The influence of academic level and course delivery mode on the use of motivational regulation strategies and learning engagement

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Motivational regulation strategies have been used as active forms of promoting motivation in online and classroom learning. Based on the motivational regulation model combining both contextual and individual factors, this study examined how students' academic levels (undergraduate vs. graduate) and the type of course delivery mode (online vs. traditional face-to-face) influence their uses of eight motivational regulation strategies and three types of engagement. A total of 190 students consisting of 95 undergraduate students and 95 graduate students participated in this study. The results of two-way multivariate analysis of variance show that students use different sets of motivational regulation strategies depending upon their academic levels and course delivery modes. Also, graduate students showed significantly higher engagement in all three types than undergraduate students did. The findings provide practical implications for designing a customised motivational support system with specific sets of motivational regulation strategies for students in different academic levels and course delivery modes.

Implications for practice or policy

- Graduate and undergraduate students need different sets of motivational regulation support.
- Undergraduate students need more engagement supporting interventions.
- Specific types of motivational regulation strategies can be used to design a customised motivational support system based on students' motivational profiles.

Keywords: learning motivation, motivational regulation, learning engagement, motivational support, quantitative

Background

Motivation and motivational regulation

Learning motivation is a critical predictor of academic performance in higher education (Busato, Prins, Elshout, & Hamaker, 2000). To design motivationally enhanced online and/or classroom learning environments, and further provide customised motivational supports, it is important to understand the mechanisms influencing students' motivational regulation in the different course delivery modes as well as in how their academic level influences the motivational regulation strategies. As an approach to support students' motivational efforts, Motivational Regulation Strategies (MRSs) offer the essential process through which a student purposefully initiates, directs, and manages their level of motivation (Wolters & Mueller, 2011). The successful implementation of MRSs can have a positive influence on students' engagement, effort, or persistence in academic tasks (Grunschel, Schwinger, Steimayr, & Fries, 2016).

Although the benefits of MRSs have been widely studied, there is little evidence of the different uses of MRSs between undergraduate students and graduate students in online learning and classroom learning. Research has argued that academic levels like undergraduate versus graduate and high school versus college have been a crucial factor in dealing with various learning-related issues such as self-regulation (Delen, Liew, & Willson, 2014), motivation (Tseng, Yi, & Yeh, 2019), engagement (Muenks, Wigfield, Yang, & O'Neal, 2017), and procrastination (Cao, 2012). Due to the level of social and mental maturity and time commitment required in online courses, undergraduate students develop self-regulation profiles that are different from those of graduate students (Artino & Stephens, 2009). As motivation is promoted by the active use of self-regulated learning strategies (VanZile-Tamsen & Livingston, 1999), it can be reasonably inferred that undergraduate and graduate students would utilise different MRSs when they take online courses and traditional classroom courses. For example, Artino and Stephens (2009) found that graduate students in online learning showed more critical thinking skills and less procrastination than undergraduate students. Hence, there is an increasing need to document empirical evidence of the relationship between MRSs and other self-regulatory processes such as engagement (Schwinger, Steinmayr, & Spinath, 2009; Wolters & Mueller, 2011).

According to the MRS model suggested by Schwinger and Stiensmeier-Pelster (2012), the motivational regulation process starts with the three monitoring steps to select and use specific MRSs. The first step is the awareness of low motivation that initiates a student's need for higher motivation). In the second step, the student identifies reasons for the motivation problems. Then in the last step, the student selects appropriate sets of MRSs to overcome the motivation issues. Based on Schwinger, Steinmayr, and Spinath (2012) distinguished eight MRSs, as presented in Table 1.

Table 1
Motivational regulation strategies (Schwinger et al., 2012)

	Type of MRS	Description
Intrinsic motivational strategies	Enhancement of situational interest	Turning a relatively tedious task into a more fascinating one through imaginative modification.
	Enhancement of personal significance	Establishing a connection between the task and one's own personal interests and preferences.
	Mastery self-talk	Highlighting the goal to enlarge one's competence and master challenging tasks.
Extrinsic motivational strategies	Performance approach self-talk	Earning a higher exam grade than one's classmates.
	Performance-avoidance self-talk	Avoiding others who make fun of one's poor performance.
	Environmental control	Intentionally eliminating possible distractions.
	Self-consequating	Self-administered gratification for achieving a certain goal.
	Proximal goal setting	Dividing learning materials into small and manageable pieces to experience success more quickly and frequently.

The motivation regulation process is affected by moderating contextual and individual factors (Schwinger & Stiensmeier-Pelster, 2012) (Figure 1). Contextual factors include the characteristics of given tasks and learning settings, whereas individual factors refer to different groups of student profiles determined by prior knowledge, intelligence, motivational disposition, or conscientiousness. Several studies have been conducted to investigate how contextual or individual factors influence learners' perceived reasons for their motivational problems and consequent uses of MRSs. For example, Haag and Götz (2012, cited in Schwinger & Stiensmeier-Pelster, 2012) studied how high school students identified reasons for motivational problems when studying in different subject areas (mathematics vs. language arts) and how the contextual factors influenced the students' decision to choose certain MRSs. Additionally, Hulleman and Harackiewicz (2009) showed that high school science students who tried to make connections between their everyday life and the given science learning content demonstrated an increased interest in learning science. Schwinger et al. (2009) and Schwinger and Stiensmeier-Pelster (2012) presented positive associations between the use of MRSs and students' self-reported efforts. However, most of the studies were performed in the traditional classroom environment only and involved high school students and undergraduate students. Students who are enrolled in online learning and lack direct encouragements from the course instructor develop different motivational regulation profiles from those who are enrolled in traditional classroom learning (Wang & Lin, 2007). Furthermore, the academic levels in higher education need to be considered as motivation and self-regulation factors differ between undergraduate and graduate students.

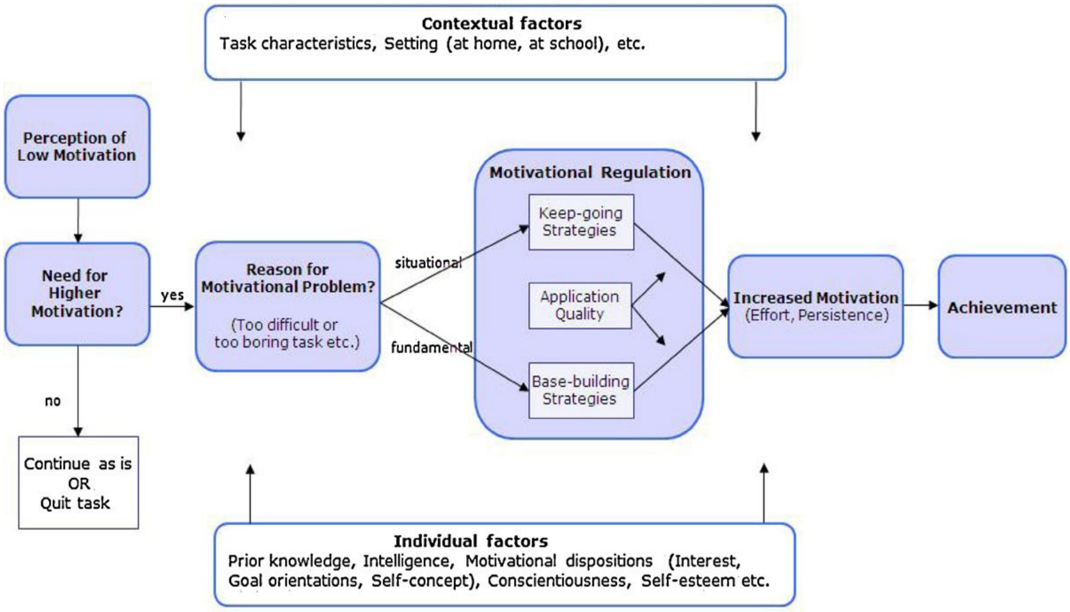


Figure 1. Motivational regulation model (Schwinger & Stiensmeier-Pelster, 2012), reprinted from *International Journal of Educational Research, 56*, Schwinger & Stiensmeier-Pelster, Effects of motivational regulation on effort and achievement: A mediation model, p. 38, Copyright (2012), with permission from Elsevier.

Self-regulated motivational differences by academic levels

Students' academic level is an important individual factor that influences their uses of MRSs due to different self-regulation development. Zimmerman (2002) referred to self-regulated learners as proactive in their learning because they are able to transform the learning experience according to their strengths and limitations. Green and Azevedo (2007) proposed that self-regulated learning behaviours could indicate individual learners' different developmental levels of self-regulation. Additionally, Rakes and Dunn (2010) investigated whether effort regulation, self-regulatory skill, and intrinsic motivation have any impact on graduate students' levels of academic procrastination. The findings revealed that effort regulation and intrinsic motivation have a significant impact on reducing the levels of procrastination in online graduate students.

Artino and Stephens (2009) investigated if there were differences between undergraduate and graduate students in their levels of self-regulation and academic motivation in online learning. They found that graduate students use more elaboration and critical thinking skills and less procrastination than undergraduate students do. It is important to note the different levels of self-regulation between undergraduate and graduate students because self-regulation was found to be a significant predictor of learning engagement (Sun & Rueda, 2012) and of students' academic success.

Motivational regulation differences by course delivery modes

The type of learning setting is a critical contextual factor, according to the motivational regulation model (Schwinger & Stiensmeier-Pelster, 2012). Ryan and Deci (2000a) proposed that an intrinsically motivated learner tends to learn more for fun or challenge. Also, the intrinsic motivation of students enrolled in online courses was found to be a strong predictor in discriminating between online and traditional classroom students (Wighting, Liu, & Rovai, 2008). In addition, Clayton, Blumberg, and Auld (2010), investigating undergraduate students' preferences for learning settings and their motivational perspectives for their learning strategy use, found that students who preferred less traditional but more online learning environments showed higher confidence in managing their own learning. On the other hand, Shelley, Swartz, and Cole (2008) found that students are more satisfied with the course instructor and overall course structure when they are enrolled in classroom learning compared to the online version of the same course. As a possible explanation, Johnson, Aragon, and Shaik (2000) suggested that students can easily build a personal connection when they meet in the classroom. In the same sense, Wisneski, Ozogul, and Bichelmeyer (2017) stated that online students prefer the flexibility of independent learning and the expected pace of the course, whereas face-to-face students are frequently motivated by their personal connection with peers and direct interactions in the course.

In summary, the motivational regulation model and relevant previous studies suggest that students' use of MRSs and engagement are linked to their academic levels and the type of course delivery modes. Taken in total, the aim of this study was to empirically examine the influences of students' academic levels (undergraduate vs. graduate) and their enrolled course delivery modes (online vs. traditional face-to-face) on the use of MRSs and learning engagement.

Research questions

This study was guided by the following research questions:

(1) What are the influences of students' academic level (undergraduate vs. graduate) and the type of course delivery mode (online vs. traditional face-to-face) on the use of the eight motivational regulation strategies?
(2) What are the influences of students' academic level (undergraduate vs. graduate) and the type of course delivery mode (online vs. traditional face-to-face) on behavioural engagement, emotional engagement, and cognitive engagement?

Methods

Research design and participants

The study used a 2 x 2 between-subjects quasi-factorial design. The grouping variables were the level of the students (undergraduate vs. graduate) and the type of course delivery mode (online vs. traditional face-to-face). The total number of participants was 196 undergraduate and graduate students. After removing the incomplete responses of six students, the data from a total of 190 students were analysed, consisting of 95 undergraduate students and 95 graduate students. All the students were recruited from the College of Education at two large research universities, one in the Midwestern United States of America (USA) and the other in the Southeastern United States of America. Undergraduate students were enrolled in the online and face-to-face sections of "Computers in Education," an introductory elective course for undergraduate students offered in the university in the Midwestern USA. Graduate students were enrolled in the online and face-to-face sections of "Current Trends in Educational Technology," an introductory elective course for graduate students offered in the university in the Southeastern USA. Table 2 shows the demographic characteristics of the study participants.

Table 2
Demographic characteristics of study participants

Academic level (*n*)	Course delivery mode	Number of participants	Gender	Average age (range)	Ethnicity
Undergrad (*n* = 95)	Face-to-face	48 (25.26%)	Female: 39 (81.3%) Male: 9 (18.7%)	20.77 (19.71–21.83)	American Indian: 0 (0%) Asian: 1 (2.1%) African American: 3 (6.3%) Native Hawaiian: 0 (0%) Caucasian: 33 (68.7%) Two or more: 11 (22.9%)
	Online	47 (24.74%)	Female: 24 (51.1%) Male: 23 (48.9%)	21.28 (20.68–21.87)	American Indian: 0 (0%) Asian: 8 (17.0%) African American: 4 (8.5%) Native Hawaiian: 0 (0%) Caucasian: 33 (70.3%) Two or more: 2 (4.2%)
Grad (*n* = 95)	Face-to-face	47 (24.74%)	Female: 32 (68.1%) Male: 15 (31.9%)	34.53 (32.03–37.03)	American Indian: 0 (0%) Asian: 15 (31.9%) African American: 7 (14.9%) Native Hawaiian: 0 (0%) Caucasian: 18 (38.3%) Two or more: 7 (14.9%)
	Online	48 (25.26%)	Female: 40 (83.3%) Male: 8 (16.7%)	34.48 (31.70–37.26)	American Indian: 0 (0%) Asian: 7 (14.5%) African American: 3 (6.3%) Native Hawaiian: 2 (4.2%) Caucasian: 35 (72.9%) Two or more: 1 (2.1%)

Study procedure

All required approvals were obtained from the participating universities prior to collecting the data. Students were invited to online surveys by the research team. At the end of the spring semester of 2017, all the students in the participating classes were given an online link to study materials that included an informed consent form, a self-report survey, and a separate survey to collect their email address to receive a reward. All students were entered into a drawing for three gift cards when they completed the survey. Only students who agreed to participate in the study were included in the final data analysis.

Instrumentation

The online survey consisted of three sections. In the first section, participants responded to demographic items such as age, gender, ethnicity, academic level at the university, and the type of course delivery mode. The second section included a motivational regulation strategy questionnaire developed by Schwinger et al. (2009). The validity of the instrument was confirmed in previous studies with university students, which provided evidence of the best model fit based on both confirmatory factor analysis and substantial correlations with external criteria (Schwinger et al., 2009). The last section of the survey contained 19 items of the engagement scale that we adopted from Sun and Rueda’s (2012) study. The validity of the revised engagement scale was tested through exploratory factor analysis and confirmed with three distinct engagement factors, which are behavioural engagement, emotional engagement, and cognitive engagement (Sun & Rueda, 2012). Unlike a 5-point Likert scale used in previous studies (Schwinger et al., 2009; Sun & Rueda, 2012), students responded to each item using a 7-point Likert scale ranging from 1 (*strongly disagree*) to 7 (*strongly agree*) because this scale would likely enhance the external validity of measurements in psychological latent factor structures than the lower numbers of response-categories Likert scales (Xu & Leung, 2018). Table 3 shows the scale, number of items, sample item, and internal consistency coefficient of the MRS and engagement instruments using Cronbach’s alpha.

Table 3
Scales and internal consistency coefficient

Measure	Scale (number of items)	Sample item	Internal consistency coefficient
Motivational regulation strategies (30)	Enhancement of situational interest (5)	I made learning more pleasant for me by trying to arrange it playfully.	.81
	Enhancement of personal significance (3)	I strived to relate the learning material to my own experiences.	.73
	Mastery self-talk (4)	I challenged myself to finish the task and thus learn a lot for me personally.	.86
	Performance-approach self-talk (5)	I told myself that I should keep on learning if I wished to achieve a good exam grade.	.83
	Performance-avoidance self-talk (3)	I told myself that I have to push me more if I do not want to make a fool of myself.	.71
	Environmental control (3)	Prior to beginning with work, I strived to eliminate all possible distractions.	.80
	Self-consequating (4)	I made a deal with myself saying that I would do something pleasant after I finish work.	.87
	Proximal goal setting (3)	I broke down the workload in small segments so I get the feeling that I can handle it more easily.	.78
Engagement (19)	Behavioural engagement (5)	I completed most of my homework on time.	.77
	Emotional engagement (6)	I felt excited by my work in this class.	.89
	Cognitive engagement (8)	When I read the course materials, I asked myself questions to make sure I understood what it was about.	.84

Data analysis

Preliminary data analyses were conducted to detect problematic observations and assumption violations. Then the main effects and the interaction effects of two grouping variables were tested for two dependent variables: MRS and engagement. The significance level for all the analyses was set at $\alpha < .05$ (Field, 2013). The descriptive data for the groups are presented in Table 4.

Table 4
Mean scores of the outcome variables (standard deviation in parentheses)

		Condition			
		Traditional face-to-face course		Online course	
Outcome variables	Measures	Undergraduate (n = 48)	Graduate (n = 47)	Undergraduate (n = 47)	Graduate (n = 48)
MRSs[a]	1. Enhancement of situational interest	4.93 (.97)	4.91 (.97)	4.63 (1.42)	4.69 (.99)
	2. Enhancement of personal significance	5.34 (.89)	6.02 (.87)	5.35 (1.08)	6.26 (.71)
	3. Mastery self-talk	5.34 (.98)	5.72 (.94)	5.37 (1.17)	6.06 (.75)
	4. Performance-approach self-talk	5.73 (.88)	5.29 (1.11)	5.59 (.96)	6.08 (.77)
	5. Performance-avoidance self-talk	3.82 (1.31)	3.02 (1.32)	3.84 (1.52)	3.42 (1.37)
	6. Environmental control	4.97 (1.35)	5.67 (.93)	5.15 (1.39)	5.77 (.84)
	7. Self-consequating	5.47 (1.07)	5.15 (1.19)	5.21 (1.29)	5.72 (1.09)
	8. Proximal goal setting	5.44 (1.06)	5.23 (1.12)	5.22 (1.14)	5.56 (.86)
Engagement[b]	Behavioural engagement	5.48 (1.12)	5.93 (.93)	5.40 (.90)	6.03 (.77)
	Emotional engagement	5.78 (1.13)	6.14 (.85)	5.55 (1.05)	6.18 (.84)
	Cognitive engagement	4.70 (.90)	5.56 (.76)	4.62 (1.28)	5.79 (.73)

Notes. [a]Possible range for the MRS (1–7); [b]Possible range for engagement (1–7).

Results

Research question 1: The influence of students' academic level and the type of course delivery mode on the use of eight motivational regulation strategies

The required sample size that was calculated by G^{*}*Power* was 168 with a medium effect size and power of 0.8. The study had a sample size of 47–48 per condition, a total of 190; hence, there was an adequate sample size for the analysis. A two-way MANOVA was run with two independent variables and eight dependent variables, including all the eight MRSs. There was a linear relationship between the dependent variables as assessed by the scatterplot, and no evidence of multicollinearity was found by the Pearson correlation ($|r| < 0.8$). No univariate outliers were identified in the data by an inspection of a boxplot, and no multivariate outliers were assessed by the Mahalanobis distance ($p > .001$). The Shapiro-Wilk's test for normality with a Bonferroni correction at 0.0125 showed that for the cell with the undergraduate-classroom condition, two MRSs variables (MRS4, MRS7) showed a violation of the normality assumption. For the cell with the graduate–classroom condition, two MRSs variables (MRS2, MRS7) also showed a violation of the normality assumption.

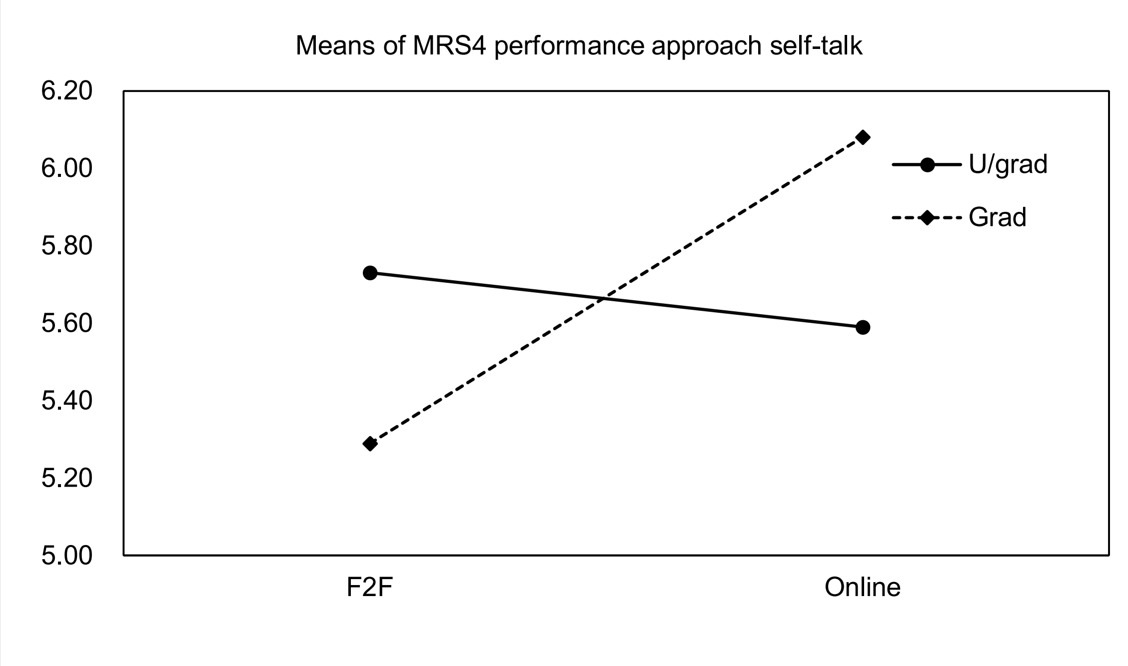
Despite the four variables that showed a violation of the normality assumption, a two-way MANOVA was performed as it is fairly robust to deviations from normality with respect to Type I error (Pituch & Stevens, 2016). All other 28 MRSs variables in the four conditions met the normality assumption. Due to the non-normality of four MRS variables, the assumption of homogeneity of the covariance matrices was violated as assessed by Box's M test ($p < .001$). However, MANOVA is considered to be robust to a violation of the homogeneity of covariance matrices assumption, as long as the sample size (i.e., number of participants) in each cell of the design is similar (i.e., a balanced design) (Tabachnick & Fidell, 2014) with a ratio of no more than 1.5 to 1 (Pituch & Stevens, 2016). As such, we continued the analysis since the sample sizes were similar in each cell (Tabachnick & Fidell, 2014). Pillai's Trace was reported as it is more robust and recommended when the Box's M result is statistically significant (Tabachnick & Fidell, 2014). To report more accurate estimates of population effect size, adjusted partial eta squared (η^2) values (Mordkoff, 2019) were manually computed and presented using Cohen’s (1988) criteria for interpretation. When interpreting effect sizes, it appears that the larger an effect size, the bigger the influence, the less the error variability the manipulated variable has and the more critical the findings of a study once all other conditions are equal (Fritz, Morris, & Richler, 2012).

Using Pillai's Trace, there was a significant effect of academic level on the combined MRSs with a large effect size, $F(8, 179) = 8.970$, $p < .0005$, $V = .286$, adjusted partial $\eta^2 = .255$. Follow-up univariate two-way ANOVAs revealed significant effects of academic level on the MRS2 enhancement of personal significance strategy score, $F(1,186) = 37.046$, $p < 0.0005$, adjusted partial $\eta^2 = .162$, the MRS3 mastery self-talk strategy score, $F(1,186) = 14.333$, $p < 0.0005$, adjusted partial $\eta^2 = .067$, the MRS5 performance-avoidance self-talk strategy score, $F(1,186) = 9.224$, $p < 0.005$, adjusted partial $\eta^2 = .042$, and the MRS6 environmental control strategy score, $F(1,186) = 15.794$, $p < 0.0005$, adjusted partial $\eta^2 = .073$.

As such, simple comparisons were run to investigate the differences in MRS2, MRS3, MRS5, and MRS6. The marginal means for MRS2 were 5.35 ($SE = 0.09$) for the undergraduate students and 6.14 ($SE = 0.09$) for the graduate students. The mean difference of 0.79 was statistically significant, 95% CI [0.54, 1.05], $p < .0005$. The marginal means for MRS3 were 5.36 ($SE = 0.10$) for the undergraduate students and 5.89 ($SE = 0.10$) for the graduate students. The mean difference of 0.53 was statistically significant, 95% CI [0.26, 0.81], $p < .0005$. The marginal means for MRS5 were 3.83 ($SE = 0.14$) for the undergraduate students and 3.22 ($SE = 0.14$) for the graduate students. The mean difference of -0.61 was statistically significant, 95% CI [-1.01, -.21], $p < .005$. Finally, the marginal means for MRS6 were 5.06 ($SE = 0.12$) for the undergraduate students and 5.72 ($SE = 0.12$) for the graduate students. The mean difference of 0.67 was statistically significant, 95% CI [0.34, 0.99], $p < .005$. The main effect of course delivery mode on the combined MRSs was not statistically significant, $F(8, 179) = 1.958$, $p = .054$, $V = .080$, adjusted partial $\eta^2 = .039$. Regarding these mean differences between undergraduate and graduate students, a 7-point Likert scale would likely show higher reliability than a 5-point Likert scale (Preston & Colman, 2000) because slight descriptive score differences of psychological traits like MRSs between groups in a 5-point Likert scale become larger in a 7-point Likert scale (Wakita, Ueshima, & Noguchi, 2012).

Pillai's Trace also showed a statistically significant interaction effect between academic level and course delivery mode on the combined dependent variables with a medium effect size, $F(8, 179) = 2.376$, $p = .019$, $V = .096$, adjusted partial $\eta^2 = .057$. Follow-up univariate two-way ANOVAs showed a statistically significant interaction effect between academic level and course delivery mode for the MRS4 performance approach self-talk strategy score, $F(1, 186) = 11.734$, $p = .001$, adjusted partial $\eta^2 = .055$, and the MRS7 self-consequating strategy score, $F(1, 186) = 5.983$, $p = .015$, adjusted partial $\eta^2 = .027$ (Figure 2). No statistically significant interaction effects were found between academic level and course delivery mode for the other MRSs. As such, a simple main effects analysis was conducted for both MRS4 and MRS7. There was a statistically significant difference between the academic levels in the traditional face-to-face delivery mode for MRS4, $F(1,186) = 5.230$, $p = 0.023$, adjusted partial $\eta^2 = .023$, and the online delivery mode, $F(1, 186) = 6.541$, $p = 0.011$, adjusted partial $\eta^2 = .030$. There was a statistically significant difference between the academic levels in the online delivery mode for MRS7, $F(1, 186) = 4.492$, $p = .035$, adjusted partial $\eta^2 = .020$, but not for the traditional face-to-face delivery mode, $F(1, 186) = 1.795$, $p = .182$, adjusted partial $\eta^2 = .006$.

Additional simple comparisons were run to examine the differences in the mean MRS4 score between academic levels for both the traditional face-to-face delivery mode and the online delivery mode. The means for the MRS4 score for the traditional face-to-face delivery mode were 5.73 ($SD = 0.88$) for the undergraduate students and 5.29 ($SD = 1.11$) for the graduate students. There was a statistically significant mean difference between the undergraduate students and the graduate students, 0.44, 95% CI [0.06, 0.82], $p = 0.023$. The means for the MRS4 score in the online delivery mode were 5.59 ($SD = 0.96$) for the undergraduate students and 6.08 ($SD = 0.77$) for the graduate students. There was a statistically significant mean difference between the undergraduate students and the graduate students, -0.49, 95% CI [-0.87, -0.11], $p = 0.011$. Another simple comparison was run to investigate the differences in the mean MRS7 score between academic levels in the online delivery mode. The means for the MRS7 score in the online delivery mode were 5.21 ($SD = 1.29$) for the undergraduate students and 5.72 ($SD = 1.09$) for the graduate students. There was a statistically significant mean difference between the undergraduate students and the graduate students, -0.51, 95% CI [-0.98, -0.04], $p = 0.035$.



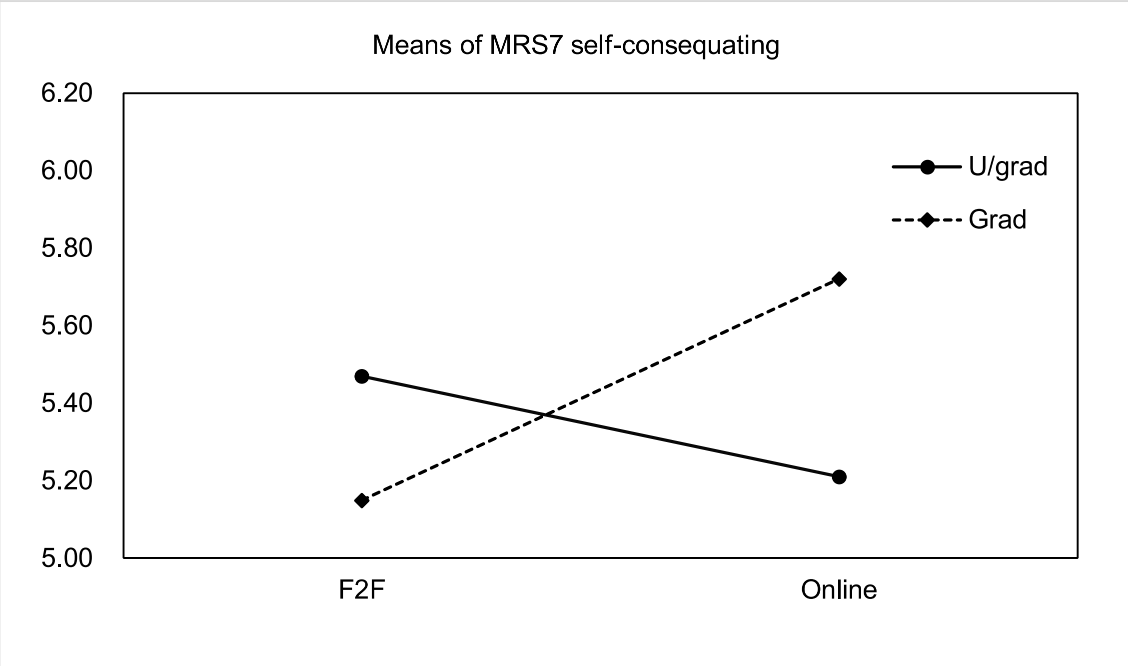


Figure 2. Interactions for MRS4 performance approach self-talk and MRS7 self-consequating

Research question 2: The influence of students' academic level and the type of course delivery mode on learning engagement

A two-way MANOVA was run with two grouping variables and each of the three engagement. A linear relationship between the dependent variables was confirmed by a scatterplot, and no evidence of multicollinearity was found by the Pearson correlation ($|r| < 0.8$). There were no univariate outliers or multivariate outliers in the data as assessed by a boxplot and the Mahalanobis distance ($p > .001$). The Shapiro-Wilk's test for normality with a Bonferroni correction at 0.0125 showed that, except the undergraduate–online condition, the normality assumption was violated for the behavioural and emotional engagement variables. Despite the violation of the normality assumption, we continued the data analysis and reported Pillai's Trace as it is robust to deviations from normality as explained in RQ1.

Using Pillai's Trace, there was a significant effect of academic level on combined engagement with a large effect size, $F(3, 184) = 23.519$, $p < .0005$, $V = .277$, adjusted partial $\eta^2 = .266$. Follow-up univariate two-way ANOVAs revealed significant effects of academic level on all three types of engagement: behavioural engagement, $F(1,186) = 15.593$, $p < 0.0005$, adjusted partial $\eta^2 = .073$; emotional engagement, $F(1,186) = 12.279$, $p < 0.001$, adjusted partial $\eta^2 = .058$; and cognitive engagement, $F(1,186) = 55.323$, $p < 0.0005$, adjusted partial $\eta^2 = .226$. Follow-up simple comparisons were run to examine the differences in the mean scores of the three types of engagement. The marginal means for the behavioural engagement score were 5.44 ($SE = 0.09$) for the undergraduate students and 5.98 ($SE = 0.09$) for the graduate students. The mean difference of 0.54 was statistically significant, 95% CI [0.27, 0.81], $p < .0005$. The marginal means for the emotional engagement score were 5.66 ($SE = 0.10$) for the undergraduate students and 6.16 ($SE = 0.10$) for the graduate students. The mean difference of 0.50 was statistically significant, 95% CI [0.22, 0.78], $p < .001$. The marginal means for the cognitive engagement score were 4.66 ($SE = 0.09$) for the undergraduate students and 5.67 ($SE = 0.1$) for the graduate students. The mean difference of 1.02 was statistically significant, 95% CI [0.75, 1.28], $p < .0005$. The main effect of the course delivery mode on combined engagement was not statistically significant, $F(3, 184) = 0.620$, $p = .60$, $V = .010$, adjusted partial $\eta^2 = .001$. No interaction effect was found between academic level and course delivery mode on the combined dependent variables, $F(3, 184) = 0.560$, $p = .642$, $V = .009$, adjusted partial $\eta^2 = .001$.

Discussion

First of all, this study found that the students' academic level was one of the main factors affecting their use of MRSs. Of the eight MRSs, the graduate students and the undergraduate students utilised different MRSs for motivational regulation. The graduate students had higher uses of three MRSs than undergraduate students, that is, the enhancement of personal significance, mastery self-talk, and environmental control strategies. On the other hand, the undergraduate students used the performance-avoidance self-talk strategy more than the graduate students did.

Of the eight MRSs, the enhancement of personal significance strategy describes the interest-enhancement strategy (Grunschel et al., 2016). Unlike the enhancement of situational interest strategy, the enhancement of personal significance strategy is used to establish a relation between a given task and the student's own individual interests and preferences (Schwinger et al., 2012). According to the interest development model (Hidi & Renninger, 2006), individual interest is the last form of interest that is fully internalised within each student. As the purpose of enrollment in a graduate program is to develop professional knowledge and skills in a chosen academic area, graduate students' academic needs are based on their individual interests. When taking a course, graduate students might try to maintain their individual interests by increasing the personal significance of the course activities. Therefore, graduate students may have already developed an individual interest in the academic area, which could also encourage them to use the enhancement of personal significance strategy more.

Second, the study also found that the graduate students used the mastery self-talk strategy more than the undergraduate students did, whereas the undergraduate students used the performance-avoidance self-talk strategy more than the graduate students did. it indicates the difference in the goal framework (Hulleman, Schrager, Bodmann, & Harackiewicz, 2010). Graduate students used MRSs with the framework of the goal-oriented approach and tried to enhance their competence and master challenging tasks. However, undergraduate students used MRSs based on the performance-oriented approach and used their classmates as points of comparison, rather than focusing on achieving their goals. These MRS patterns by the undergraduate students could be caused by the lower individual interest or lower confidence compared to the graduate students, as students who use the performance-avoidance self-talk strategy are more anxious about their own learning capabilities and focus on performing no worse than others instead of striving to achieve their goals (Schwinger et al., 2012). In turn, undergraduate students with more attention to other classmates' performance tend to be less confident in their performing capabilities at challenging tasks than graduate students do. Thus, students who use more performance-avoidance self-talk need to be provided with appropriate feedback and constructive guidance from instructors to enhance their self-efficacy beliefs and capabilities (Bradley, Browne, & Kelley, 2017), which could influence their self-regulatory behaviours and successful performance (Artino & Stephens, 2006).

Lastly, the study found that the graduate students used the environmental control strategy more than the undergraduate students did. According to Zimmerman (2002), self-regulated learners tend to seek to enhance their motivation by rearranging the learning environment. For example, they choose to work in a private space as their favourite study location where no learning interruption can possibly occur. However, understanding the differentiated effect of using the environmental control strategy between graduate and undergraduate students appears to be limited because this strategy in the MRS questionnaire (Schwinger et al., 2009) focused on only choosing learning times for concentration and removing distractions for desirable physical learning spaces regardless of course delivery mode.

In spite of the overall main effects of the academic level on the use of three MRSs, two interaction effects were found between the academic level and the course delivery mode. Two MRSs were used by undergraduate and graduate students differently, depending upon their enrolled course delivery modes. The follow-up simple main effect analysis showed that in traditional face-to-face delivery mode, the undergraduate students used the performance-approach self-talk strategy more than the graduate students did. However, in the online delivery mode, the graduate students used the same strategy more than the undergraduate students did, suggesting that undergraduate students were concerned about improving their performance compared to other classmates when they were working in the classroom setting, whereas the graduate students showed this tendency in the online delivery mode. Additionally, in traditional face-to-face delivery mode, the undergraduate students used the self-consequating strategy more than the graduate students did. However, in the online courses, the graduate students used the self-consequating strategy more than the undergraduate students did. Self-consequating is based on the principle of operant conditioning as it involves rewarding successful study behaviour and increasing the chances of repeating the study behaviour (Grunschel et al., 2016). Students use this strategy when they promise themselves a reward (e.g., watching a movie) for finishing a task. The findings of the study indicate that both the course delivery mode and students' academic level need to be considered when designing motivational supports. In particular, academic level was an important factor affecting different uses of MRSs; hence, it is necessary to design targeted motivational supports to meet the different motivational needs of students.

Similar to the findings of the first research question about the influence of students' academic level and the type of course delivery mode on the use of the eight MRSs, the academic level of students was found to be the main factor that affects all three types of engagement. Whether in the classroom or online, the graduate students showed a higher level of engagement. This finding provides supporting evidence of graduate students' active use of MRSs based on their individual interests and mastery goal–oriented approach. By facilitating to use the MRSs, undergraduate students can have more motivational supports to promote engagement in learning, considering the positive relations between motivational factors such as self-efficacy and self-regulation and learning engagement (Bates & Khasawneh, 2007; Sun & Rueda, 2012).

Implications of the study

The process of motivational regulation (Schwinger & Stiensmeier-Pelster, 2012) appears to be influenced by individual and contextual factors that moderate how students use the particular sets of motivational regulation strategies. Despite many studies that focused on the effective use of motivational regulation strategies, the influence of these individual and contextual factors on motivational regulation is scarce and less empirically evident (Schwinger & Otterpohl, 2017). Hence, we assessed the importance of individual and contextual factors while students were actively using motivational regulation strategies to enhance learning engagement. According to the findings from this study, there are several implications underlying the adaptive use of motivational regulation for supporting learning engagement. In accordance with the interest-enhancement strategies, it may be plausible to assume that students with strong individual interest can benefit from using interest-enhancement strategies because an individual's internalised interest may affect their learning persistence (Hidi & Renninger, 2006; Schwinger & Otterpohl, 2017). Furthermore, Ryan and Deci (2000b) emphasised intrinsic motivation in Self-Determination Theory, which can be connected to interest-enhancement and mastery self-talk of the MRSs. To enhance intrinsic motivation, students need three basic psychological supports: autonomy, competence, and relatedness (Ryan & Deci, 2000b). When students' intrinsic motivation is facilitated by these psychological supports, they can experience positive outcomes such as enhanced learning engagement, academic achievement, and internalisation (Ryan & Deci, 2017). Regarding the basic psychological supports to enhance intrinsic motivation, conducive instructional interventions to students should be considered to use in the classroom. For example, trained educators enable students to experience freedom and choices in light of their actions, well-organised tasks and informative feedback in accordance with students' current knowledge and skills, and interaction and collaboration among students for feeling trust and belongingness (Jeno, Vandvik, Eliassen, & Grytnes, 2019; Linnenbrink-Garcia, Patall, & Pekrun, 2016). On the other hand, Wigfield and Eccles (2000) focused on extrinsic motivation through Expectancy-Value Theory, which can be related to the rest of the MRSs. Crucially, when expectancies and values are initiated by task-specific beliefs such as ability beliefs, perceived task difficulties, and individual goals, learning performance, effort, and persistence for achieving desirable outcomes may follow (Wigfield & Eccles, 2000). Because value beliefs are strongly associated with students' activity choices, decision-making, and enhanced interest, successful educators provide opportunities for understanding the importance and values of hands-on learning activities through communication with students (Linnenbrink-Garcia et al., 2016). In doing so, students may experience actively participating in learning activities and making in-depth connections between their understanding and course content. Hence, educators can help students find critical reasons, goals, and interests for why they should stay focused on a specific task. Similarly, it is feasible that students with higher individual interest try to use more rigorously goal-oriented strategies because they may set critical goals to complete a given task and put more effort to consistently achieve learning goals (Klein & Lee, 2006; Schwinger & Otterpohl, 2017). Thus, our study seems consistent with findings that regardless of their learning environments, educators should assist students to set specific goals while learning (Lazowski & Hulleman, 2016). If students adaptively use motivational regulation strategies depending on individual and contextual factors, learning environments would work successfully to increase their motivation to complete a certain task. Regarding the differentiated use of motivational regulation strategies influenced by academic level and course delivery mode, educational practitioners need to be aware of using specific pedagogical approaches to promote motivational regulation. In addition, offering an interactive online training opportunity (e.g., using avatars) for students to understand the motivational regulation process and strategies may benefit them to further enhance their learning effort and engagement (Park, 2016). Therefore, enhanced learning effort and engagement could lead to the positive effects of motivational regulation on learning achievement.

Limitations

This study has several limitations. First, the study participants' prior experiences in online learning were not included. Although they were recruited from introductory undergraduate and graduate courses, some students might have experienced online learning during their secondary education. The level of familiarity might be a factor affecting students' use of MRSs. Future studies will need to control students' prior online learning experiences as a covariate. Second, based on previous studies, we assumed that the graduate students had higher self-regulation skills than the undergraduate students. To verify the differences in self-regulation between academic levels, a measure of self-regulation skills such as cognitive learning strategies or metacognitive skills will need to be included in future studies.

Conclusion

In conclusion, supporting students' motivational efforts is critical in higher education. This study includes empirical evidence suggesting specific types of motivational regulation strategies that can be used to design a customised motivational support system. The findings show that students have different motivational needs, depending upon their academic level and the enrolled course delivery mode. Therefore, course instructors and instructional designers will need to understand the diverse motivational profiles of students and support them with active MRSs to be engaged in their learning and achieve greater academic performance. The findings may also inform the design and development of tools for traditional classroom or online learning settings. Given the growing integration of learning management systems not only in online learning but also in classroom learning settings, more attention should be paid to how to support students who use different motivational regulation strategies. Future research may use our findings as evidence to propose instructional systems that provide tools and content tailored to different groups of students in different modes of learning.

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