Leadership Journal*, 15(2), 69–80.

Eccles, J. S., & Wigfield, A. (1995). In the mind of the achiever: the structure of adolescents' academic achievement related-beliefs and self-perceptions. Personality and Social Psychology Bulletin, 21, 215–225.

Eikner, A. E., & Montondon, L. (2006). Evidence on factors associated with Success in intermediate accounting I. *The Accounting Educators' Journal*, 13. Retrieved from http://www.aejournal.com/ojs/index.php/aej/article/view/24.

Elliot, A. J., & Dweck, C. S. (2005). Handbook of competence and motivation. Guilford Press.

Estelami, H. (2014). Determining the drivers of student performance in online business courses. *American Journal of Business Education (Online)*, 7(1), 79. Finn, J. D., & Zimmer, K. S. (2012). Student engagement: what is it? Why does it matter? In S. L. Christenson, A. L. Reschly, & C. Wylie (Eds.), *Handbook of research on student engagement* (pp. 97–131). US: Springer. Retrieved from http://link.springer.com/chapter/10.1007/978-1-4614-2018-7_5.

Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School engagement: potential of the concept, state of the evidence. *Review of Educational Research*, 74(1), 59–109. http://dx.doi.org/10.3102/00346543074001059.

Fryer, R. G. (2011). Financial incentives and student achievement: evidence from randomized trials. *The Quarterly Journal of Economics*, 126(4), 1755–1798. http://dx.doi.org/10.1093/qje/qjr045. Furrer, C., & Skinner, E. (2003). Sense of relatedness as a factor in Children's academic engagement and performance. *Journal of Educational Psychology*, 95(1), 148–162

Garcia, T., & Pintrich, P. R. (1994). Regulating motivation and cognition in the classroom: the role of self-schemas and self-regulatory strategies. In D. H. Schunk, & B. J. Zimmerman (Eds.), Self-regulation of learning and performance: Issues and educational applications (pp. 127–153). Hillsdale, NJ: England: Lawrence Erlbaum Associates. Inc.

Goldstein, L. S. (1999). The relational zone: the role of caring relationships in the co-construction of mind. *American Educational Research Journal*, 36(3), 647–673. http://dx.doi.org/10.3102/00028312036003647.

Goldstein, M. T., & Perin, D. (2008). Predicting performance in a community college content-area course from academic skill level. Community College Review, 36(2), 89–115. http://dx.doi.org/10.1177/0091552108322631.

Gracia, L., & Jenkins, E. (2003). A quantitative exploration of student performance on an undergraduate accounting programme of study. Accounting Education, 12(1), 15–32. http://dx.doi.org/10.1080/0963928032000049375.

Grolnick, W. S., & Ryan, R. M. (1987). Autonomy in children's learning: an experimental and individual difference investigation. *Journal of Personality and Social Psychology*, 52(5), 890–898. http://dx.doi.org/10.1037/0022-3514.52.5.890.

Hallahan, D. P., Kauffman, J. M., & Pullen, P. C. (2011). Exceptional learners: An introduction to special education (12 ed.). Boston: Pearson Education.

Handel, S. J. (2009). Transfer and the part-time student: the Gulf separating community colleges and selective universities. *Change: The Magazine of Higher Learning*, 41(4), 48–53.

Harter, S. (1978). Effectance motivation reconsidered toward a developmental model. *Human Development*, 21(1), 34–64. http://dx.doi.org/10.1159/000271574.

Harter, S. (1982). The perceived competence scale for children. Child Development, 53(1), 87-97. http://dx.doi.org/10.2307/1129640.

Hartnett, N., Römcke, J., & Yap, C. (2004). Student performance in tertiary-level accounting: an international student focus. Accounting and Finance, 44(2), 163–185.

Hilpert, J. C., Husman, J., Stump, G. S., Kim, W., Chung, W.-T., & Duggan, M. A. (2012). Examining students' future time perspective: pathways to knowledge building1. *Japanese Psychological Research*, 54(3), 229–240. http://dx.doi.org/10.1111/j.1468-5884.2012.00525.x.

Husman, J., & Lens, W. (1999). The role of the future in student motivation. Educational Psychologist, 34(2), 113.

Kauffman, D. F., & Husman, J. (2004). Effects of time perspective on student motivation: Introduction to a special issue. *Educational Psychology Review*, 16(1), 1–7. http://dx.doi.org/10.1023/B:EDPR.0000012342.37854.58.

Kealey, B. T., Holland, J., & Watson, M. (2005). Preliminary evidence on the association between critical thinking and performance in principles of accounting. *Issues in Accounting Education*, 20(1), 33–49. http://dx.doi.org/10.2308/iace.2005.20.1.33.

Koh, M. Y., & Koh, H. C. (1999). The determinants of performance in an accountancy degree programme. *Accounting Education*, 8(1), 13–29. http://dx.doi.org/10.1080/096392899331017.

Kuh, G. D. (2003). What We're learning about student engagement from NSSE: benchmarks for effective educational practices. Change: The Magazine of Higher Learning, 35(2), 24–32. http://dx.doi.org/10.1080/00091380309604090.

Kuh, G. D., & Hu, S. (2001). The effects of student-faculty interaction in the 1990s. *The Review of Higher Education*, 24(3), 309–332. http://dx.doi.org/10.1353/

Lens, W. (1986). Future time perspective: a cognitive-motivational concept. In D. R. Brown, & J. Veroff (Eds.), Frontiers of motivational psychology (pp. 173–190). US: Springer. Retrieved from http://link.springer.com/chapter/10.1007/978-1-4684-6341-5_10.

Maag, J. W., Rutherford, R. B., & Digangi, S. A. (1992). Effects of self-monitoring and contingent reinforcement on on-task behavior and academic productivity of learning-disabled students: a social validation study. *Psychology in the Schools*, 29(2), 157–172. http://dx.doi.org/10.1002/1520-6807(199204)29:2<157::AID-PITS2310290211>3.0.CO;2-F.

Mangum, W. M., Baugher, D., Winch, J. K., & Varanelli, A. (2005). Longitudinal study of student dropout from a business school. *Journal of Education for Business*, 80(4), 218–221. http://dx.doi.org/10.3200/JOEB.80.4.218-221.

Markus, H., & Wurf, E. (1987). The dynamic self-concept: a social psychological perspective. *Annual Review of Psychology*, 38(1), 299–337. http://dx.doi.org/10.1146/annurev.ps.38.020187.001503.

Meece, J. L., Wigfield, A., & Eccles, J. S. (1990). Predictors of math anxiety and its influence on young adolescents' course enrollment intentions and performance in mathematics. *Journal of Educational Psychology*, 82(1), 60–70. http://dx.doi.org/10.1037/0022-0663.82.1.60.

Miller, R. B., & Brickman, S. J. (2004). A model of future-oriented motivation and self-regulation. Educational Psychology Review, 16(1), 9-33.

Miller, R. B., DeBacker, T. K., & Greene, B. A. (1999). Perceived instrumentality and academics: the link to task valuing. *Journal of Instructional Psychology*, 26(4), 250–260.

Naser, K., & Peel, M. J. (1998). An exploratory study of the impact of intervening variables on student performance in a principles of accounting course. Accounting Education, 7(3), 209–223. http://dx.doi.org/10.1080/096392898331153.

Patrick, H., Ryan, A. M., & Kaplan, A. (2007). Early adolescents' perceptions of the classroom social environment, motivational beliefs, and engagement. Journal of Educational Psychology, 99(1), 83–98. http://dx.doi.org/10.1037/0022-0663.99.1.83.

Peters, M., Kethley, B., & Bullington, K. (2002). The relationship between homework and performance in an introductory operations management course. *Journal of Education for Business*, 77(6), 340–344. http://dx.doi.org/10.1080/08832320209599686.

Pintrich, P. R. (2003). A motivational science perspective on the role of student motivation in learning and teaching contexts. *Journal of Educational Psychology*, 95(4), 667–686. http://dx.doi.org/10.1037/0022-0663.95.4.667.

Pohlmann, J. T., & Leitner, D. W. (2003). A comparison of ordinary least squares and logistic regression (1). *The Ohio Journal of Science*. Retrieved from http://www.highbeam.com/doc/1G1-113647859.html.

Porter, T., & Ronit, K. (2006). Self-regulation as policy process: the multiple and criss-crossing stages of private rule-making. *Policy Sciences*, 39(1), 41–72. http://dx.doi.org/10.1007/s11077-006-9008-5.

Rahal, A. D., & Rabelo, L. C. (2006). Assessment framework for the evaluation and prioritization of university inventions for licensing and commercialization. Engineering Management Journal, 18(4), 28–36.

Raska, D. (2014). Excited, proud, and accomplished exploring the effects of feedback supplemented with web-based peer benchmarking on self-regulated learning in marketing classrooms. *Journal of Marketing Education*, 36(3), 258–271. http://dx.doi.org/10.1177/0273475314552325.

Reid, R. (1996). Research in self-monitoring with students with learning disabilities: the present, the prospects, the pitfalls. *Journal of Learning Disabilities*, 29(3), 317–331. http://dx.doi.org/10.1177/002221949602900311.

Renniger, K. A., Hidi, S., & Krapp, A. (1992). The role of interest in learning and development (Vol. xiv). Hillsdale, NJ: England: Lawrence Erlbaum Associates,

Rheinberg, F., Vollmeyer, R., & Rollett, W. (2000). Motivation and action in self-regulated learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), Handbook of self-regulation (pp. 503—529). San Diego, CA, US: Academic Press.

Rock, M. L. (2005). Use of strategic self-monitoring to enhance academic engagement, productivity, and accuracy of students with and without exceptionalities. *Journal of Positive Behavior Interventions*, 7(1), 3–17. http://dx.doi.org/10.1177/10983007050070010201.

Roderick, M., & Engel, M. (2001). The grasshopper and the ant: motivational responses of low-achieving students to high-stakes testing. *Educational Evaluation and Policy Analysis*, 23(3), 197–227. http://dx.doi.org/10.3102/01623737023003197.

Rosenholtz, S. J., & Wilson, B. (1980). The effect of classroom structure on shared perceptions of ability. *American Educational Research Journal*, 17(1), 75–82. http://dx.doi.org/10.3102/00028312017001075.

Ryan, R. M. (1992). Agency and organization: intrinsic motivation, autonomy, and the self in psychological development. *Nebraska Symposium on Motivation*. *Nebraska Symposium on Motivation*, 40, 1–56.

- Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist*, 55(1), 68–78. http://dx.doi.org/10.1037/0003-066X.55.1.68.
- Ryan, R. M., & Deci, E. L. (2009). Promoting self-determined school engagement: motivation, learning, and well-being. In *Handbook on motivation at school* (pp. 171–196). Routledge.
- Ryan, R. M., & Powelson, C. L. (1991). Autonomy and relatedness as fundamental to motivation and education. *Journal of Experimental Education*, 60(1), 49–66.
- Ryan, R. M., Stiller, J. D., & Lynch, J. H. (1994). Representations of relationships to teachers, parents, and friends as predictors of academic motivation and self-esteem. *Journal of Early Adolescence*, 14(2), 226.
- Schunk, D. H. (1991). Self-efficacy and academic motivation. *Educational Psychologist*, 26(3–4), 207–231. http://dx.doi.org/10.1080/00461520.1991.9653133. Simons, J., Dewitte, S., & Lens, W. (2000). Wanting to have vs. wanting to be: the effect of perceived instrumentality on goal orientation. *British Journal of Psychology (London, England: 1953)*, 91(Pt 3), 335–351.
- Simons, J., Dewitte, S., & Lens, W. (2004). The role of different types of instrumentality in motivation, study strategies, and performance: know why you learn, so you'll know what you learn! *British Journal of Educational Psychology*, 74(3), 343–360.
- Skinner, E. A. (1996). A guide to constructs of control. *Journal of Personality and Social Psychology*, 71(3), 549–570. http://dx.doi.org/10.1037/0022-3514.71.3.
- Skinner, E. A., & Pitzer, J. R. (2012). Developmental dynamics of student engagement, coping, and everyday resilience. In S. L. Christenson, A. L. Reschly, & C. Wylie (Eds.), *Handbook of research on student engagement* (pp. 21–44). US: Springer. Retrieved from http://link.springer.com/chapter/10.1007/978-1-4614-2018-7
- Skinner, E. A., Zimmer-Gembeck, M. J., & Connell, J. P. (1998). Individual differences and the development of perceived control. *Monographs of the Society for Research in Child Development*, 63, 2–3. http://dx.doi.org/10.2307/1166220. v–220.
- Tseng, H.-K. (2010). Has the student performance in managerial economics been affected by the class size of principles of microeconomics? *Journal of Economics and Economic Education Research*, 11(3), 15–27.
- Turner, J. L., Holmes, S. A., & Wiggins, C. E. (1997). Factors associated with grades in intermediate accounting. *Journal of Accounting Education*, 15(2), 269–288. http://dx.doi.org/10.1016/S0748-5751(97)00002-X.
- Uekawa, K., Borman, K., & Lee, R. (2007). Student engagement in U.S. Urban high school mathematics and science classrooms: findings on social organization, race, and ethnicity. *The Urban Review*, 39(1), 1–43. http://dx.doi.org/10.1007/s11256-006-0039-1.
- Wigfield, A., & Eccles, J. S. (1992). The development of achievement task values: a theoretical analysis. *Developmental Review*, 12(3), 265–310. http://dx.doi.org/10.1016/0273-2297(92)90011-P.
- Wigfield, A., Eccles, J. S., Schiefele, U., Roeser, R. W., & Davis-Kean, P. (2007). *Development of achievement motivation*. Handbook of Child Psychology. John Wiley & Sons, Inc. Retrieved from http://onlinelibrary.wiley.com/doi/10.1002/9780470147658.chpsy0315/abstract.
- Wigfield, A., & Meece, J. L. (1988). Math anxiety in elementary and secondary school students. *Journal of Educational Psychology*, 80(2), 210–216. http://dx.doi.org/10.1037/0022-0663.80.2.210.
- Willingham, W. W., Pollack, J. M., & Lewis, C. (2002). Grades and test scores: accounting for observed differences. *Journal of Educational Measurement*, 39(1), 1–37. http://dx.doi.org/10.1111/j.1745-3984.2002.tb01133.x.
- Zhang, X., yuan, P.,P., & Ewing, M. (2014). AP® potential predicted by PSAT/NMSQT® scores using logistic regression. College Board Research. Retrieved from http://research.collegeboard.org/sites/default/files/publications/2014/10/ap-potential-predicted-by-psat-nmsqt-scores-logistic-regression.pdf.
- Zimmerman, B. J. (1990). Self-regulated learning and academic achievement: an overview. Educational Psychologist, 25(1), 3-17.