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Investigating students' emotional self-efficacy profiles and their relations to self-regulation, motivation, and academic performance in online learning contexts: A person-centered approach

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Abstract

Emotional self-efficacy is a vital component in student academic engagement and performance, but few studies have identified emotional self-efficacy profiles from a person-centered perspective and examined their relations to self-regulation, motivation and academic performance in online learning environments. To address this gap, we performed latent profile analysis on a dataset of 318 students and identified four profiles, namely, low, average, above average with a low ability to handle the emotions of others and high emotional self-efficacy profiles. The results of a multinomial logistic regression further indicated that self-regulation (i.e., goal setting, time management, task strategies and help seeking) and motivation (i.e., identified regulation and external regulation) played significant roles in determining profile membership. Furthermore, students who possessed high emotional self-efficacy also achieved better academic performance than the other three profiles. The results not only reinforce the understanding of students' emotional self-efficacy in online learning but also offer researchers both methodological and theoretical insights concerning students' emotional self-efficacy. Moreover, the study also reveals a potential relationship between leveraging students' self-regulation and motivation to improve their emotional self-efficacy in an online learning context.

Keywords Emotional self-efficacy · Latent profile analysis · Self-regulation · Motivation · Academic performance

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1 Introduction

While online learning environments give students considerable autonomy and individualization, students are more likely to frequently experience negative emotional states, such as frustration and anxiety (Obergriesser & Stoeger, 2020). In order to decrease or alleviate the negative emotions that may interrupt their engagement (Cho & Heron, 2015) and interfere with academic outcomes (Lobczowski et al., 2021), students should regulate their negative emotions in the process of online learning. Therefore, how to handle negative emotions is crucial and requires special consideration in online learning environments.

Recently, many empirical studies have reported that emotional self-efficacy is a vital component in the reduction and regulation of negative emotional experiences (Dacre Pool and Qualter, 2012a; Schunk et al. 2022). Emotional self-efficacy is defined as perceptions about an individual's capacity to voluntarily regulate their negative emotions; and it is the hierarchical process through which an individual can recognize, understand and describe her or his emotions (Bassi et al. 2018). Emotional self-efficacy has been proven to be a determinant of emotional engagement and learning outcomes (Järvenoja et al., 2018). Effective self-regulation may also reduce negative emotional states, and emotion regulation strategies may support students' abilities to engage in self-regulation learning (Losenno et al., 2020). In addition, motivation may be positively correlated with emotional control, and students who enhance their efforts to achieve their learning goals by monitoring motivation tend to take the initiative in controlling emotion (Xu et al., 2014).

Previous studies have shown a complex relationship between self-regulation, motivation, academic performance, and emotional self-efficacy from the perspective of variable-centered approaches such as structural equation modeling (SEM). The variable-centered approach is limited by the hypothesis that individual students have uniformly low or high levels of emotional ability (Bassi et al., 2018; Losenno et al., 2020). However, populations are not generally homogeneous. A person-centered approach considers these interindividual differences and the heterogeneity within the study population and helps to identify diverse subgroups of individuals with potentially different levels of emotional self-efficacy. Additionally, empirical works on emotional self-efficacy were mainly concerned with conventional, face-to-face learning environments with relatively few studies investigating emotional self-efficacy in online learning contexts (Galla & Wood, 2012; Ganotice et al., 2016). Thus, this study identified emotional self-efficacy profiles and examined the relationships with self-regulation, motivation and academic performance. This is the first study to provide information on whether and how emotional self-efficacy dimensions naturally co-occur within online students and how the profiles are related to important predictors and academic performance.

The novelty of our contributions are as follows. First, we identified the latent profiles of emotional self-efficacy to represent the different configurations of students' emotional self-efficacy. Second, drawing on social cognitive perspectives, we examined to what extent the self-regulation and motivation of students predict emotional self-efficacy profile membership in online learning context. Third, we examined whether the emotional self-efficacy profiles can predict academic performance. These findings could yield significant implications and provide a better understanding of learning emotions in today's online educational context by employing a person-centered approach.

2 Literature review

2.1 Emotional self-efficacy

The significance of emotional self-efficacy for learning engagement and academic achievement has been confirmed by many studies. For example, Tariq et al. (2013) examined the role of emotional self-efficacy in academic performance among undergraduates. In a study by Mänty et al. (2020), the interplay between students' emotional regulation and negative socioemotional interactions during a collaborative physics task was discussed. Ben-Eliyahu and Linnenbrink-Garcia (2013) employed latent class analysis to explore diverse patterns of self-regulated emotion strategies in two distinctive classroom contexts. Galla and Wood (2012) found that students with higher levels of emotional self-efficacy, who tend to be more confident in their emotional regulation abilities, achieved better scores on a mathematics test than those students who had low levels of emotional self-efficacy. In addition, they also reported that high emotional self-efficacy learners effectively regulate negative emotions more than low emotional self-efficacy learners. Moreover, Nightingale et al. (2013) reported longitudinal relationships among emotional self-efficacy, emotional management, and learning performance. Overall, the above research illustrated the importance of emotional self-efficacy for student engagement and academic performance.

Recently, understanding emotional self-efficacy and related emotional regulation in online contexts has received great attention. For example, in an online group, Xu et al. (2013) reported that emotional management may be positively associated with learning-oriented feedback and reasons. As another example, Järvenoja et al. (2018) demonstrated that emotional regulation and motivation are intertwined with online learning processes from a temporal perspective. Zhang et al. (2021) examined the interplay among the emotional regulation and enjoyment of learners based on learning conversations. Despite the importance of emotional self-efficacy, very little empirical work has investigated the potential value of emotional self-efficacy in online learning and overlooked the likelihood that different emotional self-efficacy profiles may exist. Therefore, we applied a person-centered approach to examine whether different emotional self-efficacy profile subgroups exist in online learning contexts.

2.2 Self-regulation

As Dörrenbächer and Perels (2016) reported, it is vital for students' learning activities to adapt to changing personal, environmental and behavioral elements in the process of achieving learning objectives. In many studies, self-regulation has been proven to monitor and regulate individual learning by using cognitive and metacognitive strategies. Self-regulated learning is an iterative and active process that can allow students to purposefully achieve learning objectives by monitoring, managing, and regulating their learning behaviors and cognitive/metacognitive functions (Reparaz et al., 2020; Oyelere et al., 2021). To investigate students' self-regulatory processes, Pintrich's (2000) self-regulation model, which comprises six specific self-regulation strategies, was used as a theoretical framework. Goal setting concentrates on formulating learning objectives and obtaining the required effort to achieve learning goals (Wong et al., 2021). Environmental structuring is related to students' attempts to arrange and structure learning environments (Xu et al., 2013). Task strategy is connected with the arrangement of learning activities and tasks that maximize the learning outcomes and processes (Effeney et al., 2013). Time management refers to the learners' ability to divide their time between learning activities (Arguedas et al., 2016). Help seeking refers to the behavior of actively seeking help from peers and instructors (Qayyum, 2018). Self-evaluation is the process of systematically observing, analyzing and monitoring students' own actions or performance against learning goals (Raković et al., 2022). In addition, prior studies have shown that there is a positive correlation between self-regulation strategies and academic outcomes in different educational settings (Inan et al., 2017).

2.3 Motivation

In the field of education, motivation is believed to be a significant psychological construct affecting online learning. Among a series of theoretical frameworks on motivation, self-determination theory is one of the most important (Moreira-Fontán et al., 2019). Depending on the level of self-determination, motivation consists of four forms and a continuum of self-determined levels ranging from high to low. Intrinsic motivation refers to the inherent satisfaction that results from an individual's desire for learning being enjoyable or interesting (Glynn et al., 2011). As suggested by Chiu (2021), intrinsic motivation is triggered spontaneously and leads to sophisticated learning, such as behavioral, cognitive, and emotional engagement. Identified regulation and external regulation are two types of extrinsic motivation. Identified regulation develops when behavior is regarded as significant for students' values and goals (e.g., when the course content is relevant to an individual's future development) (Yilmaz, 2017). External regulation involves performing learning activities that lead to avoiding punishment or obtaining a reward (e.g., obtaining a good grade on an exam) (Barak et al., 2016). Amotivation occurs when students are unaware of the contingencies between learning activities and their utility or results (Botnaru et al., 2021). Furthermore, amotivation has been shown to be negatively related to learning outcomes and engagement (Ryan & Deci, 2020). Overall, these studies have indicated that when individuals' needs are not better met and supported, the participation and motivation of learning activities will be weaker, and the motivational orientation will change from intrinsic motivation to extrinsic motivation to amotivation.

2.4 The link between self-regulation, motivation, performance, and emotional self-efficacy

Numerous studies have explored the relationships between emotion and self-regulation. For example, Li et al. (2021) proposed that emotional fluctuations are influenced by task difficulty in the phase of self-regulated learning. Lajoie et al. (2021) examined the complex mechanisms of how self-regulatory activities and emotions impact learning performance and academic achievement. However, few studies have directly assessed the connection between self-regulation and emotional self-efficacy in online learning contexts. Studies have shown that students with higher levels of self-efficacy are more likely to achieve learning goals (Agustiani et al., 2016). Furthermore, according to the research of Su et al. (2018), students with higher levels of self-efficacy are more likely to adopt diverse self-regulated learning strategies to improve their learning performance. Thus, it seems reasonable to examine whether students' self-regulation may promote their emotional self-efficacy in online learning contexts.

Although many empirical studies have indicated the important relationships between emotional self-efficacy and psychosocial variables, such as cognition (Magen-Nagar & Cohen, 2017) and metacognition (Cho & Heron, 2015), few published works have examined the connection between motivation and emotional self-efficacy. Previous works have demonstrated that students who possess different learning motivations and goals often use diverse emotional regulation strategies that systematically affect the achievement of academic goals (Daniels et al., 2008; Di Leo & Muis, 2020). From a wider perspective, Xu et al. (2013) reported that motivation is positively related to group-level emotional management, revealing that emotion self-efficacy is strongly related to motivation in a collaborative group context.

Existing research has indicated that emotional self-efficacy is connected with academic performance. Galla and Wood (2012) found that confidence in managing and understanding emotions could moderate the impacts of anxiety and improve mathematics outcomes. The results are consistent with the study of Ganotice et al. (2016) who implied that the ability to effectively regulate students' emotions can improve their ability to allocate study time effectively and thus improve their academic performance. Taken together, emotional self-efficacy has been associated with diverse self-regulation strategies and motivational characteristics and academic performance.

2.5 Person-centered approach

A large body of research on emotional self-efficacy mainly focuses on a specific emotional regulation strategy. In addition, the existing work does not consider the fact that different emotional regulation strategies could be integrated into personal emotional regulation profiles and explored emotional self-efficacy only from the variable-centered perspective (Mänty et al., 2020). As suggested by Perera et al. (2019), the variable-centered approach focuses on building the connections among variables while neglecting the possibility of unobserved subpopulations. Therefore, this study extends the variable-centered approach to emotional self-efficacy and analyzes the complex structure of student emotional self-efficacy in more detail by adopting a person-centered approach.

The person-centered approach focuses on identifying subgroups of students who are quantitatively and qualitatively different in emotional self-efficacy dimensions. On the absolute level of emotional self-efficacy dimensions, the number of different profiles is different. There are differences in quality (i.e., differences in shape) in high, medium, and low dimensions of emotional self-efficacy (Coyle et al., 2019). However, these quantitative and qualitative profile differences cannot be obtained directly using a variable-centered approach. Therefore, this study investigates whether there are significant differences in the quantity and quality of emotional self-efficacy in online learning environments from a person-centered perspective.

2.6 Research question

Overall, our literature review clarifies that emotional self-efficacy has received increasingly more attention in the education field. However, very little person-centered research on students' emotional self-efficacy profiles in online learning contexts has been conducted. In addition, the connection between self-regulation, motivation and emotional self-efficacy has rarely been explored. Therefore, we investigate what types of emotional self-efficacy profiles can be detected and further examine whether the profiles are related to important predictors and academic performance. In this study, the following three research questions are formulated:

Q1: What types of emotional self-efficacy profiles can be identified in online learning contexts?
Q2: To what extent do the self-regulation and motivation of students in online learning contexts predict their emotional self-efficacy profile membership?
Q3: Can academic performance be predicted by emotional self-efficacy profile membership?

In order to address these research questions, we propose a hypothesized model (Fig. 1) for illustrating our quantitative research methods for them. In particular, a latent profile approach was used to identify emotional self-efficacy profiles, while logistic regression analysis was conducted to examine the predictive effects of students' self-regulation and motivation on their emotional self-efficacy profile membership in an online learning context. The relationship between emotional self-efficacy profile membership and academic performance was examined using hierarchical regression analyses.

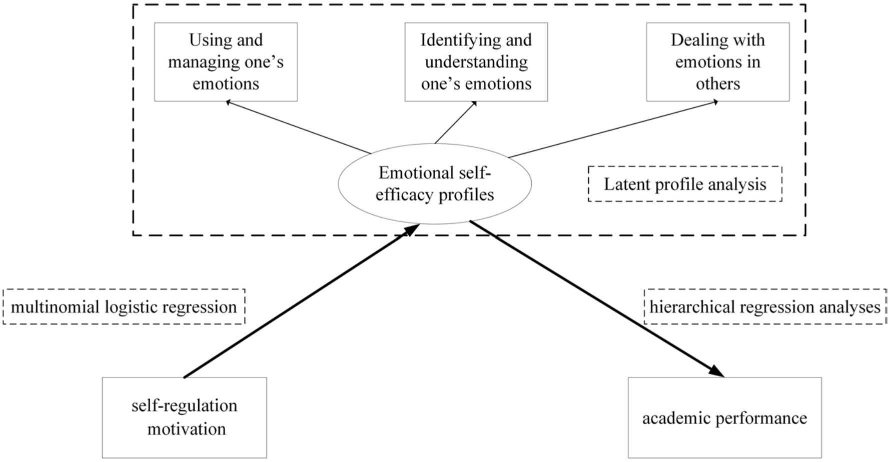

Fig. 1 The hypothesized model of this study

3 Method

3.1 Research context and participants

The study was performed using the largest MOOC (massive open online course) online education community in China (https://www.icourse163.org). We obtained data from Wenjuanxing, a widely available online survey website in China. In this study, we focused on courses related to instructional design and teaching methods because we could access participants who had experienced these courses. Participants were invited to complete the three scales online at the same time, and the final scores were collected. The sample comprised 318 students (mean age = 24, SD = 2.7), including 227 women (71.38%) and 91 men (28.62%). Regarding all participants, 56.07% had a bachelor's degree, 32.1% had a master's degree, and the remaining 11.83% had a doctoral degree. The majority of participants included educational technology, distance education, and language students. Participation was voluntary, and informed consent was obtained prior to the study. All data were used only for research purposes and treated with strict confidence in this study.

3.2 Instrument

Students' emotional self-efficacy, motivation, self-regulation and academic performance were obtained through an online survey. All items were evaluated using a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The final score obtained through the survey is regarded as the students' academic performance in this study.

To measure students' emotional self-efficacy, we employed the scale of emotional self-efficacy developed by Dacre Pool and Qualter (2012b). This scale measures students' emotional self-efficacy toward online learning activities and comprises

3 subconstructs: using and managing one's own emotions (UM), identifying and understanding one's own emotions (IU) and dealing with emotions in others (DO) (see Appendix 1, Table 6). A sample item for UM is "I change my negative emotion to a positive emotion in online learning". Internal consistency was accepted for the UM subscale ($\alpha = 0.762$), IU subscale ($\alpha = 0.724$), and DO subscale ($\alpha = 0.784$).

Regarding self-regulation, we applied the self-regulation scale proposed by Barnard et al. (2009). This scale measures students' self-regulation and comprises 6 subconstructs: goal setting (GS), environmental structuring (ES), task strategies (TS), time management (TM), help seeking (HS) and self-evaluation (SE) (see Appendix 2, Table 7). A sample item for TS is "I prepare questions before joining an online discussion". The Cronbach's alphas for GS, ES, TS, TM, HS and SE were 0.722, 0.683, 0.699, 0.604, 0.719 and 0.688, respectively.

For motivation, the scale proposed by Gagné et al. (2010) was used to assess students' motivational state with regard to online learning. This scale comprises 4 subconstructs: intrinsic motivation (IM), identified regulation (IR), external regulation (ER) and amotivation (AM) (see Appendix 3, Table 8). A sample item for IM is "Because I think online learning tasks/activities are interesting". Reliability analysis revealed that the items had acceptable internal consistency for IM ($\alpha = 0.770$), IR ($\alpha = 0.777$), ER ($\alpha = 0.773$) and AM ($\alpha = 0.835$).

3.3 Data analysis

To ensure that the emotional self-efficacy subscale could be distinguished, we first used confirmatory factor analysis (CFA) to establish measurement models of the key constructs. In addition to emotional self-efficacy, we also examined the measurement model of self-regulation and motivation, which are possible critical predictors of emotional self-efficacy profiles. The model fit was assessed using the standardized root mean square residual (SRMR), the root mean square error of approximation (RMSEA), the Tucker–Lewis index (TLI) and the comparative fit index (CFI). For the TLI and CFI, values above 0.90 indicate an acceptable fit and values higher than 0.95 imply a great fit. SRMRs and RMSEAs lower than 0.08 indicate an acceptable model fit.

Latent profile analysis is a person-centered statistical approach that aims to detect potential homogenous subgroups within heterogeneous populations based on multivariate continuous data (Vanslambrouck et al., 2019). In this study, in order to group students into different emotional self-efficacy profiles, latent profile analysis was conducted. The number of expected profiles is not predefined prior to latent profile analysis. Thus, we conducted an exploratory analysis to investigate models with two to five profiles. Furthermore, we set the variances across clusters to be equal to obtain stable solutions for latent profile analysis.

In order to perform latent profile analysis, we selected several model-selection criteria to determine the best number of profiles based on the Mplus7 statistical software. To indicate whether increasing the number of profiles could improve the model's degree of fit, we further chose the Akaike information criterion (AIC), Bayesian information criterion (BIC) and adjusted BIC (ABIC). The smaller BIC, AIC and ABIC are, the better the model fit. When the k profile model is superior to the K-1 profile model, the p value for the Lo-Mendell-Rubin likelihood ratio test is significant (Chon & Shin, 2019). Then, the entropy indicating the clear delineation of clusters was assessed to obtain a more robust and appropriate basis for the comparison of the models. Higher entropy indicates a more precise distribution of the latent profile (Jung & Wickrama, 2008). Finally, we used the number of profiles and their interpretability as a further selection criterion. In general, the number for every profile is greater than 5% of the sample. A latent profile approach was used to analyze the first research question (Q1): what types of emotional self-efficacy profiles can be identified in online learning contexts?

A multinomial logistic regression is a classification method and is commonly used to handle problems with multiple dependent variables. In this study, we conducted a multinormal logistic regression to model the connection between the self-regulation, motivation and membership of the emotional self-efficacy profiles from latent profile analysis. The dependent variable was distinct emotional self-efficacy profile membership, and the predictor variables included self-regulation and motivation. This approach was performed to analyze the second research question (Q2): to what extent do the self-regulation and motivation of students in online learning contexts predict their emotional self-efficacy profile membership?

A hierarchical regression is a common method used to test whether adding variables can significantly improve a model's prediction ability. We adapted a three-step hierarchical regression to investigate whether emotional self-efficacy profile membership would predict academic performance after controlling for individual characteristics, such as age, gender and current educational level. For the emotional self-efficacy profiles, four dummy coded variables were generated to represent group membership. Gender and age were entered in the first block, the current educational level was entered in the second block, and emotional self-efficacy profile membership was entered in the last block. This approach was conducted to analyze the third research question (Q3): can academic performance be predicted by emotional self-efficacy profile membership?

4 Result

4.1 Measurement models

The model for emotional self-efficacy was satisfactory and RMSEA = 0.045, SRMR = 0.046, CFI = 0.949 and TLI = 0.931 were obtained.

For the online self-regulation learning scale, the results found that the model fit was not acceptable (CFI = 0.876, TLI = 0.856, RMSEA = 0.051, and SRMR = 0.057). The factor loadings were low for Item 2 of the environmental structuring (ES) subscale and Item 2 of the task strategies (TS) subscale, so the decision was made to delete both items. Finally, the modified model indicated adequate fit: CFI = 0.927, TLI = 0.911, RMSEA = 0.043 and SRMR = 0.048.

The model for motivation was acceptable (CFI = 0.927, TLI = 0.905, RMSEA = 0.060, and SRMR = 0.065), but factor loading was low for Item 4 of the intrinsic motivation (IM) subscale and Item 3 of the external regulation (ER) subscale. After examining the modification indices of motivation, both items were removed. Finally, this revised CFA model revealed an acceptable model fit: CFI = 0.944, TLI = 0.926, RMSEA = 0.056, and SRMR = 0.057.

4.2 Descriptive statistics

The means, standard deviations, and correlations of the variables are displayed in Table 1. Using and managing one's emotions (UM) and identifying and understanding one's emotions (IU) in the emotional self-efficacy subscales have high means. The environmental structuring (ES) and goal setting (GS) subscales of self-regulation have the highest means, and the task strategies (TS) subscale has the lowest mean. For motivation, the identified regulation (IR) subscale has the highest mean, and the amotivation (AM) subscale has the lowest mean. Regarding the standard deviations, the AM subscale possessed the highest range of values.

Then, we conducted Pearson correlations to survey the relationships among students' emotional self-efficacy, self-regulation and motivation. Table 1 indicates the general correlational relationship among the variables based on Pearson correlation coefficients. The correlation matrix reveals moderate correlations (r = between 0.3 and 0.5) and weak correlations (r = between 0.1 and 0.3). The results imply that

Table 1 Descriptive statistics and correlation coefficients in the study

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
1. UM	–	.43**	.32**	.52**	.28**	.43**	.46**	.32**	.39**	.29**	.39**	.24**	−.13*
2. IU		–	.30**	.40**	.35**	.27**	.40**	.23**	.24**	.22**	.40**	.26**	−.19**
3. DO			–	.35**	.22**	.43**	.44**	.42**	.49**	.33**	.17**	.28**	.14**
4. GS				–	.40**	.51**	.54**	.47**	.50**	.29**	.50**	.39**	−.23**
5. ES					–	.31**	.31**	.45**	.36**	.17**	.43**	.23**	−.13*
6. TS						–	.46**	.49**	.55**	.39**	.38**	.38**	−.07
7. TM							–	.40**	.41**	.30**	.42**	.43**	−.08
8. HS								–	.58**	.29**	.38**	.28**	−.07
9. SE									–	.45**	.40**	.33**	−.02
10. IM										–	.30**	.37**	.06
11.IR											–	.50**	−.40**
12.ER												–	−.11
13. AM													–
M	3.88	3.90	3.27	3.97	4.01	3.66	3.80	3.78	3.74	3.57	4.22	3.81	2.23
SD	0.57	0.54	0.72	0.59	0.60	0.67	0.64	0.63	0.60	0.66	0.52	0.61	0.79
α	.762	.724	.784	.722	.683	.699	.604	.719	.688	.770	.777	.773	.835

UM = Using and managing one's emotions, IU = Identifying and understanding one's emotions, DO = Dealing with emotions in others, GS = Goal setting, ES = Environmental structuring, TS = Task strategies, TM = Time management, HS = Help seeking, SE = Self-evaluation, IM = Intrinsic motivation, IR = Identified regulation, ER = External regulation, and AM = Amotivation

M = mean, SD = standard deviation, and α = Cronbach's alpha. $^{*}p < .05$ and $^{**}p < .01$

emotional self-efficacy dimensions (1-3) are connected to each other. We also found that the variables within self-regulation (4-9) and motivation (10-13) are correlated. In addition, the results indicate that there is a correlation among emotional self-efficacy, self-regulation and motivation, except for amotivation (AM).

4.3 Emotional self-efficacy profiles

To identify the emotional self-efficacy profiles (Q1), we applied fit indices to estimate the best number of profiles. The results are presented in Table 2. The model with the K profile is compared with the model with the (K-1) profile to obtain the result of the model fitting. The Lo-Mendel-Rubin (LMR-LRT) test statistic demonstrates whether the model with the K profile is significantly superior to the model with the K-1 profile. When the value is greater than 0.05, the model with the K-1 profile is selected; conversely, the model with the k profile is optimal.

When the number of profiles reaches four, the model bias (log probability) continues to decrease. Of all the profile solutions, the AIC, BIC and ABIC were the lowest for the 4-cluster solution. Although the LMR indicated that the three-section model is the optimal cutoff point, an in-depth analysis of the three-section model and the four-section model showed that the four-section model has significant substantial differences. In addition, because the sample size of this study is not sufficiently large, more profiles cannot be supported. Therefore, models with more than four profiles were not considered in this study. Therefore, the optimal four-profile model with distinctive clusters and good interpretability was chosen.

Then, after analyzing the differences in these profiles, we labeled each emotional self-efficacy profile. The means of the four profiles are illustrated in Fig. 2. Since the students of a certain profile obtained the lowest means of all the subscales of emotional self-efficacy, we referred to this profile as the ‘low emotional self-efficacy profile’ (N = 49, 16.2%). Conversely, the profile of students who obtained the highest mean scores concerning all subscales of online emotional self-efficacy is called the ‘high emotional self-efficacy profile’ (N = 80, 23.9%). The third profile is called the ‘average emotional self-efficacy profile’ (N = 96, 30.6%). Students in this profile have an average means on three emotional self-efficacy subscales. The fourth profile is called the ‘above-average emotional self-efficacy with low DO profile’ (N = 93, 29.3%) and students in this profile obtain above average means for three emotional self-efficacy subscales except for DO.

Table 2 The results of latent profile analysis for emotional self-efficacy

Clusters	Log Likelihood	Parameters	AIC	BIC	ABIC	LMR p value	Entropy
2	−4673.34	37	9420.68	9559.87	9442.52	0.255	0.739
3	−4601.36	50	9302.71	9490.81	9332.26	0.066	0.757
4	−4562.42	63	9250.85	9487.86	9288.04	0.267	0.735
5	−4673.34	37	9420.68	9559.87	9442.52	0.258	0.739

AIC, Akaike Information Criterion; *BIC,* Bayesian Information Criterion; *ABIC*, Sample Adjusted Bayesian Information Criterion, and *LMR*, Lo-Mendell-Rubin test

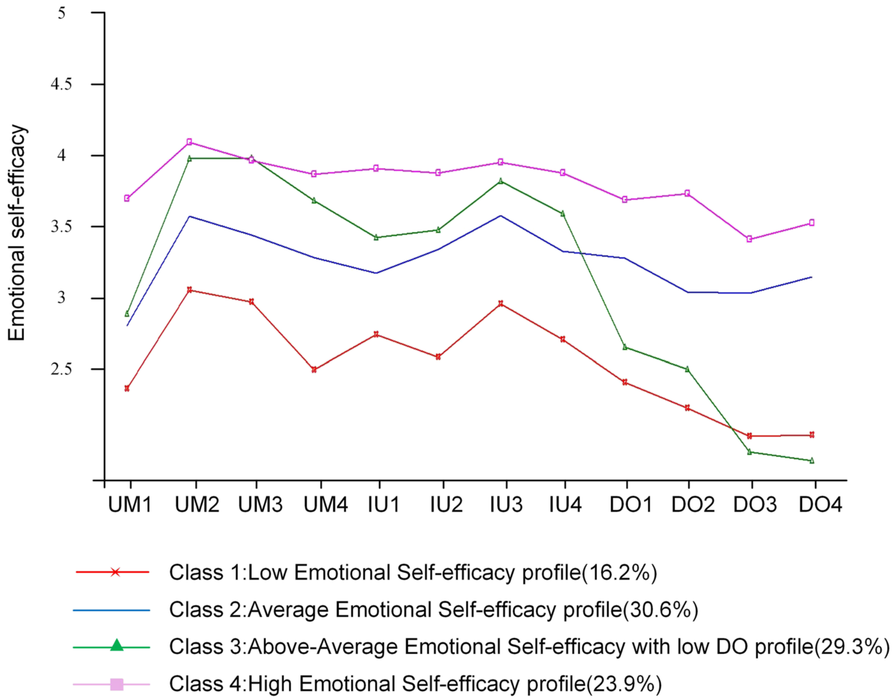

Fig. 2 Emotional self-efficacy profiles of students

To examine whether there was a difference in the means of the emotional self-efficacy variables between the four emotional self-efficacy profiles, multivariate analysis of variance (MANOVA) with all the emotional self-efficacy variables (UM, IU and DO) as dependent variables and profile membership as the grouping variable was performed. We used Box's M test ($p=0.001$, $p<0.05$) to evaluate the equality of covariances and Levene's test to test the homogeneity of variances. Then, as suggested by van Alten et al. (2021), since the homogeneity hypothesis of covariance violations is more robust, we combined Pillai's tracking statistics with conservative Bonferroni correction for post hoc testing. According to Pillai's trace statistic results, we found that profile membership has a significant influence on students' emotional self-efficacy variables: Pillai's trace $=1.328$, $F(9, 942)=83.086$, $p<.001$, and partial $\eta^2=0.443$. Table 3 shows Bonferroni's postmortem pair test, with subscripts implying significant differences between profiles.

4.4 Predicting emotional self-efficacy profile membership

A multinomial logistic regression was conducted to examine the extent to which the self-regulation and motivation of students in online learning contexts predict their emotional self-efficacy profile membership (Q2). We set the high emotional self-efficacy profile as the reference group. First, we compared the likelihood

Table 3 Bonferroni correction post hoc pairwise comparisons among the four profiles

	Low emotional self-efficacy profile $_a$	Average emotional self-efficacy profile $_b$	Above-average emotional self-efficacy with low DO profile $_c$	High emotional self-efficacy profile$_d$
Variable	M (SD)	M (SD)	M (SD)	M(SD)
1. UM	3.13 (.44) $_{bcd}$	3.68 (.37) $_{acd}$	4.09 (.44) $_{abd}$	4.35 (.32) $_{abc}$
2. IU	3.15 (.44) $_{bcd}$	3.77 (.36) $_{acd}$	4.03 (.43) $_{abd}$	4.35 (.33) $_{abc}$
3. DO	2.61 (.38) $_{bd}$	3.56 (.37) $_{acd}$	2.64 (.46) $_{bd}$	4.04 (.38) $_{abc}$

According to the Bonferroni corrected post hoc tests, subscripts a-d show significant differences ($p < .001$) from other profiles

of membership in the low emotional self-efficacy profile versus high emotional self-efficacy profiles. As indicated in Table 4, the differences in GS ($p < .001$ and OR = 0.13) and TM ($p < .001$ and OR = 0.17) were statistically significant. These results revealed that when the GS and TM of students increase by one, the odds of belonging to the low emotional self-efficacy profile rather than being assigned to the high emotional self-efficacy profile are .13 and .17 times less likely, respectively. Next, compared with the average emotional self-efficacy profile and the high emotional self-efficacy profile, TS ($p < .05$, OR = 0.38) and TM ($p < .001$, OR = 0.22) were negative and statistically significant. The results revealed that when the TS and TM of students increased by one, the odds of belonging to the average emotional self-efficacy profile rather than being assigned to the high emotional self-efficacy profile were .38 and .22 times less likely, respectively. In addition, we found that ER also had a positive significant effect ($p < .05$, OR = 1.95). The results revealed that for every one unit increase in ER, the odds of the average emotional self-efficacy profile increased by 1.95 times. Third, we also compared the likelihood between the above-average emotional self-efficacy with low DO profile and the high emotional self-efficacy profile and revealed that TM ($p < .001$, OR = 0.17) and HS ($p < .001$, OR = 0.20) had significantly negative effects. These results demonstrated that if a student were to increase TM and HS by one unit, then the odds of belonging to the average emotional self-efficacy with low DO profile compared to the high emotional self-efficacy profile would be .17 and .20, respectively. In addition, we also found that student IR ($p < .05$, OR = 3.56) had a statistically significant effect. The results revealed that if a student were to increase their IR by one unit, they were 3.56 more likely to be assigned to the above-average emotional self-efficacy with a low DO profile than the high emotional self-efficacy profile.

4.5 Emotional self-efficacy profile predicting academic performance

Next, we conducted hierarchical regression analyses to examine whether academic performance can be predicted by emotional self-efficacy profile membership. As illustrated in Table 5, the results of Step 1 ($\Delta R^2 = 0.012$, $p > .05$) and Step 2 ($\Delta R^2 = 0.015$, $p > .05$) resulted in no significant effects on students' academic

Table 4 Multinomial logistic regression results predicting profile membership

		Low emotional self-efficacy profile vs. high emotional self-efficacy				Average emotional self-efficacy profile vs. high emotional self-efficacy				Above-average emotional self-efficacy with low DO profile vs. high emotional self-efficacy			
		95% CI for Odds Ratio				95% CI for Odds Ratio				95% CI for Odds Ratio			
		B (SE)	OR	Lower	Upper	B (SE)	OR	Lower	Upper	B (SE)	OR	Lower	Upper
Self-regulation	GS	−2.06 (.59)***	.13	.04	.41	−.93 (.52)	.39	.14	1.10	−.02 (.54)	.99	.34	2.82
	ES	−.40 (.50)	.67	.25	1.77	−.32 (.41)	.73	.32	1.63	−.18 (.42)	.84	.31	1.89
	TS	−.75 (.48)	.47	.19	1.21	−.96 (.41)*	.38	.17	.85	−.54 (.40)	.58	.27	1.28
	TM	−1.79 (.53)***	.17	.06	.47	−1.50 (.47)***	.22	.09	.56	−1.80 (.47)***	.17	.07	.41
	HS	.01 (.55)	1.05	0.34	2.94	−.67 (.44)	.51	.22	1.21	−1.62 (.44)***	.20	.08	.47
	SE	−.58 (.56)	.56	.19	1.67	.22 (.47)	1.24	.49	3.11	−.45 (.45)	.64	.26	1.54
Motivation	IM	−.78 (.44)	.46	.19	1.09	−.71 (.37)	.49	.24	1.01	−.58 (.36)	.56	.28	1.13
	IR	−.43 (.61)	.65	.20	2.16	.28 (.50)	1.33	.50	3.55	1.27 (.53)*	3.56	1.25	10.10
	ER	.36 (.38)	1.43	.68	2.99	.67 (.32)*	1.95	1.05	3.63	.13 (.31)	1.14	.63	2.07
	AM	−.18 (.38)	.84	.40	1.76	.31 (.25)	1.36	.84	2.21	−.40 (.29)	.67	.38	1.20

$^{*}p < .05$ and $^{***}p < .001$

Table 5 Hierarchical regression analysis of academic performance

Academic performance	R^2	B	SE	β	ΔR^2	Sig. change
Step1	0.018				0.012	0.058
Gender		−1.96	0.88	−0.13		
Age		−0.60	0.56	−0.06		
Step2	0.024				0.015	0.148
Gender		−1.91	0.88	−0.12		
Age		−0.53	0.56	−0.05		
Current educational level		−0.73	0.50	−0.08		
Step3	0.406				0.398	< 0.001
Gender		−1.52	0.69	−0.10		
Age		−0.26	0.44	−0.26		
Current educational level		−0.18	0.39	−0.02		
emotional self-efficacy profile membership		4.61	0.33	0.62^{***}		

$^{***}p < .001$

performance. The results of Step 3 demonstrated that emotional self-efficacy profile membership was an important predictor of academic performance, explaining 39.8% of the variance in students' academic performance (β = 0.62, $p < .001$).

5 Discussion

We examined students' emotional self-efficacy in online learning contexts using a person-centered approach. Specifically, the emotional self-efficacy profiles were identified (Q1), and the influences of self-regulation and motivation on students' emotional self-efficacy profile memberships (Q2) and the connection between academic performance and emotional self-efficacy profile membership (Q3) were examined. These findings are important in understanding students' emotional self-efficacy in online learning contexts and the improvement in emotional self-efficacy by offering insights into the values of self-regulation and motivation. The findings and implications are discussed in the following sections.

5.1 Emotional self-efficacy profiles (Q1)

Although few studies have investigated the unobserved heterogeneity in emotional self-efficacy, we identified four emotional self-efficacy profiles by adopting latent profile analysis. As expected, the results demonstrated that there were at least two profiles, which were named the low emotional self-efficacy profile and the high emotional self-efficacy profile. The results also identified a third profile called the average emotional self-efficacy profile. In addition, the fourth profile was characterized by above-average emotional self-efficacy with a low DO profile. These profiles mainly indicate the number of emotional self-efficacy strategies used by students.

Then, we compared the four profiles concerning the use of specific emotion regulation strategies, comprising IM, IU and DO. The findings revealed that students with a high emotional self-efficacy profile reported using more IM, IU and DO than the other three profiles. This conclusion supports the study of Nightingale et al. (2013) who suggested that emotion regulation strategies (i.e., managing and understanding their emotions) may be used more by students with a high emotional self-efficacy profile than by students with a low emotional self-efficacy profile. Furthermore, the results also revealed that for DO, there was no significant difference between the low emotional self-efficacy profile and the above-average emotional self-efficacy with low DO profile, indicating that these learners did not well handle their emotional interactions with other students, which is reflected in the DO subscales. This finding replicated work by Dacre Pool and Qualter (2013) who found that students who are more confident in handling their emotions with others are more likely to communicate with their instructors and peers and maintain personal networks in online learning environments.

5.2 Predictive role of self-regulation and motivation (Q2)

To understand why students develop different emotional self-efficacy profiles, we draw on the self-regulation literature. In this study, a significant effect was found between self-regulation and the identified emotional self-efficacy profiles, revealing that students' self-regulation strategies shape their emotional self-efficacy in online learning environments. More specifically, goal setting, time management, task strategies and help seeking have predictive effects on students' emotional self-efficacy profile membership. This finding supports Zheng et al. (2021) who suggested that the higher the goals students set for themselves, the more likely it is that students have a higher level of emotional self-efficacy. Furthermore, the results suggested that the proportion of the high emotional self-efficacy profile (compared with the average or low emotional self-efficacy profile) increased with every unit increase in the time management of self-regulation factors. The interpretation is that students with a high emotional self-efficacy profile are likely to learn more learning content than students with a low level of emotional self-efficacy, which might be a reason why students with a high emotional self-efficacy profile need to effectively manage their time. Finally, there was no significant difference among different emotional self-efficacy profiles regarding environmental structuring (e.g., reducing or eliminating distractions and dividing the learning time and spreading it into different time periods) and self-evaluation (e.g., actively judging and monitoring the progress and performance of learners according to learning goals). This was partly in line with the findings from Ben-Eliyahu and Linnenbrink-Garcia (2013) who suggest that the relationship between evaluation and emotional regulation varies in different learning situations. Therefore, the relationship between these variables needs to be further analyzed.

In addition, learning motivation is viewed as a central factor for predicting students' emotional self-efficacy (Reindl et al., 2020). The findings corresponded to the study by Järvenoja et al. (2020) who found that emotional states were influenced by students' motivational regulation strategies; and in turn, effective emotional regulation could also stimulate students' motivation. This demonstrated that students with a high emotional self-efficacy profile have identified regulation and external regulation of motivation. The findings are the same as the multiple goal perspective, which posits that both identified regulation and external regulation are conducive to learning. Additionally, there were no predictive effects associated with intrinsic motivation and amotivation in this study. In contrast to previous research, negative emotions can be assumed to reduce intrinsic motivation (Li et al., 2021). Students adopting the identified regulation and external regulation of motivation are motivated to obtain a high level of emotional self-efficacy, and students can actively adjust their motivation and manage their emotions to channel the emotional atmosphere to focus on and complete online learning tasks.

5.3 Emotional self-efficacy profile predicting academic performance (Q3)

This study explored the predictive value of the emotional self-efficacy profile for academic performance in online learning contexts. In the hierarchical regression analyses with all of the variables together, only the emotional self-efficacy profile was a statistically significant predictor. Specifically, as the emotional self-efficacy score increased, achievement increased. These results agree well with prior studies wherein emotional self-efficacy has a significant predictive value for learning performance (Galla & Wood, 2012). We could infer that students with high emotional self-efficacy tend to be more highly engaged and achieve good learning performance. Therefore, emotional self-efficacy serves as an effective prophylactic against negative emotions to improve academic performance.

5.4 Practical implications

The study could provide a basis for establishing emotional regulation strategies to improve students' emotional self-efficacy. The findings confirm that the existence of different emotional self-efficacy profiles of students was determined by how they used different emotional regulation strategies (using and managing emotions, identifying and understanding emotions and dealing with emotions in others). By increasing students' knowledge and understanding of emotional self-efficacy, teachers could increase students' self-efficacy with their emotional functioning (Pool & Qualter, 2012). In this study, students with the low emotional self-efficacy profile could be regarded as an academically at-risk group in online learning contexts. Therefore, encouraging students to use more emotional regulation strategies might be effective, and teachers should assist students in controlling and understanding their emotions by developing students' emotional intellect and emotional efficacy beliefs. Furthermore, since time management and goal setting of self-regulation are key predictors of emotional self-efficacy profile membership, teachers should prompt students to use goal setting strategies to manage time in the learning process. In addition, the results suggest that motivation is a critical element for emotional self-efficacy and that students with stronger learning motivation also tend to have higher emotional self-efficacy. More specifically, identified regulation and external regulation are the dominant motivation types in students' online learning. Therefore, it is critical to address how students' motivation can be improved for course designers from initial enrollment to course facilitation.

6 Conclusion

A broad academic consensus has suggested that emotional self-efficacy is an essential factor for learning outcomes and academic engagement, especially in online learning contexts. By taking a person-centered approach, this study offers novel results concerning the differences in emotional self-efficacy among students in online learning contexts, which could help tailor instruction for individual learners. The findings suggest that there are four emotional self-efficacy profiles: low, average, above average with a low ability to handle the emotions of others and high emotional self-efficacy profiles. This study contributes to the literature by identifying the emotional self-efficacy profile through latent profile analysis, showing the significant influence of the identified emotional self-efficacy profile on students' academic performance, and demonstrating that self-regulation and motivation could be regarded as predictors of emotional self-efficacy. The knowledge gained from this study might offer a method to enhance students' perceptions of emotional self-efficacy.

Although this study provides critical insights into the diversity in students' emotional self-efficacy, several limitations must be addressed. First, due to its cross-sectional nature, the study did not adequately consider the dynamic changes in self-regulation, emotional self-efficacy and motivation during the learning process. As such, the dynamics of self-regulation, emotional self-efficacy, and motivation during educational activities should be considered in future work (Tuominen et al., 2020). Second, the study did not incorporate a hierarchical nested structure of data into the analysis, and future studies should consider a nested structure (e.g., students nested in instructors/lectures). Finally, the latent profile analysis method has problems such as the spurious identification of subgroups in a population that may not exist, and the constraints on data collection introduce nonnormality and nonlinearity problems (Spurk et al., 2020). Thus, further analysis is needed to verify the results of this study.

Appendix 1

Table 6 Students' Emotional Self-efficacy Questionnaire

Constructs		Measurement items
Using and managing one's own emotions	UM1	1. I change my negative emotion to a positive emotion in online learning.
	UM2	2. I use positive emotions to generate good ideas in online learning.
	UM3	3. I get into a mood that best suits the occasion in online learning.
	UM4	4. In online learning, I generate positive emotions so that creative ideas can unfold.
	UM5	5. I regulate my own emotions when under pressure in online learning.
	UM6	6. In online learning, I generate positive emotions to improve my cognitive performance.
	UM7	7. I create emotions to enhance academic performance in online learning.
Identifying and understanding one's own emotions	IU1	1. I know what causes me to feel different emotions in online learning.
	IU2	2. I know what causes me to feel negative emotions in online learning.
	IU3	3. I correctly identify my own negative emotions in online learning.
	IU4	4. I correctly identify my own positive emotions in online learning.
	IU5	5. I understand what causes my emotions to change in online learning.
	IU6	6. I know what causes me to feel positive emotions in online learning.
Dealing with emotions in others	DO1	1. I can identify what causes my classmates' positive emotions in online learning.
	DO2	2. I can help my classmates calm down when they become angry in online learning.
	DO3	3. I can identify what causes my classmates' differing emotions in online learning.
	DO4	4. I can help my classmates regulate their emotions in online learning.
	DO5	5. I can identify what causes my classmates' negative emotions in online learning.
	DO6	6. I help my online classmates change a negative emotion to a positive emotion.
	DO7	7. I understand what causes my classmates' emotions change in online learning.
	DO8	8. I correctly identify when my classmate is feeling a positive emotion in online learning.

Appendix 2

Table 7 Students' Self-regulation Learning Questionnaire

Constructs		Measurement items
Goal Setting	GS1	1. I set standards for my assignments in online learning.
	GS2	2. I set short-term (daily or weekly) goals as well as long-term goals (monthly or for the semester).
	GS3	3. I set a high standard for my learning in online learning.
	GS4	4. I set goals to help me manage study time in online learning.
	GS5	5. I don't compromise the quality of my work because it is online.
Environment Structuring	ES1	1. I choose the location where I study to avoid too much distraction.
	ES2	2. I find a comfortable place to study.
	ES3	3. I know where I can study most efficiently for online learning.
	ES4	4. I choose a time with few distractions for online learning.
Task Strategies	TS1	1. I try to take more thorough notes for online courses because notes are even more important for learning online than in a regular classroom.
	TS2	2. I read aloud instructional materials posted online to fight against distractions.
	TS3	3. I prepare questions before joining an online discussion.
	TS4	4. I work on extra problems in online learning in addition to the assigned ones to master the course content.
Time Management	TM1	1. I allocate extra study time for online learning because I know it is time demanding.
	TM2	2. I try to schedule the same study time every day or every week in online learning, and I adhere to the schedule.
	TM3	3. Although we don't have to attend daily classes, I still try to distribute my study time evenly across days.
	TM4	4. I allocate more time to study subjects with more difficult content.

Table 7 (continued)

Constructs		Measurement items
Help seeking	HS1	1. I find someone who is knowledgeable in the course content so I can consult with them when I need help.
	HS2	2. I share my problems with my classmates online so we know what we are struggling with and how to solve our problems.
	HS3	3. If needed, I try to meet my classmates face-to-face.
	HS4	4. I am persistent in obtaining help from the instructor through e-mail.
Self-evaluation	SE1	1. I summarize my learning in online learning to examine my understanding of what I have learned.
	SE2	2. I ask myself a lot of questions about the course material when studying for an online course.
	SE3	3. I communicate with my classmates to find out what I am learning that is different from what they are learning.
	SE4	4. I communicate with my classmates to find out how I am doing in my online classes

Appendix 3

Table 8 Students' Motivation Questionnaire

Constructs		Measurement items
Intrinsic motivation	IM1	1. Because I think online learning tasks/activities are interesting.
	IM2	2. Because I think online learning tasks/activities are pleasant.
	IM3	3. Because online learning tasks/activities are fun.
	IM4	4. Because I feel good when engaging in online learning.
Identified regulation	IR1	1. Because I am engaging in online learning for my own good.
	IR2	2. Because I think that online learning is good for me.
	IR3	3. Because I am engaging in online learning by personal decision.
	IR4	4. Because I believe that online learning is important to me.
External regulation	ER1	1. Because I am supposed to engage in online learning.
	ER2	2. Because online learning is something I have to engage in.
	ER3	3. Because I don't have any choice.
	ER4	4. Because I feel that I have to engage in online learning.
Amotivation	AM1	1. There may be good reasons to engage in online learning, but I don't see any personally.
	AM2	2. I do online learning, but I am not sure if it is worth it.
	AM3	3. I don't know; I don't see what online learning bring me.
	AM4	4. I do online learning, but I am not sure it is a good thing to pursue.

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