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Learning strategies, self-efficacy beliefs and academic achievement of first-year preservice teachers: a person-centred approach

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Abstract
As teacher profession can be seen as a learning profession, it is crucial that teacher education equips future teachers with high-level skills to update and increase their proficiency and expertise throughout their career. In this aim, cognitive processing strategies and metacognitive regulation strategies as well as academic self-efficacy beliefs play a crucial role. This study examined Finnish first-year preservice teachers' ($N = 538$) initial learning profiles in terms of their learning strategies and self-efficacy beliefs upon entry to teacher education. Furthermore, the association between the profiles and pre-entry factors (age, written entrance exam) as well as first-year achievement was studied. The data were gathered via questionnaire from four universities and their student registers. The person-centred approach utilising a latent profile analysis was applied to identify learning profiles among preservice teachers. Three distinct learning profiles were identified: unregulated students with low self-efficacy (37.5%), average strategists with low self-efficacy (33.1%) and self-regulated and deep learners with high self-efficacy (29.4%). The first profile performed worst in the first-year studies, whereas the last profile was characterised by the oldest students and best performers in the written entrance exam. The findings expand our understanding of the initial learning profiles of preservice teachers and thus offer valuable information for teacher educators to support teaching practices and curriculum design. Practical implications of the results are discussed.

Keywords Learning profiles · Learning strategies · Processing strategies · Regulation strategies · Academic self-efficacy beliefs · Academic achievement · Preservice teachers

Introduction

At its core, the teaching profession can be seen as a learning profession, with the expectation of continuous professional development starting with initial teacher education (ITE) and extending throughout the teaching career (e.g. Blömeke et al., 2015; Metsäpelto et al., 2022a; Niemi, 2015). Thus, it is important that ITE equips students with high-level skills

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to update and increase their proficiency and expertise throughout their career. Continuous professional development builds on deep learning and metacognitive skills, which should be employed during ITE to support active knowledge building instead of relying merely on superficial memorisation. Furthermore, it is important that preservice teachers believe in their ability to absorb scientific knowledge, which forms the foundation of research-based teacher education (Metsäpelto et al., 2022a). Efficient learning strategies and academic self-efficacy beliefs help students to cope with the crowded curricula and academically demanding teacher training as well as create a basis for further professional development during training and beyond (e.g. Vilppu et al., 2022).

In this study, we investigated the individual variations between first-year preservice teachers in their learning strategies and academic self-efficacy beliefs. The person-centred approach utilising a latent profile analysis was applied to identify learning profiles among preservice teachers (e.g. Brun et al., 2022; Pyhältö et al., 2021). Furthermore, the association with the profiles and pre-entry characteristics and first-year academic achievement was examined.

Individual competencies in teacher learning and academic achievement

In this paper, we used the multidimensional adapted process model of teaching (MAP; Metsäpelto et al., 2022a) as a reference point and focus on those specific areas that can be studied at the beginning of ITE. The model is based on Blömeke et al.'s (2015) teacher competence model, which was further elevated through an expert panel's cyclical model building process. The MAP specifies the key competence domains critical to the teaching profession, for example, to support a more theoretically driven consideration of selection criteria for students' entry to teacher education. According to the model, these competence domains are individual competencies, such as knowledge, skills and other competencies underlying effective teaching, and teacher competences, such as teacher-student interaction and situation-specific skills. In this study, we focus on the area of individual competencies and, more specifically, on cognitive and metacognitive strategies and self-efficacy beliefs, which may be interpreted to reflect one's potential to successfully complete teacher education (Metsäpelto et al., 2022a).

Cognitive and metacognitive strategies In the MAP framework (Metsäpelto et al., 2022a), cognitive abilities refer specifically to higher-order thinking skills, such as reasoning, planning and comprehension of complex ideas (Bardach & Klassen, 2020). These are considered crucial both in the complex work of teachers and in university-based teacher education, where thesis studies are required. Metacognition generally refers to the ways in which individuals monitor and control their cognitive processes, and it is central to self-regulated learning (Bjork et al., 2013). A high degree of self-regulated learning is required during teacher education, for example, to be able to integrate knowledge gained from university courses and teaching experiences in practice schools, to self-evaluate one's competencies and identify one's learning needs (Endedijk et al., 2012).

To study cognitive and metacognitive strategies, we chose the learning pattern model (Vermunt & Donche, 2017; Vermunt, 1998, 2020), which captures differences in student learning and characterises their habitual approaches, methods and strategies with respect to learning (Song & Vermunt, 2021). This multidimensional model further divides learning strategies into cognitive processing strategies and metacognitive regulation strategies and focuses on their interrelations. Processing strategies are seen as those thinking activities that students use to process the subject matter, whereas regulation strategies represent the activities students use to plan, guide and monitor their cognitive learning processes (Vermunt, 2020; Vermunt & Donche, 2017).

Within processing strategies, the subdimensions of surface (or stepwise) and deep processing are distinguished (Vermunt, 2020). Surface processing is characterised by memorising and going through the materials step by step without thinking much about the relationship between units, whereas deep processing relates to trying to understand the meaning of the learning content and trying to construct a coherent whole from separate facts or views (Vermunt & Donche, 2017). Theoretically, processing strategies should lead to lower and higher achievement, respectively; however, empirical findings are often not straightforward. Deep processing usually seems to be positively but fairly weakly related to academic achievement (e.g. Donche et al., 2014; Martínez-Fernández & Vermunt, 2015; Richardson et al., 2012; Vermunt, 2005), but not always (De Clercq et al., 2013; Jansen & Bruinsma, 2005). Furthermore, the expected negative connection between surface processing and academic achievement does not necessarily appear (Donche et al., 2014; Vermunt, 2005).

Within regulation strategies of learning, Vermunt (1998) proposed a tripartite model comprising qualitatively different strategies of self-regulation, external regulation and lack of regulation. Self-regulation refers to a situation where the student actively plans, monitors and evaluates their learning, and thus takes responsibility for it. External regulation describes a situation where the responsibility for learning is given to the teacher or the learning materials, meaning it is expected that the teacher guides, monitors and structures one's learning. Learning is unregulated when neither the student nor the teacher regulates the learning or when the student experiences that external regulation is not sufficient to support their regulation of learning (Vermunt, 1998). In higher education settings where external support is very limited, self-regulation is argued to be the most appropriate strategy (Vermunt & Verloop, 1999). However, there is typically a certain distribution of work between the student and the teacher, and problems arise when the views and expectations of this distribution diverge.

The learning pattern model (Vermunt & Donche, 2017) suggests certain combinations (i.e. patterns) between the subtypes of regulation and processing strategies. For example, deep processing and self-regulation often go together in a meaning-directed learning pattern, whereas stepwise processing and external regulation are typically combined in reproduction-directed learning. Lack of regulation is a typical feature of an undirected learning pattern, which describes students who do not know well how to approach their studies. However, learning patterns are not mutually exclusive: while some students exhibit all the features of a particular pattern, others may show characteristics of two or even more patterns (Vermunt & Donche, 2017). Combinations of learning patterns have been detected among specific subgroups of students (e.g. Donche & Van Petegem, 2009; Fryer et al., 2016).

Empirical studies show that self-regulation is usually related to higher achievement, whereas a lack of regulation is especially associated with lower academic achievement (Donche & Van Petegem, 2011; Vermunt, 2005). Furthermore, older students seem to show deeper processing and self-regulation than their younger counterparts, and a higher level of prior education is associated with less surface processing and lack of regulation (Vermunt, 2005). Developmental trends have also been documented: for example, student teachers' meaning-directed learning increased over time, whereas undirected learning decreased (Donche & Van Petegem, 2009).

Academic self-efficacy beliefs As a subdimension of individual competencies, the MAP uses the concept of personal orientation to describe the continually evolving process by which a person determines and manages aspects of self, personal and motivational characteristics and one's identity as a teacher (Metsäpelto et al., 2022a). As one aspect of personal orientation, the model lists self-conceptions, such as self-efficacy, which refers to an individual's judgement of one's ability to succeed or accomplish certain tasks (Bandura, 1997). Numerous studies have shown that confidence in one's abilities and chances of success is strongly associated with performance and also promotes other related characteristics, such as intrinsic motivation, mastery goal orientation, self-regulated learning and deep-processing study strategies (see De Clecrq et al., 2017; Vantieghem et al., 2014; Willems et al., 2019).

Previous studies on preservice teachers' academic self-efficacy also show that it predicts academic performance (Nasir & Iqbal, 2019) and is positively connected with academic motivation (Bedel, 2016; Titrek et al., 2018), whereas negatively associated with procrastination behaviours (Ozer & Yetkin, 2018). Preservice teachers' academic self-efficacy beliefs have been reported to be high (Arslantas, 2021) or moderate (Aslan & Agiroglu Bakir, 2017). While the relationship between academic motivation and academic self-efficacy beliefs among preservice teachers has been studied (e.g. Bedel, 2016; Titrek et al., 2018), little is known about the interplay between learning strategies and academic self-efficacy among this group.

Context of the study: teacher education in Finland

In Finland, academic, research-based teacher education (e.g. Krokfors et al., 2011) is organised widely across the country: for example, the primary teacher education programme is offered in eight universities. To get a teacher qualification, students must complete both a Bachelor's Degree (BA; 180 ECTS, 3 years) and a Master's Degree (MA; 120 ECTS, 2 years) (except early childhood teachers, who only complete a BA). Teacher education programmes produce teachers for different levels and categories, such as primary teachers (grades 1–6), subject teachers for lower (grades 7–9) and upper secondary schools (grades 10–12) and special education teachers (see Niemi, 2015).

In Finland, teacher education programmes have been very attractive and highly competitive. For instance, around 11% of the applicants were admitted to primary teacher education programmes during the 2010s (Mankki & Kyrö-Ämmälä, 2022; University of Helsinki, 2020). Students are selected for teacher education programmes through a two-phased national admission process. The first phase focuses on students' cognitive skills and comprises either matriculation exam grades (a national examination at the end of the Finnish upper secondary school entitling candidates to continue their studies in higher education) or a national written entrance exam. Points from either of the previous are used as the basis for selecting applicants for the second phase of selection, an aptitude test comprising multiple mini-interviews targeting at the non-cognitive key competencies, such as social skills (Metsäpelto et al., 2022b). Due to recent developments, the entire two-phase admission process is similar nationwide, allowing applicants to apply to multiple teacher education programmes.

Finnish teacher education programmes are academically demanding, but they lead to professional practice (Niemi, 2015). In Finland, teachers work as independent experts and professionals with high pedagogical freedom and responsibility (Mikkilä-Erdmann et al., 2019). A unique feature in Finnish teacher education compared to many other countries is the research orientation, aimed at learning about knowledge creation, critical thinking and an evidence-based approach to teaching. Teachers are supposed to be aware of recent advances in the subjects they teach as well as the latest research on teaching and learning (Niemi, 2015). Thus, from initial teacher education onwards, efficient learning strategies and a belief in one's learning potential should be encouraged and supported.

Current study

The aim of the current study was to examine Finnish first-year preservice teachers' learning profiles in terms of the learning strategies they employ, as well as their academic self-efficacy beliefs. Thus, the aim was to map the baseline of these dynamic characteristics at the very beginning of ITE to see what kind of students are currently admitted to teacher education programmes. Instead of a more traditional variable-centred approach, we chose person-centred analyses to focus on the individuals and how they represent combinations of different variables, and not on single variables and their interrelations. Thus, our goal was to identify student groups with similar patterns of learning strategies and self-efficacy beliefs. In this aim, the person-centred approach was seen helpful, as it considers intraindividual variation in the target variables to better represent how these multiple dimensions are organised as a whole in each individual (see, e.g. Marsh et al., 2009; Pastor et al., 2007). A further aim was to explore how these profiles are connected to students' pre-entry characteristics and their first-year academic achievement.

The research questions of the study were as follows:

RQ1: Which types of profiles concerning learning strategies and academic self-efficacy beliefs can be identified in first-year preservice teachers?

Based on previous research, we hypothesized that at least three subgroups based on processing and regulation strategies would emerge, representing certain theoretically reasonable combinations. We expected a profile with high scores on deep processing and self-regulation, a profile with high scores on stepwise processing and external regulation and a profile characterised by high scores on lack of regulation (e.g. Vermunt & Donche, 2017). However, the emergence of theoretically incongruent profiles was not excluded, such as a combination of reproduction-oriented and undirected features (Vermunt & Minnaert, 2003), inconsistent combinations of regulation and processing strategies (Vermunt & Vermetten, 2004) or combinations of both external and self-regulation as well as deep and stepwise processing (Donche & Van Petegem, 2009). Furthermore, in line with Heikkilä and Lonka (2006), we expected negative connections between undirected learning and success expectations and positive associations between self-regulated, deep learning and success expectations to be reflected in the profiles.

RQ2: To what extent do these profiles differ from each other in terms of pre-entry characteristics (previous academic achievement and age)?

We expected there to be some variation between the profiles in terms of their previous study achievement and age. For example, we believed that a more academic learning profile might be associated with previous study success and that older students would be overrepresented in this profile (Donche & Van Petegem, 2011; Vermunt, 2005).

RQ3: To what extent do these profiles differ in terms of first-year achievement?

We assumed that the profiles would differ in terms of their first-year achievement in that profiles with high self-regulation and high self-efficacy beliefs would have succeeded better in their studies than groups with lack of regulation and low self-efficacy beliefs (e.g. Donche & Van Petegem, 2011; Elias & MacDonald, 2007; Vermunt, 2005).

Methods

Participants and procedure

The data of the study consisted of two data sets collected from different sources. The first data set consisted of an electronic questionnaire administered in autumn 2020 via the Finnish Teacher Education Database (FinTED), which collects and archives national data on teacher education and its baseline study focusing on admission to teacher education (FinTED 2022). This data included scales on learning strategies and self-efficacy beliefs as well as background questions and a permission to use admission scores (matriculation exam scores, written entrance exam scores) and academic achievement scores. The second data set was obtained from the student admission offices in each university and consisted of admission scores and first year academic achievement scores. Participation in the study was voluntary, and informed consent was obtained from the participants. The study did not require a Finnish ethics review, since it did not involve intervention in the physical integrity of the participants, deviation from informed consent, studying children under the age of 15 without parental consent, exposure to exceptionally strong stimuli, causing long-term mental harm beyond the risks of daily life or risking participants' security (cf. Finnish Advisory Board on Research Integrity, 2019).

A total of 538 first-year preservice teachers from four Finnish universities completed the questionnaire. Geographically, the universities represented different areas of Finland: a northern ($n=44$), a southern ($n=243$), a central ($n=179$) and a western university ($n=72$). The response rates varied between 45 and 71% in different universities, resulting in a total response rate of 55.9%. The participants represented five different teacher education programmes: early childhood teacher education ($n=245$), primary teacher education ($n=224$), special teacher education ($n=44$), craft teacher education ($n=17$) and home economics teacher education ($n=8$). The different teacher education programmes and universities have varied curricula, but typically, for example, the first year of the primary teacher degree includes basic studies in the major subject of education (25 credits), orienting teaching practice and introduction to research-oriented thinking.

Measurements

Pre-entry characteristics As part of the electronic questionnaire, the students were asked to give their year of birth as a background variable. Data concerning prior study success comprised matriculation exam grades and written entrance exam scores. The mean grade of the matriculation exam was utilised, and the following subjects were considered: mother tongue, mathematics (basic/advanced syllabus), foreign language (advanced/intermediate level syllabi) and the best grade in humanities and natural sciences. The Latin exam grades were converted to numeric values from 0 (failed test) to 7 (outstanding) (for a more detailed description, see Finnish National Agency for Education, 2022).

The written entrance exam (see Haataja et al., 2023), based on scholarly articles on education, comprised 19 multiple-choice tasks, each including several items. Applicants were awarded one point for the correct answer and a minus point for the wrong answer. The maximum score was 116 points.

Learning strategies Learning strategies were measured with an adapted and shortened version of the Inventory of Learning Styles (ILS; Vermunt, 1994, 1998). The version used was based on a previous study (Vilppu et al., 2022) on the basis of which the current version was further condensed. In this study, we included 10 items concerning processing strategies (five related to deep processing, three to stepwise processing) and 17 items concerning the regulation of learning (five related to self-regulation of the learning processes and results, four to self-regulation of learning contents, four to external regulation, and four to lack of regulation) (cf. Vermunt, 1994). Slight modifications to the wording of the items were made to improve the cultural appropriateness of the inventory. Instead of the original temporal scale (1 = almost never, …, 5 = almost always), a scale of agreement (1 = completely disagree, …, 5 = completely agree) was used.

Academic self-efficacy beliefs Preservice teachers' self-efficacy beliefs were measured with four items assessing their trust in their abilities to achieve study goals through their own efforts, derived from the IQ Learn Tool (Niemi et al., 2003). The items, such as "I can learn even the most difficult topics, if I only do my best," were evaluated using a Likert scale ranging from 1 to 5 (1 = completely disagree, …, 5 = completely agree).

First-year academic achievement Academic achievement was measured with the number of completed study credits in the first academic year and the average study grade. In Finnish universities, courses are assessed on a scale ranging from 1 (passable) to 5 (excellent). Of the 538 participants, 492 gave permission to use their academic achievement data for research purposes.

Statistical analyses

The statistical analyses proceeded in three phases and were conducted using MPlus Software version 8.4 (Muthen & Muthen, 1998–2017). First, as a preliminary analysis, we investigated the factor structure of the processing and regulation of learning scales by confirmatory factor analyses (CFA). The CFA models were estimated using weighted least squares means and variances (WLSMV) estimation, which assumes that the observed ordinal variables stem from a set of underlying latent continuous variables (Beauducel & Herzberg, 2006). In WLSMV, the estimation of missing data is handled as a pairwise deletion. The following indices of a good model fit were applied: non-significant chi-square value, a comparative fit index (CFI) and a Tucker-Lewis index (TLI) of 0.90 or above, and a root mean square error of approximation (RMSEA) and a standardised root mean square residual (SRMR) of 0.08 or below (Hu & Bentler, 1999; Little, 2003).

Next, we performed latent profile analyses (LPA; see, e.g. Muthen & Asparouhov, 2006) with freely estimated group variances (class-varying diagonal parametrisation) using students' composite scores of learning strategies based on CFAs together with their scores on self-efficacy beliefs to identify the smallest number of latent profiles that describe the variance in the target variables. Missing data were handled via the full information maximum likelihood (FIML) estimation procedure in MPlus. To determine the best solution, models with up to six latent profiles were fitted, and the model solutions were compared using the model fit information. To infer the most appropriate number of profiles, the model fit and the theoretical interpretability of the latent profiles were used. The model fit was evaluated using the log-likelihood values (log L; higher value indicates a better fit), Akaike's information criterion (AIC), the Bayesian information criteria (BIC, aBIC) (lower values indicate a better model), the Vuong-Lo-Mendel-Rubin (VLMR) and Lo-Mendell-Rubin adjusted likelihood ratio test (aLRT) and Parametric bootstrapped likelihood test (BLRT) (a significant result indicates a higher number of latent profiles). All models were estimated using the robust maximum likelihood (MLR) estimation method.

Finally, we compared the profiles in terms of pre-entry factors (prior academic achievement, written exam point and age) and first-year study success. Prior academic achievement measures (matriculation exam and written entrance exam scores) and age were considered as predictors, and thus, we examined the effect of each of these covariates on the profile classification by using 3-step approach (Asparouhov & Muthén, 2014) based on multinomial logistic regression analyses (Mplus-option: AUXILIARY IS R3STEP). Logistic regression analysis examines the relationship between independent variables and a categorical dependent variable, as well as estimates the probability of occurrence of an event (Park, 2013.) Thus, we examined whether prior academic achievement or age had an effect on the probability of belonging to certain profiles, and the impact of these variables is explained in terms of odd ratios (OR; probability of an event occurring over the probability of an event not occurring). Concerning first-year study success, the differences between groups were examined by the Bolck-Croon-Hagenaars (BCH) approach for 3-step mixture modelling with continuous distal outcomes (Mplus-option: AUXILIARY IS BCH) (e.g. Bakk et al., 2013). The BCH procedure was chosen because it implements an overall test with multiple comparisons made for class differences so that the posterior probabilities for class membership are considered. In the BCH method, chi square (x^2) distributed Wald tests are utilised.

Results

Preliminary analyses of the factor structure of learning strategies

First, we calculated descriptive statistics and correlations for each item measuring different processing and regulation strategies. Due to weak inter-item correlations and low internal consistency ($\alpha < 0.60$), the four items concerning external regulation were omitted from further analyses. To confirm the theoretical structure underlying processing and regulation strategy items, CFAs were performed. A satisfactory model fit for both processing and regulation strategy scales was yielded (processing strategies: $x^2(30) = 161.86$, $p = 0.00$, RMSEA = 0.09 (95% CI: 0.08–0.10), CFI = 0.95, TLI = 0.93, SRMR = 0.05; regulation strategies: $x^2(60) = 150.64$, $p = 0.00$, RMSEA = 0.05 (95% CI: 0.04–0.06), CFI = 0.97, TLI = 0.96, SRMR = 0.04).

Five sum scales were formed based on the tested structure, each of which showed acceptable internal reliability measured with coefficient $\alpha = 0.65$–0.80 (see Appendix). Additionally, the four items concerning self-efficacy beliefs were combined to form a sum scale of self-efficacy beliefs (SEB) ($\alpha = 0.83$).

Identifying preservice teachers' learning profiles

LPAs were conducted on standardized sum scores based on the CFA models as well as participants' standardized sum score on self-efficacy beliefs. The LPA models with up to six latent profiles were compared concerning the relative statistical fit and interpretability of the profile structure (see Table 1). In solutions with six or more classes, the class sizes became extremely small and the solutions unstable. Based on the fit indices, deciding the number of groups was not straightforward; for example, the bigger the number of groups, the smaller the log L, BIC and aBIC values, thus suggesting a larger number of groups. However, the decrease in the BIC and aBIC values evened out after the three-group solution. Additionally, entropy values were sufficient in each of the models, and VLMR and aLRT were almost statistically significant for the three- and five-group solutions. Since the fit indices did not unambiguously prove any of the solutions the best, we chose the three-group solution because it had the best interpretability on theoretical grounds, as well as satisfactory fit based on the fit indices (Marsh et al., 2009).

Learning profile interpretation

Three profiles representing different learning strategies and self-efficacy profiles were identified (Fig. 1). The first profile ($n = 202$), *Unregulated learners with low self-efficacy beliefs*, comprised students who scored rather low on deep processing and self-regulation and high on lack of regulation. They also showed less stepwise processing and lower self-efficacy beliefs than the other groups. The second profile ($n = 178$) was called *Average strategists with low self-efficacy beliefs*, since they represented the middle scores in each of the factors and were rather low in self-efficacy beliefs. The third profile ($n = 158$) represented *Self-regulated and deep learners with high self-efficacy beliefs*, since they scored high on both areas of self-regulation, deep processing, and self-efficacy beliefs. Furthermore, they had the lowest scores on lack of regulation.

We also checked the means, standard deviations and effect sizes between each profile (Table 2). All the profiles seemed to score relatively low in stepwise processing, whereas on self-efficacy beliefs, all of them scored high. According to Cohen's *d* coefficient, the differences between the profiles were quite clear in most of the targeted variables.

Connections between preservice teacher learning profiles and pre-entry factors

Next, we examined whether prior academic achievement (matriculation exam scores: $M = 4.48$, $SD = 0.95$; written entrance exam scores: $M = 60.86$, $SD = 15.51$) or age ($M = 24.19$, $SD = 7.30$) had an effect on the probability of belonging to certain profiles (see Table 3), explaining the impact in terms of ORs. According to the analyses, the odds of belonging to a certain profile group was not higher compared to other profile groups based on the success in the matriculation exam ($OR_{\text{Prof1 vs. Prof2}} = 1.02$, 95% CI [0.76, 1.38], *ns*; $OR_{\text{Prof3 vs. Prof1}} = 1.08$, 95% CI [0.81, 1.43], *ns*; $OR_{\text{Prof3 vs. Prof2}} = 1.10$, 95% CI [0.80, 1.512], *ns*). However, the odds of belonging to *Self-regulated and deep learners with high self-efficacy* compared to belonging to *Unregulated learners with low self-efficacy* was higher based on the written exam scores ($OR_{\text{Prof3 vs. Prof1}} = 1.02$,

Table 1 LPA fit indices for different numbers of profiles

N_{Profiles}	Log L	BIC	aBIC	VLMR (p)	aLRT (p)	BLRT (p)	Entropy	Size of group	Group assignment probabilities	Number of estimated parameters
1	−4517.90	9111.26	9073.16	–	–	–	–	538	1.00	
2	−4227.94	8613.07	8533.71	.43	.43	< .001	.79	341, 197	.95, .92	25
3	**−4131.71**	**8502.35**	**8381.73**	**.07**	**.07**	**< .001**	**.72**	**202, 178, 158**	**.89, .81, .92**	**38**
4	−4068.05	8456.77	8294.88	.27	.27	< .001	.76	133, 182, 137, 86	.85, .85, .91, .89	51
5	−4017.72	8437.86	8234.70	.07	.07	< .001	.79	83, 14, 161, 149, 131	.88, .85, .87, .80, .93	64
6[a]	−3998.10	8480.37	8235.94	.31	.74	.34	.79	4, 16, 84, 123, 177, 134	1.00, .63, .88., .84, .81, .93	77

BIC Bayesian information criterion; *aBIC* sample-size adjusted Bayesian information criteria, *VLMR* Vuong-Lo-Mendell-Rubin test p value, *aLRT* Lo-Mendell-Rubin adjusted likelihood ratio test, *BLRT* parametric bootstrapped likelihood ratio test. Final model is bold

[a]In six profiles model, trustworthy solution was not found (the best log likelihood value was not replicated, even with large amount of random starts)

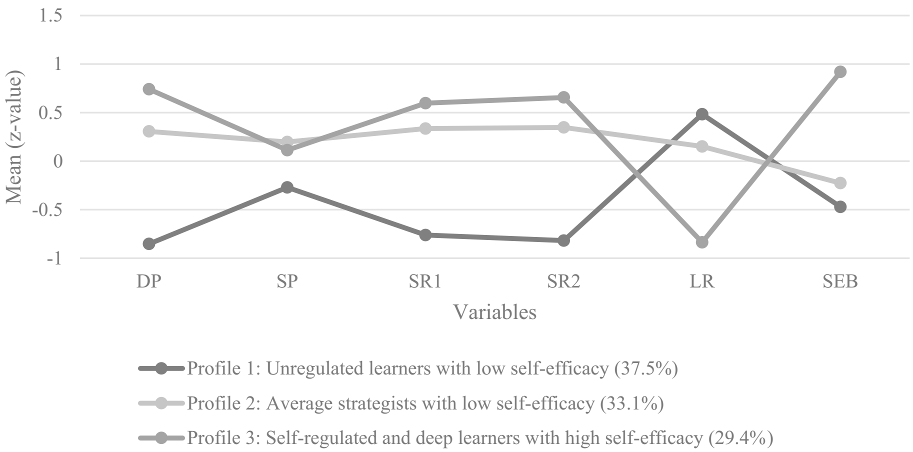

Fig. 1 Identified learning profiles among first-year preservice teachers. DP deep processing, SP stepwise processing, SR1 self-regulation of learning processes and results, SR2 self-regulation of learning contents, LR lack of regulation, SEB self-efficacy beliefs

95% CI [1.01, 1.04], $p = 0.010$), whereas between the other groups, the odds ratio did not statistically significantly differ from 1 ($OR_{Prof2\ vs.\ Prof1} = 1.01$, 95% CI [0.99, 1.03], *ns*; $OR_{Prof3\ vs.\ Prof2} = 1.01$, 95% CI [0.99, 1.03], *ns*). Thus, higher scores in the written entrance exam predicted a higher likelihood of belonging to *Self-regulated and deep learners with high self-efficacy*, meaning that one-unit increase in the written entrance exam scores increases the odds of belonging to that profile by 1.02. Additionally, the odds of belonging to *Self-regulated and deep learners with high self-efficacy* or to *Average strategists with low self-efficacy* compared to belonging to *Unregulated learners with low self-efficacy* were higher based on participant's age ($OR_{Prov3\ vs.\ Prof1} = 1.17$, 95% CI [1.08, 1.27], $p < 0.001$; $OR_{Prof2\ vs.\ Prof1} = 1.13$, 95% CI [1.03, 1.24], $p = 0.010$), whereas the odds of belonging to *Self-regulated and deep learners with high self-efficacy* compared to belonging to *Average strategists with low self-efficacy* were close to being higher ($OR_{Prov3\ vs.\ Prof2} = 1.04$, 95% CI [1.00, 1.07], $p = 0.055$).

Connections between preservice teacher learning profiles and first-year academic achievement

Finally, we studied whether the learning profiles differed in terms of first-year academic achievement, measured by the average study grade ($M = 3.80$, $SD = 0.45$) and the number of completed study credits ($M = 62.97$, $SD = 13.30$) (Table 4). In terms of the average grade, a statistically significant difference between the profiles was found ($x^2(2) = 41.52$, $p = 0.00$). Pairwise comparisons with Bonferroni-corrected *p*-values showed that *Unregulated learners with low self-efficacy* performed worse than *Average strategists with low self-efficacy* ($x^2(1) = 17.49$, $p = 0.00$) and *Self-regulated and deep learners with high self-efficacy* ($x^2(1) = 39.16$, $p = 0.00$). Similar results were obtained concerning the number of completed credits ($x^2(2) = 16.14$, $p = 0.00$). *Unregulated learners with low self-efficacy* had completed fewer study credits during the first year than *Self-regulated and deep learners with high self-efficacy* ($x^2(1) = 14.96$, $p = 0.00$).

Table 2 Means, standard deviations and effect sizes of learning strategies and self-efficacy beliefs between profiles

	Profile 1: Unregulated learners with low self-efficacy	Profile 2: Average strategists with low self-efficacy	Profile 3: Self-regulated and deep learners with high self-efficacy	Effect size	
	M (SD)	*M (SD)*	*M (SD)*	Cohen's *d*	$F(2, 535)$; p
DP	3.42 (0.49)^{a}	4.08 (0.30)^{b}	4.31 (0.35)^{c}	$d_{12}=1.60$, $d_{13}=2.05$, $d_{23}=.71$	253.11; <.001
SP	2.33 (0.85)^{a}	2.75 (0.75)^{b}	2.68 (0.92)^{b}	$d_{12}=.52$, $d_{13}=.40$, $d_{23}=.08$	14.05; <.001
SR1	2.56 (0.60)^{a}	3.42 (0.58)^{b}	3.59 (0.59)^{c}	$d_{12}=1.46$, $d_{13}=1.73$, $d_{23}=.29$	162.08; <.001
SR2	2.44 (0.61)^{a}	3.34 (0.51)^{b}	3.59 (0.62)^{c}	$d_{12}=1.59$, $d_{13}=1.87$, $d_{23}=.44$	208.43; <.001
LR	3.29 (0.67)^{a}	3.04 (0.67)^{b}	2.23 (0.58)^{c}	$d_{12}=.37$, $d_{13}=1.68$, $d_{23}=1.29$	126.75; <.001
SEB	4.08 (0.65)^{a}	4.20 (0.40)^{b}	4.90 (0.13)^{c}	$d_{12}=.22$, $d_{13}=1.66$, $d_{23}=2.30$	153.32; <.001

Different lowercase letters in the same row indicate significant difference at $p<.05$. Cohen's d 0.20 — 0.50 — 0.80: small — medium — large (Cohen, 1988). Effect sizes (d) are calculated pairwise between profiles (e.g. $d12$: effect size between profiles 1 and 2)

DP deep processing, *SP* stepwise processing, *SR1* self-regulation of learning processes and results, *SR2* = self-regulation of learning contents, *LR* Lack of regulation, *SEB* self-efficacy beliefs

Table 3 Means, standard deviations and effect sizes of pre-entry factors between profiles

	Profile 1: Unregulated learners with low self-efficacy	Profile 2: Average strategists with low self-efficacy	Profile 3: Self-regulated and deep learners with high self-efficacy	Effect size
	M (SD)	*M (SD)*	*M (SD)*	Cohen's $\|d\|$
Matriculation exam scores	4.47 (1.19)	4.45 (1.24)	4.53 (1.23)	$d_{12} = .02$, $d_{13} = .05$, $d_{23} = .07$
Written entrance exam scores	58.51 (19.91)	61.19 (19.33)	63.55 (17.21)	$d_{12} = .14$, $d_{13} = .27$, $d_{23} = .13$
Age	21.97 (5.57)	24.34 (9.53)	26.81 (9.62)	$d_{12} = .31$, $d_{13} = .64$, $d_{23} = .26$

Cohen's *d* 0.20 — 0.50 — 0.80: small — medium — large (Cohen, 1988). Effect sizes (*d*) are calculated pairwise between profiles (e.g. *d*12: effect size between profiles 1 and 2)

Table 4 Means, standard deviations, and effect sizes of first-year academic achievement between profiles

	Profile 1: Unregulated learners with low self-efficacy	Profile 2: Average strategists with low self-efficacy	Profile 3: Self-regulated and deep learners with high self-efficacy	Effect size
	M (SD)	*M (SD)*	*M (SD)*	Cohen's *d*
Average study grade	3.61 (.54)	3.87 (.55)	3.94 (.50)	$d_{12}=.48$, $d_{13}=.63$, $d_{23}=.13$
No. of completed study credits	59.79 (12.92)	63.23 (15.62)	66.77 (19.43)	$d_{12}=.24$, $d_{13}=.43$, $d_{23}=.20$

Cohen's *d* 0.20 — 0.50 — 0.80: small — medium — large (Cohen, 1988). Effect sizes (*d*) are calculated pairwise between profiles (e.g. *d*12: effect size between profiles 1 and 2)

Discussion

The aim of the study was to examine whether diverging profiles of learning strategies and academic self-efficacy beliefs could be identified among Finnish first-year preservice teachers, and whether these profiles related to the preservice teachers' pre-entry characteristics and first-year achievement. By shedding light on the initial learning profiles, we aimed to see what kind of students are currently admitted to teacher education programmes and thus raise the awareness of teacher education providers.

Instead of studying the relationships among separate variables, we chose a person-centred approach to identify groups of students based on different characteristics. Utilising LPA, our goal was to sort individual students into groups of individuals who are similar to each other and different from those in other groups (Marsh et al., 2009). This approach could also consider the fact that certain students may exhibit features from different patterns instead of the theoretically consistent combinations (Vermunt & Donche, 2017). The analyses yielded three different learning profiles which were named according to their main features.

Surprisingly, almost 40% of the students belonged to the first group, named *Unregulated students with low self-efficacy beliefs*, characterised by higher levels of lack of regulation and lower scores on other learning strategies, as well as the lowest academic self-efficacy beliefs compared to the other groups. Thus, these students experienced trouble in regulating their learning and had lower confidence in themselves than the other groups. Furthermore, their academic achievement in the first year was the worst, yet still fairly good, compared to other profiles. These students might have experienced friction between their learning strategies and the university environment (Vermunt & Verloop, 1999), for example, if more independent learning is required than the students are used to. Stress and uncertainty about the learning required in the new educational context might contribute to students experiencing a great lack of regulation in their learning (Coertjens et al., 2017). It is important to note that in line with Arslantas (2021), self-efficacy scores were rather high in each of the profiles. Since the group of unregulated learners comprised mostly students who came straight from upper secondary school and were younger than the students in other groups, their relatively low academic self-efficacy beliefs might originate from social comparison to other students: they might feel less competent than older and more experienced students.

The second largest group, *Average strategists with low self-efficacy beliefs* (33.1%), was the hardest to name, since none of the variables was clearly emphasised in their profile. These students represented quite high levels of deep processing, but also highest levels of stepwise processing compared to the other profiles. Similarly, they reported quite high levels of self-regulation but also a relatively high level of lack of regulation. Considering certain qualities, such as high levels in multiple processing strategies, this profile resembles the one of 'flexible' learning pattern (Donche & Van Petegem, 2009). However, high levels of lack of regulation deviate from their grouping and suggest another kind of labelling. Additionally, these students' self-efficacy beliefs were almost as low as those of the first group. Compared to the two other profile groups, their first-year study success was also somewhere in between.

The third profile, *Self-regulated and deep learners with high self-efficacy beliefs* (29.4%), comprised students with the most academic learning strategies: they scored the highest on self-regulation and deep processing, as well as the lowest on lack of regulation. Furthermore, they had the highest academic self-efficacy beliefs. This profile stood out from the others in terms of success in the written entrance exam and first-year study success measures in line with studies showing that self-regulation is typically associated with higher achievement, whereas lack of regulation is related to lower academic success (Donche & Van Petegem, 2011; Vermunt, 2005), and that higher levels of academic self-efficacy are related to academic success (e.g. D'Lima et al., 2014; Hsieh et al., 2007; Nasir & Iqbal, 2019). It might be that preservice teachers representing this profile had adjusted the best to the new academic environment, where self-regulated learning behaviour plays a crucial role (Van Rooij et al., 2018).

Additionally, the second and third profiles were characterised by older students compared to the first profile. Thus, beneficial learning strategies might also develop as a result of experience and maturation (Vermunt, 2005). Age and previous studies are often intertwined, in that older students have previous studies or even a bachelor's or master's degree more often. Hence, they are probably better acquainted with university studies than their younger counterparts, who come straight from upper secondary school.

It is worth noting that the data collection of the study took place during the COVID-19 pandemic, which might at least partly explain the large number of students in the first profile, *Unregulated students with low self-efficacy*. As they started in the teacher education programmes in autumn 2020, most of their studies were organised online, a format which they probably were not used to. They had limited access to university facilities and less contact with peers and teachers, while they simultaneously were exposed to more autonomy (Biwer et al., 2020). These exceptional circumstances might have disrupted their integration to the new learning environment. Use of self-regulated learning strategies have been considered an efficient way to cope with the new situation (Yeung & Yau, 2022), and positive study experiences during COVID-19 have been associated with good distance learning skills and self-directedness (Ruhalahti et al., 2021). Furthermore, sense of self-efficacy along with positive feelings towards distance learning has been reported as key factor in adapting to online learning (Cicha et al., 2021.) Thus, partly the differences in first-year academic achievement may lie in different profiles' diverse abilities to adapt to the exceptional teaching and learning arrangements due to pandemic.

Limitations

A few limitations of our study should be noted. First, the person-centred approach revealed quantitatively, but not qualitatively different profiles. While this shows that the same students may simultaneously exhibit features from different learning patterns (Vermunt & Donche, 2017), and even theoretically inconsistent combinations (e.g. Vermunt & Vermetten, 2004), in the future studies, person- and variable-centred approaches could be used simultaneously to maximize the benefits of both approaches (see Marsh et al., 2009). As LPA groups are formed to maximise the distinctiveness of the groups, some of the variance in the scores that make up those groups is probably lost (Marsh et al., 2009). Second, although our sample represents half of the teacher education units scattered around Finland, the sample is not fully representative. While the response rate was fair (55.9%), we cannot rely that it is representative of all the first-year preservice teachers in the participating universities. Third, it is important to acknowledge that some of the first-year courses, such as orienting teaching practice, are not assessed numerically, indicating that the average grade highlights more theoretical courses in the study programmes. Fourth, as the ILS (Vermunt, 1994) was developed to measure learning in higher education in general, it might overlook the domain-specific features of teacher education programmes, such as the diverse learning environments of university campuses and teacher training schools (cf. Endedijk et al., 2014). Additionally, the Cronbach alpha of one of the scales, lack of regulation, remained lower than 0.7, which is often considered desirable (Taber, 2018), and the RMSEA for processing strategies was slightly higher (0.09) than what is usually considered acceptable (<0.08) (Little, 2003). Furthermore, we recognise that due to the modifications made to the original ILS, comparisons to other studies should be made with caution.

Practical implications and future perspectives

The current study expands our understanding of the initial learning profiles of preservice teachers and thus offers valuable information for teacher educators to support teaching practices and curriculum design. Even in a highly selected group of preservice teachers, variation exists, and multiple factors might influence how they proceed in their studies. In particular, university staff teaching first-year students should not take for granted that all of them possess the required learning skills, but should pay attention to developing these skills (van Rooij et al., 2018). Although secondary education should prepare students for higher education, this is not always the case, as students may consider themselves ill-prepared for both the teaching styles and study skills required in higher education (Lowe & Cook, 2003).

The person-centred approach enables detecting students at risk to whom early interventions and support could be targeted, for example, via student counselling. The early identification of problematic profiles could be useful for preventing failure (De Clercq et al., 2017), and in the crowded curricula of teacher education programmes, this would be especially important to help students keep up with their prescheduled studies. As lack of regulation has also been associated with problems of well-being, such as relatively high levels of stress and exhaustion (Heikkilä et al., 2011, 2012), it is important to recognise these students and promote their self-regulation.

Simultaneously, it is crucial to consider the kinds of learning strategies to which students are socialised in teacher education programmes. A fruitful balance between the standards of the programmes and support should be the goal. If uncertainty about the required learning in the new environment causes high levels of lack of regulation (Coertjens et al., 2017), the requirements should be made more explicit; in addition, awareness should be raised and guidance should be given on learning strategies. While a questionnaire such as the one used in our study might function as a small, thought-provoking intervention, some scholars suggest more explicit methods, such as categorical frameworks (Ohst et al., 2015) or addressing prior knowledge concerning learning strategies (Glogger-Frey et al., 2018) to promote students' knowledge on learning. Attention should be paid to the cultivation of deep processing strategies and capacity for self-regulation, but teacher educators should also guide learners to reflect on their ways of learning as well as to increase their capacity to flexibly choose between the most appropriate way of learning in a given situation (Song & Vermunt, 2021). Clear and specific goals as well as realistic and frequent feedback should also increase students' self-efficacy beliefs (Bulfone et al., 2021).

This study shed light on preservice teachers' learning strategies and self-efficacy beliefs upon entry into teacher training, an area of research of which surprisingly little is known and which gives crucial information for the curriculum development of teacher training programmes. An important question for future studies is to examine how these competencies develop during ITE and interact with the learning opportunities offered by the programmes. Additionally, longitudinal designs should be utilised to get information on how teacher education programmes are able to respond to various students' needs and support their development as teachers.

Appendix. Processing and regulation strategy items adapted from ILS (Vermunt, 1994, 1998)

Processing strategy scales

1. Deep processing ($\alpha = 0.80$)

   2. I try to combine the subjects that are dealt with separately in a course into one whole.
   9. I try to see the connection between the topics discussed in different chapters of a textbook.
   13. I compare the conclusions drawn in different chapters.
   17. I try to construct an overall picture of a course for myself.
   22. I try to apply what I learn from a course in my activities outside my studies.
   27. I relate specific facts to the main issue in a chapter or article.

2. Stepwise processing ($\alpha = 0.74$)

   3. I memorize lists of characteristics of a certain phenomenon.
   21. I make a list of the most important facts and learn them by heart.
   26. I repeat the main parts of the subject matter until I know them by heart.

Regulation strategy scales

1. Self-regulation of learning processes and results ($\alpha = 0.73$)

   8. To test my own learning, I try to describe the content of a chapter in my own words.
   16. When I start reading a new chapter or a complex whole of issues, I first think about the best way to study it.
   20. To test my learning progress, I try to answer questions about the subject matter which I make up myself.
   23. To test my learning when I have studied a text book, I try to formulate the main points in my own words.
   25. To test whether I have mastered the subject matter, I try to think up other examples besides the ones given in the study material or at the lecture.

2. Self-regulation of learning contents ($\alpha = 0.74$)

   If I do not understand a study text well, I try to find other literature about the subject concerned.
   6. In addition to the syllabus, I study other literature related to the content of the course.
   15. I add something to the subject matter from other sources.
   19. I do more than I am expected to do in a course.

3. Lack of regulation ($\alpha = 0.65$)

4. It is difficult for me to determine whether I master the subject matter sufficiently.
11. I miss someone, for example a tutor, to fall back on in case of difficulties with my studying.
14. The objectives of the course are too general for me to offer any support.
24. I have trouble processing a large amount of subject matter.

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Data Availability Raw data of the study are not publicly available to preserve individuals' privacy under the European General Data Protection Regulation.

Declarations

Competing interests The authors declare no competing interests.

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Current themes of research:

Learning and teaching in higher education contexts. Teacher professional development.

Most relevant publications:

Vilppu, H., Mankki, V., Lähteenmäki, M., Mikkilä-Erdmann, M., & Warinowski, A. (2022). Debunking the myth of high achievers in Finnish primary teacher education: first-year preservice teachers' study profiles and study success. *European Journal of Teacher Education*, https://doi.org/10.1080/02619768.2022.2047175

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Current themes of research:

Application of quantitative research methods in behavioral sciences, e.g. statistical multivariate methods, structural equations models, statistical computing.

Most relevant publications:

Yang, W., Laakkonen, E., & Silvén, M. (2022). Closeness, conflict, and culturally inclusive pedagogy: Finnish pre- and in-service early education teachers' perceptions. Frontiers in Psychology, 13. https://doi.org/10.3389/fpsyg.2022.834631

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Current themes of research:

Co-constructing mathematics motivation in primary education. Functional numeracy assessment.

Most relevant publications:

Peixoto, F., Radišić, J., Krstic, K., Hansen, K., Laine, A., Baucal, A., Sörmus, M. & Mata, L. (accepted). Contribution to the validation of the expectancy-value scale for primary school students. Journal of Psychoeducational Assessment.

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Current themes of research:

Children. Leisure reading. Family literacy.

Most relevant publications:

Vilppu, H., Mankki, V., Lähteenmäki, M., Mikkilä-Erdmann, M., & Warinowski, A. (2022). Debunking the myth of high achievers in Finnish primary teacher education: first-year preservice teachers' study profiles and study success. European Journal of Teacher Education, https://doi.org/10.1080/02619768.2022.2047175

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Lähteenmäki, M., Hakyemez-Paul, S., & Pihlaja, P. (2019). Formal and informal sources of paternal support in early parenthood. *Early Child Development and Care, 189*(11), 1786–1799. https://doi.org/10.1080/03004430.2017.1412956

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Current themes of research:

Processes of teaching and learning. Teachers' professional development from student selection phase to teacher education and working life. Children and youth with externalizing and internalizing problems.

Most relevant publications:

Metsäpelto, R-L., Utriainen, J., Poikkeus, A-M., Muotka, J., Tolvanen, A., & Warinowski, A. (2022). Multiple Mini Interview in student selection for initial teacher education admissions. Teaching and Teacher Education, 113. https://doi.org/10.1016/j.tate.2022.103660

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Haataja, E., Tolvanen, A, Vilppu, H., Kallio, M., Peltonen, J., & Metsäpelto., R.-L. (Manuscript in press). Measuring higher-order cognitive skills with multiple choice questions - Potentials and pitfalls of Finnish teacher-education entrance. *Teaching and Teacher Education.*

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Current themes of research:

Research-based teacher training. Science literacy. Text comprehension processes.

Most relevant publications:

Vilppu, H., Mankki, V., Lähteenmäki, M., Mikkilä-Erdmann, M., & Warinowski, A. (2022). Debunking the myth of high achievers in Finnish primary teacher education: first-year preservice teachers' study profiles and study success. European Journal of Teacher Education, https://doi.org/10.1080/02619768.2022.2047175

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Current themes of research:

Teacher education. Teacher competencies. Student selection. Family studies. International mobility.

Most relevant publications:

Metsäpelto, R-L., Utriainen, J., Poikkeus, A-M., Muotka, J., Tolvanen, A., & Warinowski, A. (2022). Multiple Mini Interview in student selection for initial teacher education admissions. Teaching and Teacher Education, 113. https://doi.org/10.1016/j.tate.2022.103660.

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