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Latent profile analysis of students' motivation and outcomes in mathematics: an organismic integration theory perspective

Chee Keng John Wang[a,*], Woon Chia Liu[a], Youyan Nie[a], Yen Leng Stefanie Chye[a], Boon San Coral Lim[a], Gregory Arief Liem[a], Eng Guan Tay[a], Ying-Yi Hong[b], Chi-Yue Chiu[b]

[a] *Nanyang Technology University, National Institute of Education, Singapore*

[b] *Chinese University of Hong Kong, Hong Kong*

* Corresponding author at: Physical Education and Sports Science, National Institute of Education, 1 Nanyang Walk, Singapore 637616.

E-mail address: john.wang@nie.edu.sg (C.K.J. Wang).

Abstract

The purpose of the current study was to identify the motivation profiles at the intraindividual level using a latent profile analyses (LPA) approach. A total of 1151 secondary school students aged 13 to 17 years old from Singapore took part in the study. Using LPA, four distinct motivational profiles were identified based on four motivation regulations. Profile 1 has very low introjected and low autonomous motivation (6% of sample). Profile 2 had high external and identified regulations and very low intrinsic regulation (10%). Profile 3 consisted of students with high identified and intrinsic regulations (51%). Profile 4 had moderately low identified and intrinsic regulations (33%). The results showed that the four profiles differed significantly in terms of effort, competence, value, and time spent on math beyond homework. The best profile (Profile 3) reported highest scores in effort, value, competence and time spent on Math beyond homework. The worst profile (Profile 1) reported lowest scores in all the four outcome variables.

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1. Introduction

STEM (science, technology, engineering, and mathematics) has been always a focal point of education in many developed countries, including Singapore. This is because the role STEM plays in global economy through technological innovation, creation, and problem solving. As the world becomes more technologically advanced, there is a need to develop more skilled workforce in STEM fields. However, there is a decline in students taking STEM subjects in countries like USA (Hossain and Robinson, 2012) and UK (The Institution of Engineering and Technology, 2008), particularly amongst the 11 to 14 age group. What is even more worrying is that secondary school students in developed countries placed low value on or interest in STEM subjects (Sjøberg and Schreiner, 2005). A recent study (Skatova and Ferguson, 2014) found that undergraduate students in engineering courses tend to choose their degree based on career prospects (extrinsic motivation) but had low interest (intrinsic motivation) in the degree.

In the psychology literature, studies have shown that intrinsic motivation or interest predicts higher self-esteem, life satisfaction, creativity, and self-actualisation, relative to extrinsic motivation (e.g., Deci and Ryan, 2008; Gottfried et al., 2001; Kasser and Ryan, 1993). It is thus important to understand the motivation and interest development in STEM subjects (Krapp and Prenzel, 2011). This study focuses on mathematics because it is the only subject that is taught from the first year of elementary school in the Singapore school system as the foundation subject of STEM.

Several studies found through international assessments that intrinsic motivation, engagement, and achievement of students in their secondary school years declined in mathematics (Grades 7–10, approximately 13–16 years old; Gottfried et al., 2001; Wilson and Mack, 2014). Although Singaporean secondary students typically perform well in international mathematics assessments (OECD, 2010; Wilkins, 2004), as far as mathematics is concerned, these students are not free from psycho-educational factors (such as anxiety and self-doubt) potentially impeding their subsequent engagement and achievement in the subject (see Stankov, 2010). In addition, mathematics is an important subject that many students find difficult. Thus, mathematics is a challenging subject that is likely to trigger the distinctive motivational patterns related to student views of their ability which may manifest less strongly in situations in which perceived difficulty is low (Blackwell et al., 2007; Dweck and Leggett, 1988).

The self-determination theory (SDT) focuses on intrinsic interest or motivation as the primary driver of self-regulated learning. The theory features the needs for autonomy (the need to feel ownership of one's behavior), competence (need for

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producing desired outcomes and to experience mastery and effectiveness; Deci et al., 1991), and relatedness (the need to feel that one can relate to others and with the social world in general; Ryan, 1993) as three basic psychological needs. Transactions with the environment may lead to fulfillment or frustration of these needs. For example, the need for autonomy is satisfied when people experience choice and freedom in their actions and frustrated when they feel coerced to do certain things (Deci and Ryan, 1987).

The organismic integration theory (OIT) is one of the sub-theories of SDT to explain the process through which extrinsically motivated behaviours can be transformed into more intrinsically regulated behaviours (Ryan and Deci, 2017). That is, a process of 'internalisation' can take place if the targeted intervention is applied to individuals with different profiles (Ng et al., 2016). There are different types of motivation regulations or behavioural regulations in OIT. Intrinsically motivated individuals engage in fully regulated activities that are performed for the activities' own sake and in the absence of any external inducement. That is, the activities are carried out for the interest and pleasure the activities provide. Individuals who are not intrinsically motivated may still engage in self-regulated behavior they do not enjoy when they perceive the behavior to be important or consistent with their self-identity (identified regulation), when they have partially internalized external expectations and feel proud of being able to carry out the behavior or guilty of not being able to do so (introjected regulation), or when they will be rewarded for carrying out the behavior and punished for not doing so (external regulation; Deci and Ryan, 1985).

There are two ways to measure intrinsic motivation in the SDT framework. The most common way is to measure intrinsic motivation is through the use of self-reports of enjoyment and interest of the target activities. Intrinsic Motivation Inventory (IMI; McAuley et al., 1989) is the most commonly used questionnaire. The second way is to measure the amount of time spent on the target activity in a free-choice period (Ryan et al., 1991), such as doing or reading about Mathematics beyond homework.

Many studies have shown that the self-determined forms of motivation (intrinsic motivation and identified regulation) predict positive behavioral, cognitive, and affective outcomes, including strong interest in the activity (Grolnick and Ryan, 1987), preference for continuing the activity when given a choice, and high level behavioral engagement in the learning task (Deci and Ryan, 2008; Jang et al., 2010). Similarly, in the domain of physical education, self-determined forms of motivation predict positive affect toward sports and physical activities (Ntoumanis, 2001; Standage et al., 2003), interest in sports and physical activities (Goudas et al., 1994), the amount of effort put in these activities (Ntoumanis, 2001), and the intention to be physically active in leisure time (Standage et al., 2003). In contrast,

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non-self-determined forms of motivation are associated with less desirable outcomes, such as boredom, and negative attitudes toward physical activity and low intention to be physically active (Standage et al., 2003).

In recent years, some researchers (e.g., Chemolli and Gagné, 2014; Wang and Biddle, 2001) suggest that these behavioural regulations interact within individuals on outcome variables. That is, people can have different combinations of these regulations represent a motivation profile. Howard and his colleagues (Howard et al., 2016) argue that there is a need to examine the interaction effects of the behavioural regulations within a person. In their study, it was found that there were four motivation profiles characterised as: high levels of amotivation and average to low levels of all other regulations (Profile 1), very low levels of amotivation, external, and introjected regulation and moderate identified and intrinsic regulations (Profile 2), low levels of amotivation and moderate to high levels of other types of regulations (Profile 3), and a profile with all average levels of all regulations (Profile 4). These profiles could be differentiated with different predictors and outcomes.

Typically, there are two ways to examine the relationships between motivation types and outcome variables. The most common approach is the variable-centered approach such as regressions or structural equation modelling, which essentially differentiates variables into dependent variables and independent variables on common underlying factors, and examines the relationship between the two (e.g. Morris and Kavussanu, 2008). The other less common but increasingly popular approach is the person-centered approach, in which people are grouped together according to their responses on the constructs (e.g., Wang and Biddle, 2001).

Recently, some researchers suggest that Latent Profile Analysis (LPA) can be used to identify homogenous groups within the total sample with distinct motivation types and to use the outcome variables as covariates to examine the validity of the latent profiles (Howard et al., 2016; Wang et al., 2016). If the different profiles can be differentiated according to the outcomes, it implies that there is convergent validity of the extracted motivational profiles. Subsequently, interventions can be designed to the person's whole motivational profile, rather than on one single behavioural regulation.

1.1. The present study

The purpose of the current study was to identify subgroups of students with distinct motivation types. In addition, four outcomes (effort, value, competence, and time spent beyond homework) were used as covariates to examine the concurrent validity of the latent profiles obtained.

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Based on findings from previous studies (Howard et al., 2016; Wang et al., 2016), the following hypotheses were formulated:

H1: There will be at least four distinct profiles based on the four motivation types of SDT constructs.

H2: Different levels of motivation type will be related to different levels of effort, value, competence and time spent on Math beyond homework. Specifically, participants with more autonomous motivation will report higher effort exertion, value, competence and time spent on Math beyond homework, compared to those from more controlling motivation latent profiles.

2. Methods

2.1. Participants

Data were collected from 1151 normal stream students in five Singapore secondary schools. The sample comprised of 679 males and 444 females (28 did not state their gender), ranging from 13 to 17 years old ($M = 14.69$, $SD = .58$). Prior to the sample collection, approvals from the university's Institutional Review Board and the Ministry of Education were attained. The heads of departments for Math were then contacted to arrange for the administration of the questionnaire. Participants took about 20 min to complete the questionnaires. Before responding to the questionnaires, students provided informed consent after having been informed of the nature of the research project, that participation in the study was voluntary, that they could withdraw at any time, and that their confidentiality would be maintained.

2.2. Measures

2.2.1. Academic self-regulation scale (SRQ-A)

The Academic self-regulation scale (SRQ-A; Ryan and Connell, 1989) was employed to assess four types of behavioral regulation in the Math class. The common stem used for all items was 'I do my work in Math . . . ', followed by the items. External regulation (e.g., "because I'll get into trouble if I don't") and introjection (e.g., "because I'll feel bad about myself if I didn't") were assessed through four items each. Identification (e.g., "because it is important for me to do well in Math") and intrinsic motivation (e.g., "because Math is fun") were measured through three items each. Response for all the 14 items were given on a 7-point Likert-type scale ranging from 1 (strongly disagree) to 7 (strongly agree).

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2.2.2. *Intrinsic motivation inventory*

The effort, value and competence subscales of the Intrinsic Motivation Inventory (IMI; McAuley et al., 1989) were adapted to assess the three outcomes of student learning in Math. There are three items in effort (e.g., "I put a lot of effort in Math"), four items in value (e.g., "I believe Math can be beneficial to me"), and three items in competence (e.g., "I am good at Math"). The items were rated on a 7-point Likert-type scale ranging from 1 (strongly disagree) to 7 (strongly agree).

2.2.3. *Time spent in math beyond homework*

We used three items to capture time spent per week in school for Math lessons, homework time for Math (include tuition), and time spent on Math beyond homework in Math. In the analysis, we only use the time spent on Math beyond homework time per week as this is a behavioural indicator of intrinsic motivation in the SDT literature (Deci and Ryan, 1985). The students were asked to fill in the time in hours and minutes per week.

2.3. Data analysis

First, we conducted two confirmatory factor analyses (CFA) to examine the factor structure of the SRQ-A and IMI using EQS for Windows 6.1 (Bentler, 2006). To assess the fit of these models to the data, we used Bentler-Bonett normed fit index (NFI), Bentler-Bonett non-normed fit index (NNFI); the comparative fit index (CFI); and the mean square error of approximation (RMSEA) and its 90% confidence intervals to evaluate the adequacy of the CFA models. Values greater than .90 and .95 for the NFI, NNFI, and CFI are considered to indicate adequate and excellent fit to the data, respectively, while values smaller than .08 or .06 for the RMSEA reflects acceptable and excellent model fit (Hu and Bentler, 1999; Marsh et al., 2005). Next, the reliability coefficients (Rhos; Fornell and Larcker, 1981) of the scales were computed, and the descriptive statistics and the latent variable correlations of the main variables were tabulated.

In the main analyses, LPA using the four behavioural regulations (external, introjected, identified, and intrinsic regulations) from the SRQ-A as profile variables were conducted using Mplus 7.2 (Muthén and Muthén, 2014). Robust maximum likelihood (MLR) estimator was used and we estimated the solutions from one to eight profiles. The number of initial stage random starts was set at 10,000 with the 500 best solutions retained for final stage of the optimisations. The number of iterations was set at 1000. To obtain the best solution, we relied on the Akaike's Information Criterion (AIC), the Constant AIC (CAIC), the Bayesian Information Criterion (BIC), the sample-size adjusted BIC (SSA-BIC), and the Lo-Mendell-Rubin likelihood ratio test (LMR) as suggested by previous research (e.g., Marsh et al., 2009; Morin and Wang, 2016). For the first four indicators, a lower

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value suggests better fit. The LMR compares the estimated model (k) with a model that has one class less than the estimated model ($k - 1$). Non-significant p values support the k-1 profile model. Next, the entropy summarises the classification accuracy, ranging from 0 to 1 with higher value indicating greater accuracy. In addition, we also examined the models with number of groups that had less than 1% and less than 5% of the cases. It is suggested that solutions with small number of cases may not be feasible (Marsh et al., 2009).

After the final solution has been identified, we added the four outcomes (effort, value, competence, and time spent on Math beyond homework) to the LPA models as the distal outcomes, that is, including them as additional profiles indicators without allowing them to influence the solution (see Muthén and Muthén, 2014). The inclusion of these covariates in the model helps to limit Type 1 errors by combining analyses (e.g., Bolck et al., 2004; Marsh et al., 2009; Wang et al., 2016). Differences among the profiles in the four outcome variables were compared.

3. Results

3.1. Preliminary analyses and descriptive statistics

The results of the CFA for SRQ-A (Scaled $\chi^2 = 493.94$, $df = 63$, NFI = .923, NNFI = .902, CFI = .932, RMSEA = .079, 90% CI of RMSEA = .072 to .085) and the IMI measures (Scaled $\chi^2 = 220.76$, $df = 29$, NFI = .942, NNFI = .921, CFI = .949, RMSEA = .078, 90% CI of RMSEA = .068 to .087) revealed acceptable fit indices, supporting the factor validity of these measures. The means, standard deviations, internal reliabilities, and correlations of the main variables used in this study are presented in Table 1. The rho coefficients ranged from .71 to .91, indicating satisfactory internal reliability of all the subscales. The participants

Table 1. Descriptive Statistics and Correlations between All Variables of the Overall Sample.

	Rho	Mean	SD	1	2	3	4	5	6	7
1. External Regulation	.71	4.57	1.43							
2. Introjected	.72	4.38	1.43	.50**						
3. Identified	.85	5.60	1.31	.13**	.47**					
4. Intrinsic	.91	4.82	1.66	.01	.38**	.71**				
5. Hours	–	177.03	165.23	-.05	.05	.13**	.16**			
6. Effort	.76	5.39	1.09	-.01	.23**	.59**	.56**	.15**		
7. Value	.78	5.15	1.27	.01	.38**	.55**	.60**	.13**	.62**	
8. Competence	.79	4.01	1.43	-.01	.21**	.38**	.58**	.12**	.55**	.55**

Note. * $p < 0.05$. ** $p < 0.01$.

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scored relatively high in identified regulation, effort exertion, and values, and moderately in perceived competence and introjection. The correlations showed that identified and intrinsic regulations correlated positively with effort, value, and competence. Value and competence were positively associated with effort.

3.2. Latent profile analyses

Table 2 presents the results of the LPA. The AIC, BIC, and ABIC decreased as the number of profiles increased, but only marginally from four to eight group-solutions. The entropy values were also greater than 0.7 for all the models. The *p* values of the LMR for K versus K-1 classes were also not significant from four profiles onwards. In other words, the four or more group solutions were not significantly better than the three-group solution but the three-group solution had one profile with less than 5% of the cases. Based on all considerations, a four-group solution was considered the best.

The descriptive statistics of the four profiles are presented in Table 3. Profile 1 consisted of 5.8% of the sample and is characterised by "very low levels of introjected, identified, and intrinsic regulation". There are 62.0% male students and 38.0% female students. Profile 2 is characterised by "high external, high identified, and low intrinsic motivation, as the Z scores had indicated. There are 10.2% of the students in this profile with 57.0% male students and 43.0% female students. Profile 3 had about half of the sample (50.7%) with 58.7% males and 41.3% females. The characteristic of this profile is 'high in identified and intrinsic motivation'. Finally, profile 4 consisted of 33.2% of the sample with 63.9% boys

Table 2. Latent Profile Fit Statistics for Models Based on the Four Motivational Types.

Model	LL	Scaling	#FP	AIC	BIC	ABIC	aLMR	BLRT	Entropy	<5%
1 Profile	-7674.40	1.11	10	15368.80	15419.28	15387.52	–	–	–	–
2 Profiles	-7496.46	1.30	15	15022.91	15098.64	15050.99	≤.001	≤.001	.733	0
3 Profiles	-7399.37	1.24	20	14838.75	14939.71	14876.19	≤.001	≤.001	.851	1
4 Profiles	-7309.96	1.80	25	14669.93	14796.14	14716.73	.431	≤.001	.830	0
5 Profiles	-7260.67	1.75	30	14581.33	14732.79	14637.50	.355	≤.001	.842	2
6 Profiles	-7203.93	1.54	35	14477.86	14654.56	14543.39	.152	≤.001	.803	1
7 Profiles	-7168.56	1.42	40	14417.13	14619.06	14492.01	.119	≤.001	.817	2
8 Profiles	-7131.06	1.46	45	14352.13	14579.30	14436.37	.293	≤.001	.815	3

Note. #FP: Free Parameters; LL: Model Loglikelihood; Scaling = scaling factor associated with MLR loglikelihood estimates; AIC = Akaike's Information Criterion; BIC = Bayesian Information Criterion, ABIC = sample-size adjusted BIC; aLMR = Adjusted Lo-Mendell-and Rubin likelihood ratio test, BLRT: Bootstrap Likelihood ration Test.

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Table 3. Cluster Means, Standard Deviations, and z Scores for the Four-Profile Solution of the LPA.

Variables	Cluster 1			Cluster 2			Cluster 3			Cluster 4		
	Mean	**SD**	***Z***	**Mean**	**SD**	***Z***	**Mean**	**SD**	***Z***	**Mean**	**SD**	***Z***
3. External	4.42	1.67	-.10	5.21	1.34	.44	4.67	1.53	.07	4.25	1.15	-.22
4. Introjected	2.32	.95	-1.44	4.38	1.47	.00	4.97	1.38	.41	3.84	.94	-.38
3. Identified	2.66	.87	-2.25	6.08	.67	.37	6.54	.52	.72	4.53	.62	-.82
4. Intrinsic	1.87	1.01	-1.77	2.93	.87	-1.14	6.11	.83	.77	3.97	1.00	-.51
5. Hours	133.61	174.85	-.26	149.70	149.77	-.16	200.32	165.86	.14	157.48	162.32	-.12
6. Effort	4.04	1.13	-1.23	5.20	.99	-.17	5.95	.82	.52	4.81	.95	-.53
7. Value	3.59	1.31	-1.23	4.65	1.31	-.39	5.79	.96	.51	4.58	1.08	-.44
8. Competence	2.69	1.30	-.92	2.99	1.21	-.71	4.65	1.28	.45	3.58	1.22	-.30
Cluster characteristics												
Cluster n	67			118			584			382		
Male's n (%)	41 (62.0)			65 (57.0)			336 (58.7)			237 (63.9)		
Female's n (%)	25 (38.0)			49 (43.0)			236 (41.3)			134 (36.1)		

and 36.1% female. This profile had "low identified and intrinsic motivation" but scored moderately low in external and introjected regulations. A chi-square test using profile and gender was conducted and there were no gender difference among the profiles. The most adaptive profile should be the Profile 3, followed by Profile 2, the most maladaptive profile should be Profile 1 (see Fig. 1).

3.3. Covariates of the profiles

The four covariates were added to the final LPA model, and the results from this analysis are reported in Table 4. The results confirmed that students from Profile 3

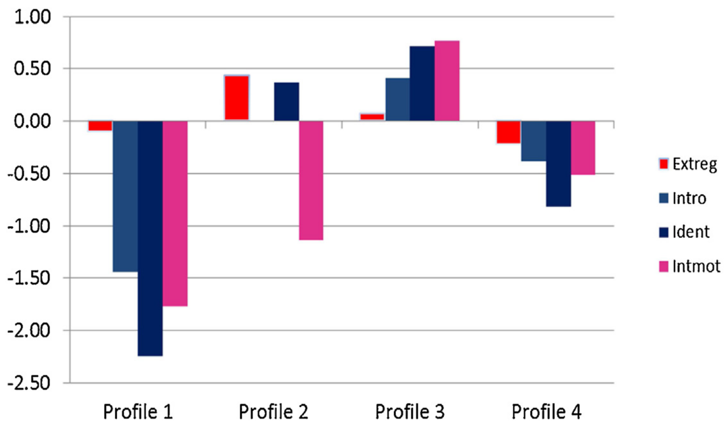

Fig. 1. Characteristics of the latent profiles on motivational regulations. (Note: The results were standardised to help in the interpretation of this histogram).

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Table 4. Relationships between LPA Membership and Outcome Variables.

Outcome	Profile 1	Profile 2	Profile 3	Profile 4	Differences between Profiles
	Mean (SE)	Mean (SE)	Mean (SE)	Mean (SE)	
Hours	133.61 (19.99)[a]	149.70 (15.06)[a]	200.32 (6.77)[b]	157.48 (8.37)[a]	3 > 4 = 2 = 1
Effort	4.04 (.11)[a]	5.20 (.08)[b]	5.95 (.04)[c]	4.81 (.05)[d]	3 > 2 > 4 > 1
Value	3.59 (.13)[a]	4.65 (.10)[b]	5.79 (.04)[c]	4.58 (.05)[b]	3 > 2 = 4 > 1
Competence	2.69 (.15)[a]	2.99 (.11)[a]	4.65 (.05)[b]	3.58 (.06)[c]	3 > 4 > 2 = 1

Note. Different superscripts in the same row indicate significant difference at $p < .05$.

had the best motivation, that is, they had the highest effort, value, competence and spent more time in doing Math beyond homework, compared to other profiles (all $ps < .05$). Profile 2 reported higher effort than Profiles 1 and 4 ($ps < .05$) and higher value compared to Profile 1 ($p < .05$). Profile 4 had higher effort and value compared to Profile 1, and higher perceived competence compared to Profiles 1 and 2. There were no differences in terms of time spent beyond homework between Profiles 1, 2 and 4. Overall, the results showed that only students with in Profile 3 with high autonomous motivation (identified and intrinsic) reported spending additional time in Math beyond homework, they also valued the subject, exerted more effort and had higher perceived competence in the subject, than all other profiles (see Fig. 2).

4. Discussion

The aim of this study was to identify distinct motivational profiles of students and how distinct these motivation profiles relate to four outcomes (effort, value, competence, and time spent on Math beyond homework). Recent studies have examined the factor structure of the four motivation types of SDT using different methodologies such as Rasch analysis (Chemolli and Gagné, 2014), Exploratory

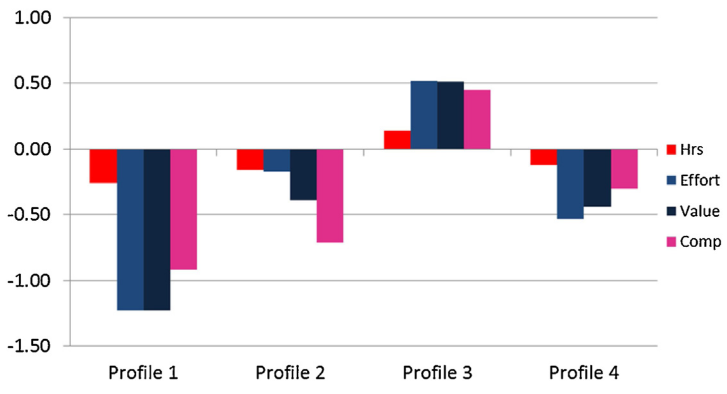

Fig. 2. Characteristics of the latent profiles on the outcomes variables. (Note: The results were standardised to help in the interpretation of this histogram).

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Structural Equation Modelling (ESEM, Gagné et al., 2015) and LPA (e.g., Morin and Wang, 2016). The latest study shows that LPA analysis is a promising approach as it could help to identify prototypical profiles of students with well-defined and clearly differentiated configurations of behavioural regulations. In addition, the convergent validity of the extracted LPA profiles could be tested with different outcome variables. This is shown in this study.

The results of the current study support the first hypothesis (H1); it has identified four distinct profiles based on the four motivation types. The most adaptive profile should be Profile 3 with half of the sample, with high identified and intrinsic motivation; this is followed by Profile 2, with high external and low intrinsic with about 10% of the students. Next, Profile 4 is characterized by low identified and low intrinsic motivation (about 33%), and the least adaptive profile is Profile 1, characterized by very low levels of introjected, identified, and intrinsic regulation (6%).

In Wang et al.'s (2016) recent study in physical education context, they found five profiles with totally different combinations of the four motivation types. They found two profiles with high external and low in other three motivation types, and one profile with distinctively high introjected motivation, and one profile with low externals and high identified and intrinsic motivation and a near zero Z score profile. The motivation profiles found in this study has no similarity to the previous study. Similarly, Howard et al. (2016) also found very different profiles in the workers from two countries (Canada and Belgium). This may suggest that motivation profiles are specific to a particular context.

In addition, introjected regulation does not seem to stand out among the four profiles. Only one profile shows introjected regulation lower than a standard score (Z) of .50 (Profile 1). The other three profiles have introjected regulation at moderate levels. Recently, there are a few studies found that introjected regulation could be related to adaptive outcomes in the exercise setting (e.g., Thøgersen-Ntoumani and Ntoumanis, 2006; Wang et al., 2016), however, this was not found in the current study. A recent meta-analysis conducted by Howard (2017) with 486 samples and 205,000 data points across five domains found that introjected regulation is not a very strong external factor using multidimensional scaling method. Specifically, it was found that introjected regulation was equidistant from both external and identified regulation on a one-dimensional model. This could explain the inconsistent findings of introjected regulation in previous studies.

The current study found that identified regulation seems to play a pivotal role in all the four profiles. Identified regulation refers to behaviour that is acted out in accordance to one's choice and values (Ryan and Deci, 2017). It is possible that Singaporean students rely on this regulation in their behaviour in Math. Although

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they see Math as an important subject and will put in effort in the subject, but, this is still considered as a form of extrinsic motivation.

It was found that about 51% of the students are in the most adaptive profile (Profile 3), these students have highest identified and intrinsic motivation towards the subject. This shows that more than half of the students are interested in the subject. This may serve as a success indicator of Mathematic teaching in Singapore. The achievements of Singapore Mathematics are well known in the world. According to the Trends in International Mathematics and Science Study (TIMSS) or Program of International Student Assessment (PISA; OECD, 2011), Singapore is one of the top achieving countries in Mathematics. There is also no gender gap in Mathematical achievement at any age. This study shows that the autonomous motivation (identified and intrinsic motivation) of the students may have a part to play in mathematical performance or vice versa. This is in line with OIT prediction that the self-determined forms of motivation (intrinsic and identified regulations) predict positive outcomes and achievement (Deci and Ryan, 2008; Grolnick and Ryan, 1987). However, it is also equally worrying that 39% of the students from Profiles 1 and 4 (5.8% and 33.2%, respectively) are not motivationally adaptive towards Mathematics. It is important to note that the students from this study are from the normal stream of the Singapore Education system. The normal stream is a 4 year secondary school programme caters for the bottom 40% of the cohort based on their performance in the Primary School Leaving Examination results. This study highlights that although Singapore may be successful in student achievement in Mathematics, there seems to be a large proportion of normal stream students at the bottom end who are not optimally motivated towards the subject.

The second hypothesis states that different motivational profiles will be related to different levels of effort, value, competence and time spent on Math beyond homework. Time spent beyond homework was used as an indicator of intrinsic motivation. The findings of the present study support this hypothesis in that participants with more adaptive motivation profiles reported higher in effort exertion, value, competence and time spent on Math beyond homework, compared to those from more less adaptive motivation profiles. Specifically, it was found that Profile 3 with high identified and intrinsic motivation is the only group that reported significantly higher on the mean scores in effort, value, competence, and time spent on Math beyond homework. Contrastingly, students from Profile 1 with the lowest introjected, identified, and intrinsic regulations reported lowest in all the four covariate outcome variables. The differences between Profiles 2 and 4 may not be that clear cut. Students in Profile 2 are those with high external, high identified, and low intrinsic motivation, they reported higher effort exertion compared to students from Profile 4, but students in Profile 4 seems to have higher competence and spent more time on Math beyond homework compared to students from Profile 2.

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These results suggest that promoting higher autonomous regulation (identified and intrinsic) is key if teachers want their students to value, feel competent, and put more effort and time into Mathematics. According to the motivational sequence proposed by Vallerand and Losier (1999), autonomous forms of motivation are the consequences of the three psychological needs (competence, autonomy, and relatedness) being satisfied (Ryan and Deci, 2017). This in turns results in positive behavioural, cognitive, and affective outcomes (Deci and Ryan, 1985; Grolnick and Ryan, 1987; Jang et al., 2010). On the other hand, controlled forms of motivation (introjected and external regulations) are due to the three basic psychological needs not being satisfied. This leads to less positive outcomes (Chemolli and Gagné, 2014; Standage et al., 2003; Wang and Biddle, 2001).

There are important practical implications for teachers to promote self-determined forms of motivation. This can be done through creating a conducive classroom using the autonomy-supportive teaching approach (Deci and Ryan, 2016). Reeve (2016) has outlined six aspects of autonomy-supportive teaching specifically to help teachers enact these instructional behaviours. These six categories are: (1) take the student's perspective; (2) vitalize inner motivational resources; (3) provide explanatory rationales for requests; (4) acknowledge and accept student's expressions of negative affect; (5) rely on informational, nonpressuring language; and (6) display patience.

As teachers plan and prepare for lessons, it is important for teachers to take the students' perspective (e.g., needs, interest, ability, progress, class dynamics). Once the lesson begins, teachers aim to vitalize their students' inner motivational resources. This can be done by increasing students' curiosity, and nurturing their needs for competence, autonomy and relatedness. Teachers need to provide strong rationale particularly for tasks that are difficult or uninteresting. During the lesson, teachers need to accept that students may display negative behaviours (disengagement, misbehavior, or poor performance) or affect (complaints, protests, negative emotion). Instead of reacting defensively to students' negative affect, teachers should accept and acknowledge these and try to communicate to their students using informational and nonpressuring language. This is important for maintaining a positive teacher-student relationship and allows students to take ownership of their learning. In order to do this, teachers need to display a lot of patience. It is only through providing students with the time and space they need to learn, will the students' intrinsic interest for the subject be ignited (Reeve, 2016). Research has shown that using this autonomy-supportive teaching approach facilitates the fulfilment of the three psychological needs, and this in turn, promotes autonomous motivation among the learners (Jang et al., 2010).

This study makes some significant contributions to the literature in the use of LPA models incorporating the use of "distal outcome" as covariates within a LPA

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model. This approach helps to reduce the type I errors by combining the analyses into one step. Secondly, this study showed that autonomous motivation is associated with effort, value, competence and intrinsically motivated behaviours. However, there are also a few limitations that need to be highlighted. Firstly, the data from this study is cross-sectional in nature and therefore causal relationships between the variables cannot be inferred. The possibility remains that the outcome variables used in this study could be the predictors of the motivation profiles. Secondly, the measurement for time spent beyond math homework was self-reported and required participants to recall time spent in the past 7 days, thus, it may include some subjectivity. There is a need for more valid, direct, and objective measures in future studies. Thirdly, this study only measures positive outcomes. There could be some negative cognition, affect, or behavioural consequences of controlling regulation. Finally, this study did not measure teachers' autonomy-support in the classroom and students' need satisfaction. If these variables are included, the motivation sequence proposed by Vallerand and Losier (1999) could be tested using structural equation modelling.

Declarations

Author contribution statement

Chee K. J. Wang: Conceived and designed the experiments; Analyzed and interpreted the data; Wrote the paper.

Woon C. Liu: Performed the experiments; Wrote the paper.

Youyan Nie: Analyzed and interpreted the data.

Yen L. S. Chye: Contributed reagents, materials, analysis tools or data; Wrote the paper.

Boon S. C. Lim, Gregory A. Liem: Performed the experiments.

Eng G. Tay: Performed the experiments; Contributed reagents, materials, analysis tools or data.

Ying-Yi Hong, Chi-Yue Chiu: Conceived and designed the experiments.

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Competing interest statement

The authors declare no conflict of interest.

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Additional information

No additional information is available for this paper.

References

Bentler, P.M., 2006. EQS for Windows (Version 6.1). Multivariate Software, Encino, CA.

Blackwell, L.S., Trzesniewski, K.H., Dweck, C.S., 2007. Implicit theories of intelligence predict achievement across an adolescent transition: A longitudinal study and an intervention. Child Dev. 78, 246–263.

Bolck, A., Croon, M., Hagenaars, J., 2004. Estimating latent structure models with categorical variables: One-step versus three-step estimators. Polit. Anal. 12, 3–27.

Chemolli, E., Gagné, J., 2014. Evidence against the continuum structure underlying motivation measures derived from self-determination theory. Psychol. Assessment 26 (2), 575–585.

Deci, E.L., Ryan, R.M., 1985. Intrinsic motivation and self-determination in human behavior. Plenum Press, New York.

Deci, E.L., Ryan, R.M., 1987. The support of autonomy and the control of behavior. J. Pers. Soc. Psychol. 53, 1024–1037.

Deci, E.L., Ryan, R.M., 2008. Self-determination theory: A macrotheory of human motivation, development, and health. Can. Psychol. 49 (3), 182–185.

Deci, E.L., Ryan, R.M., 2016. Otimizing students' motivation in the era of testing and pressure: A self-determination theory perspective. In: Liu, W.C., Wang, C.K. J., Ryan, R.M. (Eds.), Building autonomous learners: Perspectives from research and practice using self-determination theory. Springer, Singapore, pp. 9–30.

Deci, E.L., Vallerand, R.J., Pelletier, L.G., Ryan, R.M., 1991. Motivation and education: The self-determination perspective. J. Educ. Psychol. 26, 325–346.

Dweck, C., Leggett, E., 1988. A social-cognitive approach to motivation and personality. Psychol. Rev. 95, 256–273.

Fornell, C., Larcker, D., 1981. Evaluating structural equation models with unobservable variables and measurement error. J. Mark. Res. 18, 39–50.

Gagné, M., Forest, J., Vansteenkiste, M., Crevier-Braud, L., Van den Broeck, A., et al., 2015. The Multidimensional Work Motivation Scale: Validation evidence in seven languages and nine countries. Eur. J. Work Organ. Psychol. 24, 178–196.

 http://dx.doi.org/10.1016/j.heliyon.2017.e00308

Gottfried, A.E., Fleming, J.S., Gottfried, A.W., 2001. Continuity of academic intrinisc motivation from childhood through late adolescence: A longitudinal study. J. Educ. Psychol. 93, 3–13.

Goudas, M., Biddle, S., Fox, K., 1994. Perceived locus of causality, goal orientations and perceived competence in school physical education classes. Brit. J. Educ. Psychol. 64, 453–463.

Grolnick, W., Ryan, R., 1987. Autonomy in children's learning: An experimental and individual difference investigation. J. Pers. Soc. Psychol. 52, 890–898.

Hossain, M.M., Robinson, M.G., 2012. How to motivate US students to pursue STEM careers. US-China Education Review 2 (4a), 442–451.

Howard, J.L., 2017. The radex structure of motivation. Unpublished doctoral dissertation. University of Western Australia, Perth, Australia.

Howard, J., Gagne, M., Morin, A.J.S., Van den Broeck, A., 2016. Motivation profiles at work: A self-determination theory approach. J. Vocat. Behav. 95, 74–89.

Hu, L., Bentler, P.M., 1999. Curoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Struct. Equ. Modeling 6 (1), 1–55.

Jang, H., Reeve, J., Deci, E.L., 2010. Engaging students in learning activities: It is not autonomy support or structure, but autonomy support and structure. J. Educ. Psychol. 102, 588–600.

Kasser, T., Ryan, R.M., 1993. A Dark Side of the American-Dream – Correlates of Financial Success as a Central Life Aspiration. J. Pers. Soc. Psychol. 65 (2), 410–422.

Krapp, A., Prenzel, M., 2011. Research on interest in Science: Theories, methods, and findings. Int. J. Sci. Educ. 33 (1), 27–50.

Marsh, H.W., Hau, K.T., Grayson, D., 2005. Goodness of fit evaluation in structural equation modeling. In: Maydeu-Olivares, A., McArdle, J. (Eds.), Psychometrics. A Festschrift to Roderick P. McDonald. Hillsdale Erlbaum, NJ, pp. 275–340.

Marsh, H.W., Lüdtke, O., Trautwein, U., Morin, J.S.A., 2009. Classical latent profile analysis of academic self-concept dimensions: Synergy of person- and variable-centered approaches to theoretical models of self-concept. Struct. Equ. Modeling 16, 191–225.

McAuley, E., Duncan, T.E., Tammen, V.V., 1989. Psychometric properties of the Intrinsic Motivation Inventory in a competitive sport setting: A confirmatory factor analysis. Res. Q. Exerc. Sport 60, 48–58.

 http://dx.doi.org/10.1016/j.heliyon.2017.e00308

Morin, A.J.S., Wang, C.K.J., 2016. A gentle introduction to mixture modeling using physical fitness performance data. In: Ntoumanis, N., Myers, N. (Eds.), An Introduction to Intermediate and Advanced Statistical Analyses for Sport and Exercise Scientists. Wiley, UK, West Sussex, pp. 195–220.

Morris, R.L., Kavussanu, M., 2008. Antecedents of approach-avoidance goals in sport. J. Sports Sci. 26, 465–476.

Muthén, L.K., Muthén, B.O., 2014. Mplus user's guide, seventh ed. Muthén & Muthén, Los Angeles, CA.

Ng, B., Wang, C.K.J., Liu, W.C., 2016. Student motivation and learning in mathematics and science: A cluster analysis. Int. J. Sci. Math. Educ. 14 (7), 1359–1376.

Ntoumanis, N., 2001. Empirical links between achievement goal theory and self-determination theory in sport. J. Sports Sci. 19, 397–409.

Reeve, J., 2016. Autonomy-supportive teaching: What it is, how to do it. In: Liu, W.C., Wang, C.K.J., Ryan, R.M. (Eds.), Building autonomous learners: Perspectives from research and practice using self-determination theory. Springer, Singapore, pp. 129–152.

Ryan, R., 1993. Agency and organisation: Intrinsic motivation, autonomy and the self in psychological development. In: Jacobs, J. (Ed.), Nebraska symposium on motivation: Developmental perspectives on motivation, 40, University of Nebraska Press, Lincoln, Nebraska, pp. 1–56.

Ryan, R.M., Connell, J.P., 1989. Perceived locus of causality and internalization: Examining reasons for acting in two domains. J. Pers. Soc. Psychol. 57, 749–761.

Ryan, R.M., Deci, E.L., 2017. Self-deteremination theory: Basic psychological needs in motivation, development, and wellness. The Guilford Press, New York.

Ryan, R.M., Koestner, R., Deci, E.L., 1991. Ego-involved persistence: When free-choice behavior is not intrinsically motivated. Motiv. Emot. 15 (3), 185–205.

Sjøberg, S., Schreiner, C., 2005. How do learners in different cultures relate to science and technology? Asia-Pacific Forum on Science Learning and Teaching 6, 14–31.

Skatova, A., Ferguson, E., 2014. hy do different people choose different university degrees? Motivation and the choice of degree. Front. Psychol. 5.

Standage, M., Duda, J.L., Ntoumanis, N., 2003. Predicting motivational regulations in physical education: the interplay between dispositional goal orientations, motivational climate and perceived competence. J. Sports Sci. 21, 631–647.

 http://dx.doi.org/10.1016/j.heliyon.2017.e00308

Stankov, L., 2010. Unforgiving Confucian culture: A breeding ground for high academic achievement, test anxiety and self-doubt? Learn. Individ. Differ. 20 (6), 555–563.

The Institution of Engineering and Technology, 2008. Studying Stem: What are the barriers? The Institution of Engineering and Technology, Stevenage.

The Organisation for Economic Co-operation and Development, 2010. PISA 2009 results: What students know and can do-Student performance in reading, mathematics and science. OECD Publishing, France, Paris.

The Organisation for Economic Co-operation and Development, 2011. Lessons from PISA for the United States: Strong performers and successful; reformers in education. OECD Publishing, France, Paris.

Thøgersen-Ntoumani, C., Ntoumanis, N., 2006. The role of self-determined motivation in the understanding of exercise-related behaviours, cognitions and physical self-evaluations. J. Sports Sci. 24, 393–404.

Vallerand, R.J., Losier, G.F., 1999. An integrative analysis of intrinsic and extrinsic motivation in sport. J. Appl. Sport Psychol. 11, 142–169.

Wang, C.K.J., Biddle, S.J.H., 2001. Young people's motivational profiles in physical activity: A cluster analysis. J. Sport Exerc. Psychol. 23 (1), 1–22.

Wang, C.K.J., Morin, A.J.S., Liu, W.C., Chian, L.K., 2016. Predicting physical activity intention and behaviour using achievement goal theory: A person-centered analysis. Psychol. Sport Exerc. 23, 13–20.

Wilkins, J.L.M., 2004. Mathematics and Science self-concept: An international investigation. J. Exp. Educ. 72 (4), 331–346.

Wilson, R., Mack, J., 2014. Declines in high school mathematics and science participation: Evidence of students' and future teachers' disengagement with maths. Int. J. Innov. Sci. Math. Educ. 22 (7), 35–48.

 http://dx.doi.org/10.1016/j.heliyon.2017.e00308