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Self-determination and STEM education: Effects of autonomy, motivation, and self-regulated learning on high school math achievement

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ABSTRACT

To improve mathematics education and achievement, research needs to identify factors that support and motivate students to learn and achieve in math.
The purpose of this study was to test, using structural equations, a model with a sample of 1412 high-school students where autonomy would predict autonomous motivation, which in turn, has a positive effect on effort regulation and deep-processing, and both variables would predict math achievement.
Results confirmed all hypothesized paths, except deep-processing unexpectedly did not predict math achievement.
Findings suggest that when students feel that their schoolwork is purposeful and interesting, and that the classroom environment and teachers are responsive and supportive, they will be autonomously motivated to engage in self-regulated learning. Autonomous motivation propels students to engage in deep-processing of information and to persist and exert effort in their studies even when the school subject or studying becomes boring or taxing. Self-regulation of effort ultimately results in enhanced mathematics achievement.

1. Introduction

Education and academic achievement are key pathways to personal and professional success, and have become gatekeepers to institutions of higher education, career paths, occupational attainments, and individual life trajectories (Ritchie & Bates, 2013; von Stumm, Hell, & Chamorro-Premuzic, 2011). Furthermore, academic achievement predicts lower rates of school dropout, delinquency, and drug or substance use (Bryant, Schulenberg, O'Malley, Bachman, & Johnston, 2003; Vitaro, Brendgen, Larose, & Tremblay, 2005). Education in the 21st century has increasingly placed heavy emphasis on Science, Technology, Engineering, and Mathematics (STEM) education (National Mathematics Advisory Panel, 2008), partly because STEM skills contribute to the development and growth of industrialized and modern societies (Ratelle, Larose, Guay, & Senécal, 2005). Because of the importance of math skills in the success of many STEM subjects (Seymour & Hewitt, 1997) and its key role in the decision to choose a STEM degree (Wang, 2013), there is an urgent societal and educational need to better understand the mechanisms and processes underlying students' learning and achievement in school subjects such as mathematics (Turner & Varley, 2012), as well as understanding factors that support and motivate students to learn and achieve in mathematics (Singh, Granville, & Dika, 2002).

1.1. Motivation: self-determination theory

Motivation has often been broadly classified into intrinsic and extrinsic motivation, with *intrinsic motivation* referring to doing something because it is inherently interesting or enjoyable and *extrinsic motivation* referring to doing something because it leads to a reward. Within *Self-Determination Theory* (SDT; Deci & Ryan, 1985) we can also differentiate between autonomous motivation and controlled motivation. Students with *autonomous motivation* engage in learning from their own volition and interest without external force or pressure. In contrast, students with *controlled motivation* engage in learning because of external force or pressure (Black & Deci, 2000; Gagne & Deci, 2005). So, while not all students engage in learning and achievement out of intrinsic motivation, those who pursue learning and achievement out of external motivation but fully accept the value and importance of learning and achievement and feel a high degree of autonomous motivation are exhibiting *identified motivation* (Cheon & Reeve, 2014). For example, engineering students may be pursuing their studies for extrinsic reasons such as career opportunities but may still fully recognize and accept the value and importance of learning compulsory coursework in mathematics and science and engage in this work autonomously.

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According to SDT, competence, autonomy, and relatedness are basic human needs and teachers play a critical role in providing for students´ needs, which then contributes to their motivation for learning and achievement (Niemiec & Ryan, 2009). Importantly, it is the degree to which students feel that they have autonomy in their classroom environments that determines their autonomous motivation (Gagne & Deci, 2005). For example, Hafen et al. (2012) found that adolescents' perceptions about autonomy within the classroom most strongly predicted change in student engagement. Students would feel their need for autonomy is satisfied when they find some degree of meaningful choice and purpose in their school activities and when their teachers are responsive and supportive (Reeve & Halusic, 2009; Skinner & Belmont, 1993).

Supporting autonomous motivation has emotional, cognitive, and behavioral consequences for students and their self-regulated learning (Ng et al., 2012; Radel, Pelletier, Baxter, Fournier, & Sarrazin, 2014). Effort regulation and deep-processing of information are two specific aspects of self-regulation (Pintrich, 2004). *Effort regulation* refers to persistence in the face of challenges or failures and *deep-processing* refers to critical and reflective thinking and meaning-making (Biggs & Tang, 2011; Pintrich, 2004; Richardson, Abraham, & Bond, 2012). Given the importance of students' autonomous motivation in self-regulated learning, mastery, and achievement, there has been much interest in the design and implementation of programs and interventions that can effectively foster students' autonomy and motivation. School-based interventions aimed at supporting students' autonomy have shown to be effective. A meta-analysis of 19 studies on interventions targeting students' autonomy conducted by Su and Reeve (2010) found that results generally affirmed interventions´ effectiveness and that effect sizes were bigger if the intervention provided students with meaningful rationales, acknowledged students' feelings, used non-controlling language, offered choices, and nurtured inner motivational resources.

Studies have demonstrated the linkages between autonomous motivation and self-regulated learning. For instance, Vansteenkiste, Zhou, Lens, and Soenens (2005) studied Chinese students who were learning English and found that autonomy predicted learning thoughts and strategies. In a study on medical students, Kusurkar, Ten Cate, Vos, Westers, and Croiset (2013) found that motivation was linked to exam performance, but this link was mediated by the amount of time students' spent studying (which could be interpreted as a measure of students' effort). In a study that compared student test performance across conditions of goal content, intrinsic versus extrinsic, learning climates, and autonomy-supportive versus controlling, Vansteenkiste, Simons, Lens, Sheldon, and Deci (2004) observed that students in the intrinsic and the autonomy conditions showed deeper processing and test performance that in the other conditions; furthermore, they showed that this effect was mediated by autonomous motivation (a composite of intrinsic and identified motivation).

1.2. Effort regulation

Effort regulation or effortful persistence has been defined as "self-perceptions of continued investment and overall amount of time, energy, or work expended on a task or goal" (Liew, Xiang, Johnson, & Kwok, 2011, p. 235), and refers to students´ ability to exert effort and to persist even when doing so is not easy or fun (Pintrich & de Groot, 1990). A body of studies has shown that effort regulation is a strong predictor of achievement in a variety of domains, including in academic achievement. For example, Komarraju and Nadler (2013) observed in a sample of undergraduates that, after accounting for motivation and metacognitive learning strategies, effort regulation predicted grade point averages (GPA). Moreover, Richardson et al. (2012) in a meta-analysis concluded that effort regulation is strongly related to students' school grades.

1.3. Deep-processing

Students use a variety of strategies to learn and process the information presented at school. These learning strategies range from memorization to deep-processing, in order to analyze or think critically, reflect, make meaning and connections, and apply learned information (Duncan & McKeachie, 2005; Pintrich, Smith, Garcia, & McKeachie, 1993). Understanding the precursors and outcomes of deep-processing has attracted attention from educators and researchers, because deep-processing facilitates information to be stored in long-term memory so it could be used and applied in meaningful or useful ways (Craik & Lockhart, 1972; Dinsmore & Alexander, 2012; Evans & Vermunt, 2013; Pintrich, 2004). According to Information Processing Theory, deep-processing of information allows for retention of information so it could be accessed and used in the future (Lockhart & Craik, 1990)

Educating students to become self-regulated learners who can think critically, make connections between existing and new information, and process information deeply has become a priority for modern education (Yang, 2012). As Weinstein and Palmer (2002) explained, using prior knowledge, experiences, attitudes, beliefs and reasoning to make sense of new information is critical to success in school and at work in the 21st century. The difference between someone with and without experience is not just the amount of knowledge they possess, but also, and perhaps more importantly, the way in which this new knowledge is acquired and organized.

Students who are motivated to learn are likely to engage in deep-processing of information that they acquire (Biggs & Tang, 2011), including paying attention to details and making connections between ideas (Entwistle & McCune, 2013). The consequences of using deep-processing strategies depends on the framework used, but is generally accepted that the more students think and process information learned, the more they will understand and remember it. Although there is some debate about the academic consequences of using a deep-processing approach (Baeten, Kyndt, Struyven, & Dochy, 2010) researchers have observed that the use of deep-processing strategies is related to academic performance. For example Salamonson et al. (2013) found that deep learning approaches predicted academic performance in university students, even after accounting for the weekly time spent working and English language usage. In a different study, Kusurkar et al. (2013) found that medical students´ learning strategy (a proxy computed as the difference between surface and deep strategies) predicted GPA.

1.4. The present study

Much remains unknown about the mechanisms and processes underlying self-regulated learning and achievement in classrooms (de Bruin & van Gog, 2012; Efklides, 2012), and limited studies have examined motivation and self-regulation simultaneously (Helle, Laakkonen, Tuijula, & Vermunt, 2013). Moreover, many students view mathematics as either boring or overly difficult and some students suffer from math anxiety (Gersten et al., 2009). For this reason, guided by a Self-Determination Theory framework, the present study aims to answer the following questions:

Is autonomy in the classroom related with autonomous motivation to study? Taking into account SDT tenets and previous studies (Jang, Kim, & Reeve, 2012; Reeve & Halusic, 2009), teachers help students' develop a sense of autonomy by acknowledging students' interests and building choice into school curricula. In a classroom climate that is responsive and supportive of students' need for autonomy, students will likely feel autonomously motivated to learn and to achieve. Thus, we hypothesized that a classroom environment that supports student's autonomy will promote students' autonomous motivation.

Does autonomous motivation to study predict effort regulation and deep-processing? Consistent with SDT tenets and previous research findings (Kusurkar et al., 2013; Vansteenkiste et al., 2004), autonomously motivated students are likely to engage in self-regulated learning practices such as effort regulation and deep-processing. Thus, we hypothesized that autonomous motivation to study will predict effort regulation and deep-processing.

Is effort regulation related with math grades? Komarraju and Nadler (2013) observed that effort regulation predicted GPA and Richardson et al. (2012) concluded from a meta-analysis that effort regulation predicted GPA. However, to our knowledge, no previous studies have specifically tested the effect of effort regulation on math grades. Thus, we address this research gap by testing the hypothesis that effort regulation predicts math achievement.

Does deep processing predict math grades? According to Biggs and Tang (2011), motivated students are likely to spend time thinking about what they are learning in class. While studies have shown that deep-learning predicts overall grades, the relation between deep-learning and math achievement has not specifically been tested in prior studies. Therefore, we address this research gap by testing the hypothesis that deep processing predicts math achievement.

In conclusion, we will test a model where effort regulation and deep-processing are two self-regulated learning mechanisms by which autonomy and autonomous motivation predicts math achievement.

2. Method

2.1. Procedure

This study was conducted at five high schools located in Las Palmas de Gran Canaria, Spain. Students provided informed consent to participate, and participation was strictly voluntary and confidential. All measures except for math grades were collected during December of 2012, and data on students' math grades were collected approximately 6 months later in June (at the end of the math course). During the data collection in December, a researcher administered all measures to students in the classroom, and provided students with instructions and clarifications if needed to complete the measures. At the end of the school year in June, students' final course grades in mathematics were obtained from school records. All students went through schooling in the same cohort and had the same coursework each year, except for any students who were retained. Therefore, majority of students went through secondary school with the same classmates in their classrooms each year.

2.2. Participants

Participants were 1412 compulsory secondary students (670 males, 681 females, 61 gender not reported; mean age = 14 years, SD = 1.27) grouped in 71 classrooms from five schools. The schools comprised of a mix of urban and outlying rural public schools with students predominantly from middle class families.

2.3. Measures

To examine reliability in study measures, we used McDonald's Omega (McDonald, 1999) instead of Cronbach's alpha, because the latter requires that the factor loadings are the same for all items (Yang & Green, 2010) and that the nature of the data is continuous (Elosua & Zumbo, 2008). Furthermore, McDonald´s Omega has shown evidence of better accuracy than Cronbach's alpha (Revelle & Zinbarg, 2009). Taking into account that participants' ratings were on Likert-type scales so their responses are ordered in systematic and categorical ways (Flora & Curran, 2004), we followed Zumbo, Gadermann, and Zeisser (2007)'s recommendations to treat the data as categorical measures and computed ordinal McDonald's Omega. The calculations were conducted with package "psych" 1.4.2.3 (Revelle, 2014) of R 3.0.3 (R Core Team, 2014). With regards to evidence of construct validity we performed a confirmatory factor analysis (CFA) for each scale, using the software Mplus 7.2 (Muthén & Muthén, 2014). More information about the method used to estimate parameters and standard error can be found in the data analysis section.

2.3.1. Autonomy

To assess student autonomy in the classroom, students responded to five items from the autonomy subscale from the Basic Psychological Needs in Education (León, Domínguez, Núñez, Pérez, & Martin-Albo, 2011) on a 7-point scale (1 = *strongly disagree* to 7 = *strongly agree*). Items were prefaced with "in class" in order to assess student autonomy in the classroom (e.g. "I feel free in my decisions"), and this measure has been reliable in prior research (León & Núñez, 2013; León et al., 2011) and the present study ($\omega = .84$). With regards to the CFA, residual correlation between two of the five items that were worded in a similar way was allowed. The χ^2 value and fit indexes were χ^2 (1404, 4) = 100.48 ($p = .00$), RMSEA = .13 [.11, .15], CFI = .97, TLI = .94. With standardized loadings ranging between .49 and .83. In summary, χ^2 values and RMSEA are high, something expected due to the large sample size and the simplicity of the model (Kenny, Kaniskan, & McCoach, 2014), but CFI and TLI values indicate the scale is adequate.

2.3.2. Autonomous motivation

To assess students' autonomous motivation, participants rated four items from the intrinsic motivation toward knowledge subscale and four from the identified subscale of the Academic Motivational Scale (AMS; Vallerand, Blais, Brierè, & Pelletier, 1989) on a 7-point scale (1 = *strongly disagree* to 7 = *strongly agree*). All items were prefaced by "Why do you go to high-school?" followed by each item. Sample items included "Because for me it is a pleasure and satisfaction to learn new things". These items have been reliable in prior research (Doménech & Gómez, 2014; Núñez, Martín-Albo, Navarro, & Suárez, 2010; Vallerand et al., 1993) and the present study ($\omega = .84$). With regards to the CFA, the χ^2 value and fit indexes were χ^2 (1406, 20) = 438.83 ($p = .00$), RMSEA = .12 [.11, .13], CFI = .95, TLI = .92. With standardized loadings ranging between .50 and .83. In summary, χ^2 values and RMSEA are high, which is expected due to the large sample size and the simplicity of the model (Kenny et al., 2014) but CFI and TLI values indicate the scale is adequate.

2.3.3. Effort regulation

Students' effort regulation was assessed using four items from the effort regulation subscale of the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich et al., 1993) on a 7-point scale (1 = *strongly disagree* to 7 = *strongly agree*). Sample items included "When work is difficult I either give up or study only the easy parts", and all items on this measure have demonstrated adequate reliability in prior research (Hilpert, Stempien, van der Hoeven, & Husman, 2013; Pintrich et al., 1993) and in the present study ($\omega = .74$). With regards to the CFA, residual correlation between two of the four items that were worded in a similar way was allowed, the χ^2 value and fit indexes were χ^2 (1402, 1) = 3.05 ($p = .08$), RMSEA = .04 [.00, .09], CFI = .99, TLI = .99. With standardized loadings ranging between .38 and .89. In summary, the RMSEA superior limit is high, something expected due to the large sample size and the simplicity of the model (Kenny et al., 2014), but CFI and TLI values indicate the scale is adequate.

2.3.4. Deep-processing

To assess students' deep-processing, participants rated items from the critical thinking subscale of the MSLQ (Pintrich et al., 1993) on a 7-point scale (1 = *strongly disagree* to 7 = *strongly agree*). Sample items include "I try to play around with ideas of my own related to what I am learning", and this measure has been reliable in previous work (Hilpert et al., 2013; Pintrich et al., 1993) and the present study ($\omega = .84$). With regards to the CFA, the χ^2 value and fit indexes were

χ^2 (1403, 2) = 19.85 (p = .00), RMSEA = .08 [.05, .11], CFI = .99, = .99. With standardized loadings ranging between .68 and .81. In summary, χ^2 values and RMSEA are high, something expected due to the large sample size and the simplicity of the model (Kenny et al., 2014), but CFI and TLI values indicate the scale is adequate.

2.3.5. Math grades

Students' math performance was indexed by students´ final course grades in mathematics, which were obtained from official high-school records. Grades were coded as 1 being the lowest and 10 being the highest possible mark.

2.4. Data analysis

2.4.1. Preliminary analyses

Descriptive analyses were conducted, including Pearson´s correlations between major variables.

2.4.2. Structural equation model

We tested study hypotheses with structural equation modeling. Because the observed variables or the scale items were ordered categorically, we decided to use weighted least square mean and variance adjusted (WLSMV) as the estimation method which is more accurate than Maximun Likelihood (Schmitt, 2011). Importantly, students were grouped by schools and violate the assumption of independence. To statistically correct for nesting of students within schools which may inflate the value of χ^2 and underestimate standard errors (Stapleton, 2006), parameters were estimated by maximizing a weighted logarithmic function and standard errors using a sandwich type estimator (Muthén & Muthén, 2014). Then we estimated the indirect effects hypothesized in the structural equation model: 1) The effect of autonomy on Math via motivation and effort regulation; 2) the effect of autonomy on Math via motivation and deep-processing; 3) the effect of autonomy on effort regulation via motivation; and 4) the effect of autonomy on deep-processing via motivation.

To account for potential gender effects on major variables, we first tested if there were gender differences on the items of major variables by comparing a model with loadings and thresholds unconstrained or freed across gender (Model 1) versus a model with loadings and thresholds constrained or fixed to be the same across gender (Model 2). Next, to test if the means on major variables differed across gender we compared between Model 2 and a model with equal loadings, thresholds and means across gender (Model 3). To test if relationships between variables differed across gender, we compared Model 3 with a model with equal loadings, thresholds, means and regression coefficients (Model 4) across gender. For model comparisons, we used χ^2 difference tests and, bearing in mind that this technique can be too conservative in multigroups comparisons, we also looked for changes in CFI and RMSEA (Cheung & Rensvold, 2002; Morin et al., 2011; Vandenberg & Lance, 2000). With the WLSMV estimator, the chi-square values are adjusted, instead of exact values as when using the Maximum Likelihood estimator, therefore the χ^2 difference test cannot be computed by hand, but need to follow the procedure described by Asparouhov and Muthén (2006). Lastly, we used full information maximum likelihood method (Enders, 2010) to estimate missing data. All of the calculations were done with Mplus 7.2 (Muthén & Muthén, 2014).

3. Results

3.1. Preliminary analyses

Descriptive statistics (means and standard deviations) and Pearson's correlation for all major variables are displayed Table 1.

Table 1
Mean, standard deviation and Pearson's correlations.

	Mean	SD	1	2	3	4
1. Autonomy	5.03	1.31				
2. Motivation	5.54	1.05	.39			
3. Effort regulation	4.88	1.39	.25	.36		
4. Deep-processing	4.80	1.41	.57	.49	.35	
5. Math grades	5.12	2.42	.14	.22	.40	.18

3.2. Structural equation model

The χ^2 test and the fit indexes were χ^2 (1411, 205) = 961.85 (p = .00), CFI = .91, TLI = .90, and RMSEA = .05[05, 05]. Autonomy predicted motivation β = .65 [.64, .67], and this, in turn, predicted both effort regulation, β = .58 [.54, .62], and deep-processing, β = .77 [.74, .80]. Lastly, effort regulation predicted math grades, β = .47 [.42, .53], but there was no relation between deep-processing and math grades, β = −.03 [−.06, .01]. Although this initial model adequately fit the data, model results from the latent correlations and modification indexes suggested the addition of a path directly from autonomy to deep processing. The χ^2 test and the fit indexes for the revised model were χ^2 (1411, 205) = 689 (p = .00), CFI = .94, TLI = .94, and RMSEA = .04[04, 04]. We conducted χ^2 difference test and compare CFI and RMSEA between both models, we observed that the revised model fit the data significantly better than the initial model and that CFI and RMSEA showed a meaningful improvement. Results can be seen in Fig. 1. The model explained 20% of math variance.

The indirect effect of autonomy on Math via Motivation and effort regulation was β = .14 [.12, .16] and via Motivation and deep-processing was β = .00 [−.01, .01]. While the indirect effect of Motivation on Math via effort regulation was β = .27 [.23, .31] and via deep-processing was β = .00 [−.01, .02].

Multiple-groups analyses were conducted to examine potential gender differences in model results. According to results from χ^2 difference tests (See Table 2), no gender differences were found in the item loadings and thresholds or the means of major variables and regression coefficients. Although the χ^2 difference test was significant in all models comparison the differences in RMSEA and CFI across the constrained and unconstrained models were minimal and suggest that the model paths do not differ across males and females in substantial or meaningful ways.

4. Discussion

Using a SDT framework, this study identified the mechanisms by which autonomy in the classroom predicts autonomous motivation as well as self-regulated learning that then predicts math performance in students. Specifically, effort regulation and deep-processing were tested as two mechanisms by which autonomous motivation leads to enhanced math achievement. Study results support all but one of our hypotheses; deep-processing did not predict math achievement.

Table 2
Models' χ^2 values and fit indexes to assess differences across gender groups

Model	χ^2	*df*	*p*	RMSEA	90% CI	CFI
Model 1	1403.178	509	.000	.043	.041, .046	.949
Model 2	1370.146	526	.000	.042	.039, .044	.952
Model 3	1288.462	532	.000	.039	.036, .042	.957
Model 4	1277.234	538	.000	.038	.036, .041	.958

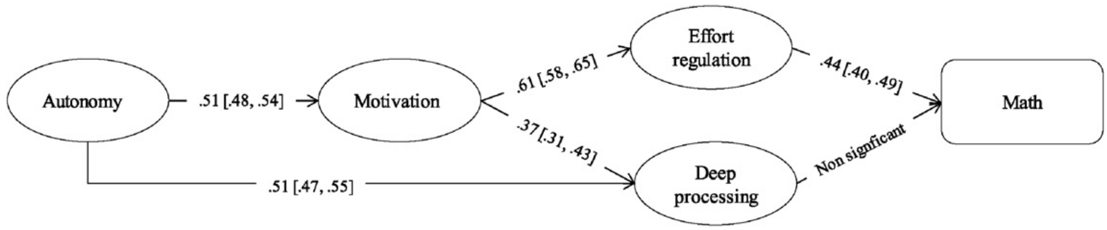

Fig. 1. Standardized regressions with 95% confidence interval between brackets.

4.1. Motivation: self-determination

Our findings are consistent with previous research within the SDT framework that posits autonomy support would contribute to autonomous motivation because individuals would experience some degree of meaningful choice and a sense of psychological freedom and volition (Gillet, Berjot, Vallerand, & Amoura, 2012; Katz, Kaplan, & Gueta, 2009). In the school or classroom context, students who perceive a high degree of meaningful choice in their school and learning activities would experience greater autonomous motivation. Thus, our findings support the view that a school or classroom environment with teachers who are responsive and supportive in helping students to cultivate a sense of meaningful choice and purpose in their learning is imperative to developing students' autonomous motivation for learning and achievement.

4.2. Motivation, deep-processing and effort regulation

Autonomous motivation has been posited to predict positive outcomes, such as study strategies. For instance, Vansteenkiste, Simons, Lens, Soenens, and Matos (2005); Vansteenkiste, Zhou, et al. (2005) observed that autonomous motivation, a composite of intrinsic and identified motivation, predicted students' optimal learning and active–voluntary school behavior. Our findings are consistent with Vansteenkiste, Simons, et al. (2005); Vansteenkiste, Zhou, et al. (2005)'s results; as shown in Fig. 1, students who report experiencing greater levels of autonomous motivation also report engaging in deep-processing and critical thinking of their school work. Deep-processing of course content is necessary for learned information to be retained and applied in meaningful ways. Thus, educators who create classroom environments that support students' autonomy and autonomous motivation are providing students with prerequisites for deep processing and mastery learning.

4.3. Effort regulation and math achievement

Consistent with findings from prior studies that have examined effort regulation and GPA or academic achievement (Komarraju & Nadler, 2013; Richardson et al., 2012; Schwinger, Steinmayr, & Spinath, 2009), we observed that effort regulation is a strong predictor of final course grades in mathematics. Effort regulation is one component of self-regulated learning, referring to students´ ability to focus attention, direct effort, and persist even when doing so is not easy or fun. Some students will undoubtedly find mathematics difficult and not inherently fun or interesting. Furthermore, students often experience anxiety and evaluative threat from the pressures associated with standardized and achievement tests in mathematics that often determine students' opportunities and futures in STEM areas (Liew, Lench, Kao, Yeh, & Kwok, 2014). Thus, effort regulation may be required for students to overcome obstacles or distractions so they could learn and achieve.

4.4. Deep-processing and math achievement

Educating learners to engage in deep-processing of information so that they could retain and then apply that information or skill in critical, constructive, or adaptive ways is one of the principle goals in education in the 21st century. Researchers have found that deep-processing predicts academic performance (Sierens, 2010; Vansteenkiste, Zhou, et al., 2005). Furthermore, in a meta-analysis, Richardson et al. (2012) found that critical thinking and deep approach to learning were both correlated to academic achievement, and strengths of correlations were similar across both variables. We speculate that our measure of deep-processing captures a similar construct as the critical thinking and deep approach to learning measures used in the meta-analysis of Richardson et al. (2012). Surprisingly, we did not find that deep-processing predicted math achievement (see Fig. 1). Similar to our study, Diseth (2011) also observed a lack of relation between deep-processing and academic performance in Norwegian students. One possible explanation for why we did not observe a link between deep-processing and math achievement may pertain to the model of domain learning that deep information processing is domain specific (Dinsmore & Alexander, 2012). In other words, students' deep-processing may be evident and specific only to school subjects for which they are encouraged or taught to think in innovative or critical ways. For example, if students are taught in formulaic ways in mathematics, then deep-processing may not necessarily contribute to their final course grade in mathematics. Furthermore, the relationship between deep-processing and math achievement may be moderated by factors such as instructional and assessment methods (Boyle, Duffy, & Dunleavy, 2003; Richardson, 1995). Indeed, it was reported in the 2014 PISA report (OECD, 2014) that Spanish students perceived that their mathematics teachers taught them using primarily formulas and routinized procedures to solve problems rather than using real-world or applied problems to teach math skills and illustrate math concepts. Taking together the results from PISA (OECD, 2014) and our study findings, we speculate that the use of applied or every-day math problems to not only teach but also to assess mastery of math concepts and skills would facilitate students' engagement in deep-processing that then contributes to math achievement. In this sense, we recommend paying close attention to the connection between curriculum and its applicability and relevance to students' lives so that learning becomes interesting and meaningful for students.

4.5. Indirect effect of motivation on math achievement

Our results indicate that effort regulation is one mechanism that mediates the link between autonomous motivation and math achievement. Similarly, Kusurkar et al. (2013) observed that the medical students' effort and deep learning approach mediated the effect of autonomous motivation on academic achievement. Vansteenkiste, Simons, et al. (2005); Vansteenkiste, Zhou, et al. (2005) also found that an optimal learning composite mediated the effect of autonomous motivation on achievement in Chinese students' test performance in English courses. In a study on effort regulation, Komarraju and Nadler (2013) observed that effort regulation mediated the link between motivation and GPA. Particularly for school subjects that students perceive as difficult or not inherently interesting, schools could promote students' academic performance through designing classroom environments and activities that are responsive to students' need for autonomy. For example, classroom activities or assignments that offer students meaningful choice and highlight the purpose of learning activities could stimulate autonomous motivation that would then propel students to exert effort and persist in the face of challenges to attain achievement.

4.6. Limitations and future perspectives

Our study included a number of strengths, including two waves of data collection to allow for prediction of math achievement at the end of the school year from predictor variables collected approximately 6 months earlier. One limitation of this study is not having data on the assessment method used by math teachers to determine students' final course grades. However, we were able to infer from the PISA report (OECD, 2014) about majority of assessment methods used by math teachers in Spain. Future research examining the relationship between deep-processing and academic performance need to take into account the assessment method used by teachers to determine academic performance.

It is important to acknowledge that caution needs to be taken when generalizing study results because we collected all data, except from math, from self-report measures and because our sample was from one state in Spain. However, research on students in Spain offer a unique opportunity to examine motivation and achievement processes that differ from educational systems such as that of the United States because secondary compulsory students in Spain have no choice in the coursework they take. The lack of choice in curriculum or courses might have some influence on how they develop general- and domain-specific academic abilities or motivations that could then influence their academic performance. For example, it is plausible that restriction of choice in coursework may diminish the importance of domain specificity and increase the global academic significance.

With regards to using grades to assess academic performance, we are aware of disagreements within the field about the validity and reliability of school grades in the assessment of academic performance (Randall & Engelhard, 2010; Stanley & Baines, 2004). However, school grades assigned by teachers have real-world significance on students' academic standing and progress in grade school. Thus, teacher-assigned grades are one valid measure of academic performance. Furthermore, teachers systematically assign student grades based on specified criteria, such as knowledge, good behavior, attendance, etc. (Lekholm & Cliffordson, 2009). Taken as a whole, teachers' criteria and rubric for grade assignment reflect the qualities and level of mastery needed to attain various levels of academic performance. Importantly, school grades predict educational attainment and success (Thorsen & Cliffordson, 2012). Thus, research that identifies influential factors and processes in student grades may reveal ways for educators and practitioners to motivate and help students in their academic performance.

Lastly, an important consideration for future research is to assess domain-specific constructs when examining academic achievement. In our study, we did not evaluate autonomy, motivational, and self-regulated learning constructs specifically in the math domain. That is, we did not ask student how motivated they were to study mathematics. Rather, we assessed students in a general domain within the high-school for autonomy, autonomous motivation, effort regulation, and deep-processing. We recognize Bong (2001) and Alexander, Sperl, Buehl, Fives, and Chiu (2004)'s recommendations of using domain-specific measures to assess interests, motivation, and cognitive strategies. Nonetheless, our findings support the view that global academic constructs influence specific school subjects, with the effect of effort regulation on math achievement, but we understand that specific measures might show stronger effects.

In terms of application, our findings have implications for educational reform and practice. With regards to autonomy support, an intervention can be designed and implemented that takes into account students' experiences and perspectives, displaying patience to allow students time for reflection and processing of information to understand new topics, offering schoolwork that matches students' interests, providing explanatory rationales for schoolwork, using noncontrolling language and acknowledging students´ frustrations during their learning process. Additionally, interventions can also target deep-process and effort regulation directly. For example Yang (2012) taught preservice teachers during an 18-week course on how to promote critical thinking at school, and observed that students with teachers who participated in the program demonstrated deeper thought and evaluated new ideas more critically than students with teachers who did not participate in the program. In another intervention study, Kim and Kellert (2010) observed that by supporting students' volition using email messages, students showed better study habits and attitudes toward math.

5. Final conclusion

Study results contribute to a better understanding of how to improve students' learning and achievement in math. Our findings suggest that building choice into both instruction and assessment methods for students may facilitate students' math achievement. In a classroom climate that supports students' need for autonomy, students are likely to find their schoolwork purposeful and interesting. When students feel autonomous motivation in the classroom, they are likely to engage in self-regulated learning strategies such as effort regulation and deep-processing. Our findings indicate that students who are adept at effort regulation (one of the self-regulated learning strategies) are able to attain high final course grades in mathematics, a school subject that some students find challenging, anxiety-provoking, or even boring but is nonetheless imperative if they want to pursue STEM careers in the future. In conclusion, our study contributed to the existing research literature on motivation and learning by identifying the mechanisms and processes that underlie the linkages between autonomy, autonomous motivation, self-regulated learning, and math achievement.

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