PATTERNS OF LEARNING STRATEGIES AND THEIR ROLE IN MOTIVATION AND ACADEMIC SUCCESS IN UNDERGRADUATE MATHEMATICS

Martin Mayerhofer, Michael Eichmair, Marko Lüftenegger

University of Vienna

Learning strategies are central for self-regulated learning and linked to achievement and motivation in learning mathematics. Since learners typically use multiple strategies simultaneously, this study used a person-centered approach, identifying four distinct combinations of learning strategies used by incoming STEM students during their first semester. The resulting profiles ranged from a maladaptive profile to highly adaptive profiles. Although exam performance did not differ significantly between profiles, the descriptive differences suggested lower achievement in the least favorable profile. Self-efficacy was higher in the adaptive profiles. These findings offer first evidence that learning-strategy profiles may help explain variations in motivation and performance and may act as a starting point for further person-centered research.

INTRODUCTION

University students face a range of challenges during the transition from secondary school to tertiary education. This transition typically requires substantial changes in one's lifestyle and learning approaches to meet the demands of university. Heublein et al. (2017) have identified *problems with performance*, *lack of study motivation*, and *vocational orientation* as the main reasons for many students to withdraw from their degree programs in the fields of science, technology, engineering, and mathematics (STEM) early on. Interestingly, mathematics achievement in school does not predict achievement in the first semester of mathematics degrees at university, which can be attributed to differences in the nature of mathematics as taught in schools and as taught at university (Rach & Heinze, 2017). This requires students to adopt different learning strategies as they transition to university.

In this work, we shed light on which learning strategies might lead to higher mathematics achievement at university. Concretely, the research question in this work is the following:

Which learning strategies and combinations thereof lead to higher achievement and self-efficacy among first-semester university mathematics students?

THEORETICAL BACKGROUND

Liebendörfer et al. (2021) define *learning strategies* as behaviors and thoughts employed by learners to influence their acquisition of knowledge (p. 26). Although there are different operationalizations, their structure is largely consistent. The

2026. In H. Krzywacki, M. Hähkiöniemi, E. Haataja, M.S. Hannula & P. Hästö (Eds.). *Proceedings of the 49th Conference of the International Group for the Psychology of Mathematics Education: Research Reports*, pp. 1003-1010. PME.

dimensions typically include cognitive, metacognitive, and resource-related strategies (e.g., Wild & Schiefele, 1994). For the specific context of learning mathematics at the university level, Liebendörfer et al. (2021) developed a measurement instrument that focuses on *cognitive learning strategies* and *resource management strategies*. Cognitive learning strategies are strategies that are employed to acquire, process, and store information. They are further divided into *elaboration strategies*, *organization strategies*, and *rehearsal strategies*. Resource management strategies comprise *internal* and *external* strategies. In the school context, the *Programme for International Student Assessment (PISA)* obtained inconclusive results regarding the influence of rehearsal strategies on mathematics performance, while they identified a largely positive association between organization strategies (PISA: "control strategies") and mathematics achievement, as well as between elaboration strategies and mathematics achievement (Organisation for Economic Co-operation and Development, 2010). Also, for studying mathematics at university, elaboration strategies and organization strategies are considered crucial (Liebendörfer et al., 2021; Rach & Heinze, 2011). Learning strategies focusing on deep learning, e.g., elaboration and organization strategies, are related to higher motivation in terms of self-efficacy or self-concept (Liebendorfer et al., 2021; Ning & Downing, 2015; Vettori et al., 2020). Interestingly, in the setting of online university mathematics courses, cognitive learning strategies did not predict achievement, while management resource strategies were positively linked to academic performance (Broadbent & Poon, 2015).

Together with motivational aspects, learning strategies are key components of successful learning, which mutually reinforce each other. Motivational beliefs prompt forethought processes which mark the beginning of the cycle of using self-regulation strategies (Zimmerman, 2000). In turn, self-regulatory processes have been found to foster motivation (Zimmerman & Schunk, 2008).

The relation between particular learning strategies with motivational aspects and academic achievement has been investigated extensively in prior research. However, since students usually employ not one but several strategies varying by the degree, the current literature lacks studies that consider the interplay of learning strategies. Therefore, in this study, we aim to identify the prevalent configurations of learning strategies and their relation to mathematics achievement and self-efficacy among university freshmen in STEM fields.

We hypothesize that there is (H1) a configuration of learning strategies with more pronounced elaboration and organization strategies and less pronounced rehearsal strategies. Conversely, we hypothesize that there is (H2) a configuration of learning strategies with more pronounced rehearsal strategies and less pronounced elaboration and organization strategies. We also hypothesize that there is (H3) a balanced configuration of learning strategies with comparable levels of elaboration, organization, and rehearsal strategies. Finally, we hypothesize that profiles with more

favorable learning strategies show higher mathematics achievement (H4) and higher self-efficacy (H5).

METHODS

We conducted a repeated-measures questionnaire study to capture the learning strategies of first-year students in STEM fields at TU Wien, Austria, in September 2022, before the start of their degree program as part of a bridging course offered by the university. The second measurement point was conducted about two months into the first semester.

We surveyed the constructs used by Liebendörfer et al. (2021) capturing the three dimensions of cognitive learning strategies (elaboration, organization, rehearsal) and the two dimensions of resource management strategies (internal, external), using the same questionnaire developed and validated by these authors. All items were rated on a six-point Likert scale ranging from 1 (lowest agreement) to 6 (highest agreement). Additionally, we retrieved the results of a mathematics exam that the students took at the end of their preparatory course.

To be able to relate a configuration of several learning strategies to mathematics achievement, we employed a latent profile analysis using five indicator variables, each representing a different dimension of learning strategies. We chose *use of examples* (number of items: k = 3; sample item: “I searched for practical examples to apply the formulas.”; McDonald’s $\omega = .65$) as the scale representing elaboration strategies, *simplification* (k = 3; “To help myself memorize the material, I reduced it to essential aspects.”; $\omega = .76$) as the scale representing organization strategies, *rote learning* (k = 4; “I tried to memorize the material by repeating it several times.”; $\omega = .73$) as the scale representing rehearsal strategies, *effort when solving problems* (k = 4; “I kept thinking about the tasks, even when I got stuck.”; $\omega = .68$) as the scale representing internal resource management strategies, and *studying with peers* (k = 3; “I met other students to work together on finding solutions.”; $\omega = .85$) as the scale representing external resource management strategies.

The questionnaire study yielded answers from 487 participants. After excluding cases with values missing in all indicator variables, 479 observations remained for the data analysis. Missing values in the resulting dataset were imputed using multiple imputation with five imputation cycles following Rubin (1987). The latent profile analysis was carried out using *Mplus 8.8* following the recommendations of Yanagida (2024) to test six specified variance-covariance structures of the indicator variables to identify a model with good fit of the data. For each of these six structures (A to F), model solutions with 1 to 6 profiles were numerically computed. From the 36 models tested, those that met the necessary criteria—replication of the optimal loglikelihood value, entropy of at least 0.7 (indicating good profile separation; 0 = strong overlap, 1 = clear separation), and profile sizes of at least 5% of the sample—were considered as candidates for the final model (see Table 1). Among these candidates, the model that

showed the best fit values, i.e., lowest values in AIC, CAIC, BIC, and SABIC, was accepted as the final solution. When the optimal values in these indicators are ambiguous, preference is given to the BIC value.

Table 1: Fit indices of the models tested during latent profile analysis

#Profiles	AIC	CAIC	BIC	SABIC	Entropy
Structure A: profile invariant variances, covariances fixed to 0					
2	6486.8	6569.6	6553.6	6502.8	0.733
4	6329.7	6474.5	6446.5	6357.6	0.770
Structure B: profile varying variances, covariances fixed to 0					
3	6351.9	6517.4	6485.4	6383.8	0.766
4	6297.9	6520.3	6477.3	6340.8	0.706
Structure C: profile invariant variances and covariances					
2	6271.5	6406.0	6380.0	6297.5	0.882
3	6246.3	6411.8	6379.8	6278.3	0.855
4	**6219.3**	**6415.8**	**6377.8**	**6257.2**	**0.844**
5	6317.6	6545.2	6501.2	6361.5	0.795
Structure D: profile invariant variances, profile varying covariances					
2	6270.5	6456.7	6420.7	6306.4	0.864
Structure E: profile varying variances, profile invariant covariances					
5	6145.2	6476.2	6412.2	6209.1	0.741
Structure F: profile varying variances, profile varying covariances					
3	6180.9	6501.6	6439.6	6242.8	0.707

Note. #Profiles = Number of profiles, AIC = Akaike information criterion, CAIC = consistent AIC, BIC = Bayesian information criterion, SABIC = sample size–adjusted BIC; only profile solutions meeting the necessary criteria are listed; model in bold is the final model.

The final model was a four-profile solution with profile invariant variances and covariances and an average latent class probability of at least 0.795 in each profile, which corresponds to high probability of reliably assigning cases to their respective profiles.

To identify how strongly each profile correlates with academic achievement and self-efficacy, we computed equality tests of means for pairwise comparison of profiles following the BCH method of Bolck et al. (2004) to relate profiles to outcomes.

RESULTS

Using latent profile analysis, we identified four distinct combinations of learning strategies employed by first-semester university students. Descriptive statistics of the manifestation of the indicator variables are presented in Table 2.

Table 2: Mean values (and variances) of the indicator variables in the final profiles

Profile	Elaboration	Organization	Rehearsal	Internal Management	External Management
1	3.65 (0.83)	3.55 (0.84)	3.00 (0.59)	3.24 (0.58)	2.50 (0.61)
2	4.50 (0.83)	4.17 (0.84)	4.31 (0.59)	4.84 (0.58)	2.15 (0.61)
3	4.82 (0.83)	4.84 (0.84)	2.76 (0.59)	4.68 (0.58)	4.94 (0.61)
4	4.30 (0.83)	4.29 (0.84)	4.16 (0.59)	4.54 (0.58)	4.89 (0.61)

The profiles are shaped as follows (see Figure 1):

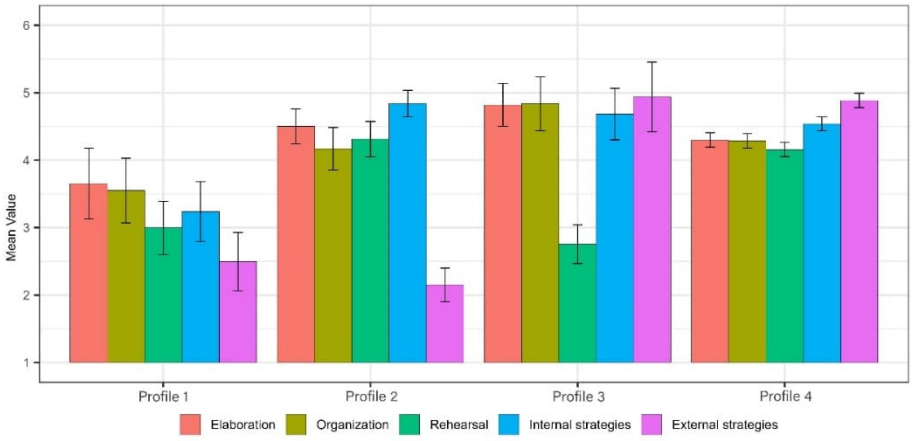
Profile 1 – Moderately regulated learners: Profile 1 has medium values in all indicator variables, with none of the variables standing out in either direction. It comprises 8.6 % of the sample.

Profile 2 – Independent strategic learners: Profile 2 has medium to high values in all indicator variables, except for low external management strategies. It describes students who have well-established learning strategies who hardly consider the help of others as beneficial to them. The profile comprises 14.3 % of the sample.

Profile 3 – Deep-processing learners: Profile 3 has medium to high values in all indicator variables, except for rehearsal strategies. It describes students who do not rely on rote learning but apply more elaborate, deep learning approaches. The profile comprises 8.1 % of the sample.

Profile 4 – Comprehensively self-regulated learners: Profile 4 has medium to high values in all indicator variables. Students with this profile consider every kind of learning strategy as relevant for them. The profile comprises 69.0 % of the sample.

Figure 1: Mean values and 95% confidence intervals of variables in the identified profiles



We also tested the relationship between the four profiles with the exam results of the students using equality tests of means across profiles using the BCH procedure. Even though the exam results do not differ statistically significantly between the profiles, a tendency that aligns with the shape of the profiles can be identified. The results of the equality tests are summarized in Table 3.

Table 3: Equality tests of means of exam results (0-1) and self-efficacy (1-6) across profiles using the BCH procedure

Profile	Exam result M (SE)	Self-efficacy M (SE)	Profile comparison	Exam result χ^2	Self-efficacy χ^2
1	0.512 (0.081)	2.760 (0.209)			
2	0.596 (0.042)	4.360 (0.179)			
			2 vs. 1	0.73	29.54***
3	0.601 (0.064)	3.515 (0.280)			
			3 vs. 1	0.72	4.63*
			3 vs. 2	<0.01	6.40*
4	0.614 (0.016)	3.564 (0.074)			
			4 vs. 1	1.47	12.61***
			4 vs. 2	0.16	16.51***
			4 vs. 3	0.04	0.03

Note. M = Mean, SE = Standard error, χ^2 = Chi-square test statistic; *** p < .001, ** p < .01, * p < .05

DISCUSSION AND CONCLUSIONS

Learning strategies play an important role in both academic success and learning motivation in mathematics at school and university; in particular, elaboration and organization strategies have repeatedly been highlighted as influential (e.g., Organisation for Economic Co-operation and Development, 2010; Liebendörfer et al., 2021; Rach & Heinze, 2011). Since learners typically do not rely on any one strategy exclusively, this work aimed to identify which *combinations* of learning strategies are applied by learners. Such an approach has so far been applied only rarely in scientific investigations of this context (Liu et al., 2014; Ning & Downing, 2015).

The latent profile analysis resulted in four distinct profiles of learning strategies. Among them, Profile 1 displayed the most maladaptive pattern. The three remaining profiles were clearly more adaptive than Profile 1 and differed qualitatively from each other, although their characteristics do not justify a hierarchical ranking of these profiles. As hypothesized (H1), one profile showed high elaboration and organization

strategies and low rehearsal strategies (Profile 3). Other than expected (H2), there was no profile with a shape complementary to Profile 3. This suggests that the predominant use of deep learning strategies (elaboration, organization) does not exclude the use of surface learning strategies (rehearsal).

Two profiles exhibited the hypothesized balanced manifestation (H3) of the three cognitive learning strategies (Profiles 2 and 4), which differ primarily in very high versus very low use of external resource management strategies. This pattern implies that external strategies may act independently from other strategies.

Exam performance did not differ statistically significantly across profiles (H4). Yet, the mean score for Profile 1 was descriptively lower than for the other profiles. It hints that the favorable profiles had higher achievement than the least favorable profile. A possible explanation for the absence of stronger differences may be the nature of the exam, which was taken at the end of the bridging course and shortly before the start of the first semester. It can therefore only be viewed as a proxy for academic achievement. Further research should examine whether clearer differences emerge when using exam results collected later in students' academic career.

In line with our hypothesis (H5), the least favorable profile also showed the lowest self-efficacy. Higher self-efficacy was seen in Profiles 3 and 4, while Profile 2 outperformed all the other profiles in self-efficacy. Since Profile 2 is the profile with the lowest external strategies, it may indicate that the high level of self-efficacy does not require these students to get external confirmation or support and could be an expression of an effective and self-guided working style preferred by these students.

Our work introduces a virtually new approach to examining the relationship between learning strategies, motivation, and academic achievement. Even though this study could not give clear and robust results in all examined aspects, the observed tendencies are consistent with theoretical expectations and the approach presented here could be used as a model for larger-scale investigations on the mechanisms of learning strategies in educational contexts.

References

Bolck, A., Croon, M., & Hagenaars, J. (2004). Estimating latent structure models with categorical variables: One-step versus three-step estimators. *Political Analysis, 12*(1), 3–27. https://doi.org/10.1093/pan/mph001

Broadbent, J., & Poon, W. L. (2015). Self-regulated learning strategies & academic achievement in online higher education learning environments: A systematic review. *The Internet and Higher Education, 27*, 1–13. https://doi.org/10.1016/j.iheduc.2015.04.007

Heublein, U., Ebert, J., Hutzsch, C., Isleib, S., König, R., Richter, J., & Woisch, A. (2017). *Zwischen Studienerwartungen und Studienwirklichkeit. Ursachen des Studienabbruchs, beruflicher Verbleib der Studienabbrecherinnen und Studienabbrecher und Entwicklung der Studienabbruchquote.* Forum Hochschule.

Liebendörfer, M., Göller, R., Biehler, R., Hochmuth, R., Kortemeyer, J., Ostsieker, L., Rode, J. & Schaper, N. (2021). LimSt – Ein Fragebogen zur Erhebung von Lernstrategien im mathematikhaltigen Studium. *Journal für Mathematik-Didaktik, 42*, 25–59.

Liu, W. C., Wang, C. K. J., Kee, Y. H., Koh, C., Lim, B. S. C., & Chua, L. (2014). College students' motivation and learning strategies profiles and academic achievement: a self-determination theory approach. *Educational Psychology (Dorchester-on-Thames), 34*(3), 338–353. https://doi.org/10.1080/01443410.2013.785067

Ning, H. K., & Downing, K. (2015). A latent profile analysis of university students' self-regulated learning strategies. *Studies in Higher Education, 40*(7), 1328–1346.

Organisation for Economic Co-operation and Development (2010). *Mathematics Teaching and Learning Strategies in PISA.* https://www.oecd.org/content/dam/oecd/en/publications/reports/2010/09/mathematics-teaching-and-learning-strategies-in-pisa_g1ghbd7b/9789264039520-en.pdf

Rach, S., & Heinze, A. (2011). Studying Mathematics at the University: The Influence of Learning Strategies. In Ubuz, B. (Ed.), *Proceedings of the 35th Conference of the International Group for the Psychology of Mathematics Education* (pp. 9–16). Middle East Technical University.

Rach, S., & Heinze, A. (2017). The Transition from School to University in Mathematics: Which Influence Do School-Related Variables Have? *International Journal of Science and Mathematics Education, 15*(7), 1343–1363. https://doi.org/10.1007/s10763-016-9744-8

Rubin, D. B. (1987). Multiple imputation for nonresponse in surveys. John Wiley & Sons. https://doi.org/10.1002/9780470316696

Vettori, G., Vezzani, C., Bigozzi, L., & Pinto, G. (2020). Upper secondary school students' conceptions of learning, learning strategies, and academic achievement. *The Journal of Educational Research, 113*(6), 475–485. https://doi.org/10.1080/00220671.2020.1861583

Wild, K. P. & Schiefele, U. (1994). Lernstrategien im Studium: Ergebnisse zur Faktorenstruktur und Reliabilität eines neuen Fragebogens. *Zeitschrift für Differentielle und Diagnostische Psychologie, 15*, 185–200.

Yanagida, T. (2024). *Querschnittliche Latent Class Modelle in Mplus.* FDZ-Frühjahrsakademie 2024, 29 February 2024.

Zimmerman, B. J. (2000). Attaining Self-Regulation: A Social Cognitive Perspective. In *Handbook of Self-Regulation* (pp. 13–39). Elsevier Inc. https://doi.org/10.1016/B978-012109890-2/50031-7

Zimmerman, B. J. & Schunk, D. H. (2008). Motivation. An Essential Dimension of Self-Regulated Learning. In D. H. Schunk, & B. J. Zimmerman (Eds.), *Motivation and Self-Regulated Learning: Theory, Research, and Applications* (1st ed., pp. 1–30). Routledge. https://doi.org/10.4324/9780203831076