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Replicability and stability of self-regulated learning profiles of teacher education students

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A R T I C L E I N F O

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A B S T R A C T

Self-regulated learning (SRL) is essential for preservice teachers, who have to manage their own learning and foster SRL in their future pupils. Despite its complexity, SRL has rarely been studied using person-centered approaches in teacher education, and existing findings are seldom replicated or tested for stability. This study addresses these gaps by (1) replicating previously validated SRL profiles, covering all three SRL phases, in a face-to-face context ($N = 383$), and (2) examining their temporal stability over one semester ($N = 90$). Latent profile analysis confirmed five distinct profiles: process-oriented competent, preaction-volitional competent, action-cognitive competent, repetitive-low reflective, and avoiding-unreflective learners. Across the semester, 51.11% of participants moved into more competent profiles, 33.33% remained stable, and 15.56% shifted to less competent profiles. The results highlight substantial heterogeneity in SRL competencies among preservice teachers and underscore the relevance of longitudinal, profile-based approaches. Implications for differentiated support strategies and professional development in teacher education are discussed.

1. Introduction

Self-regulated learning (SRL) is a complex construct composed of a variety of interacting variables (e.g., Schmitz & Schmidt, 2007; Zimmerman, 2000). As a result, learners differ substantially in their learning prerequisites. These differences are difficult to capture using traditional variable-centered statistical approaches. In contrast, person-centered approaches allow for the identification of subpopulations within a larger population, so-called profiles, that are internally homogeneous and meaningfully distinct from each other (Wang & Wang, 2019). These profiles offer a systematic perspective on learners' characteristic constellations, highlighting diverse levels of competence and developmental potential in SRL. Consequently, such insights can form a foundation for designing differentiated support strategies tailored to the specific needs of learners (Dörrenbächer & Perels, 2016; Tetzlaff et al., 2023).

A growing body of research confirms that SRL competencies are central to students' academic success (e.g., Dent & Koenka, 2016; Theobald, 2021). However, Parpala et al. (2022) have shown that SRL profiles vary across academic disciplines, which calls into question the generalizability of findings across student populations. There is thus a pressing need for studies that focus specifically on preservice teachers, who are not only responsible for regulating their own learning but are also expected, in their future professional roles, to diagnose and foster SRL among their pupils (Michalsky & Schechter, 2013).

Teachers with stronger SRL competencies are more successful in promoting SRL in their students (Shahmohammadi, 2014) and can serve as important role models in this regard (Kramarski & Michalsky, 2009). A detailed understanding of the SRL profiles of preservice teachers, including their strengths and developmental needs, is therefore especially relevant for the early and targeted promotion of such competencies (Barz et al., 2024).

Despite the importance of this topic, only a few studies have applied person-centered approaches, such as latent profile analysis (LPA), to investigate SRL among preservice teachers (e.g., Schel & Drechsel, 2025b; Barz et al., 2024; Heikkilä et al., 2012; Muwonge et al., 2020). Moreover, the majority of LPA models in the literature is not replicated (Spurk et al., 2020), which poses a challenge for assessing the validity and generalizability of identified profiles across different educational contexts (e.g., online versus face-to-face learning; Bettis et al., 2016; Hertel et al., 2024). Additionally, replication within the same sample over time is needed to determine the stability of profiles, particularly in the light of the professional development that preservice teachers undergo throughout their studies.

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To address these gaps, the present study builds on previously validated SRL profiles of preservice teachers (Schel & Drechsel, 2025b), which were linked to learning outcomes and achievement goal orientations. Specifically, the study addresses the following research questions:

1. Can SRL profiles identified during online learning (due to the pandemic) be replicated in a new sample of preservice teachers engaged in face-to-face learning?
2. How stable are these SRL profiles within a single cohort of preservice teachers over the course of one academic semester?

2. Theoretical framework

2.1. Person-centered approaches to self-regulated learning in (teacher education) students

Self-regulated learning (SRL) is defined as "an active, constructive process whereby learners set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behavior, guided and constrained by their goals and contextual features in the environment" (Otto et al., 2011, p. 34). As a multidimensional and complex construct, SRL comprises a wide range of interrelated variables (e.g., Boekaerts, 1999; Schmitz & Schmidt, 2007). Consequently, the parameters selected for latent profile analyses (LPAs) in person-centered SRL research can vary significantly across studies, which can result in divergent profile models.

Despite these variations, most LPA studies on SRL among higher education students tend to identify models with three (e.g., Bouchet et al., 2013; Heikkilä et al., 2012; Jeong & Feldon, 2023; Li et al., 2020; Muwonge et al., 2020; Räisänen et al., 2016; Vanslambrouck et al., 2019) or four profiles (e.g., Dörrenbächer & Perels, 2016; Fryer & Vermunt, 2018; Liu et al., 2014; Ning & Downing, 2015) as best fitting the data. Many of these studies primarily focus on quantitative differences (e.g., low, average, and high SRL competencies) between students (e.g., Dörrenbächer & Perels, 2016; Fryer & Vermunt, 2018; Muwonge et al., 2020; Vanslambrouck et al., 2019).

Other studies also emphasize qualitative differences in SRL profiles, revealing that students with high SRL competencies tend to use deep learning strategies (e.g., Heikkilä et al., 2012; Parpala et al., 2022; Schulz et al., 2014), engage in reflective practices such as self-testing, and actively regulate their learning processes (e.g., Bouchet et al., 2013; Hong et al., 2020; Li et al., 2020). These learners are less dependent on co-regulation from others (Räisänen et al., 2016) and more likely to set adaptive and personalized learning goals (Bouchet et al., 2013).

Given the complexity of SRL, the diversity in parameter selection, and variation in student samples (e.g., across degree programs, cultural contexts, and learning environments), the profiles identified in existing studies reflect different emphases. Nevertheless, findings consistently demonstrate substantial heterogeneity in SRL competencies among higher education students.

This heterogeneity is particularly relevant in the context of teacher education, where SRL is doubly important: preservice teachers must regulate their own learning and also foster SRL in their future classrooms. Despite this dual relevance, person-centered studies on SRL in teacher education remain scarce (e.g., Barz et al., 2024; Michalsky & Schechter, 2013; Muwonge et al., 2020; Vanslambrouck et al., 2019), highlighting the need for further research in this population.

To date, only a limited number of person-centered studies have been conducted specifically with preservice teachers. Heikkilä et al. (2012) examined 213 preservice teachers in Finland and identified three SRL profiles: *non-regulating*, *self-directed*, and *non-reflective* learners. Among them, *self-directed* learners (28%) demonstrated the highest academic achievement, optimism, and regulatory skills, reported the lowest levels of exhaustion, and predominantly used deep rather than surface learning strategies. *Non-regulating* learners (50%) showed the greatest lack of regulation, low interest in their studies, high avoidance, and the lowest levels of optimism and well-being. *Non-reflective* learners (22%) were characterized mainly by a low use of deep strategies and displayed average scores across most other measured parameters.

Similarly, Muwonge et al. (2020) identified three quantitatively differentiated SRL profiles in a sample of 527 preservice teachers in Uganda: low (12.5%), average (39.7%), and high SRL competencies (47.8%). Students with high SRL competencies showed the greatest academic success and learning motivation. In a German sample of 141 preservice teachers, Barz et al. (2024) also found three profiles that differed quantitatively in their self-reported use of learning strategies and their declarative knowledge of SRL, classified as low, moderate, and high.

Together, these studies highlight both quantitative (Barz et al., 2024; Muwonge et al., 2020) and qualitative (Heikkilä et al., 2012) differences in SRL among preservice teachers. Consistent with findings from other academic disciplines, preservice teachers with high SRL competencies tend to show beneficial associations with academic achievement, motivation, and well-being. However, it is important to note that the SRL parameters used in these person-centered analyses varied across studies, and the samples were drawn from diverse cultural and educational contexts. Despite these differences, the findings consistently point to significant heterogeneity in SRL competencies among preservice teachers. Nevertheless, the overall body of person-centered research in this population remains limited.

Moreover, across all disciplines, only one study was identified that attempted to replicate its SRL profiles in an independent sample. Barnard-Brak et al. (2010) conducted a latent class analysis to replicate previously identified SRL profiles of students from 22 different degree programs in online learning contexts. Their LPA was based on Zimmerman's (2000) three-phase model of SRL (forethought, performance, and reflection) and included the following parameters: structuring the learning environment, goal setting, time management, help-seeking, task strategies, and self-evaluation. Five distinct SRL profiles were successfully replicated with similar distribution patterns across two independent samples: *non- or minimal self-regulators* (22% and 19%, respectively), *performance/reflection self-regulators* (12% and 6%), *forethought-endorsing self-regulators* (16% and 15%), *competent self-regulators* (41% and 39%), and *super self-regulators* (9% and 20%). *Super self-regulators* demonstrated the highest competencies across all SRL dimensions, while *competent self-regulators* also exhibited strong but slightly lower competencies. In contrast, *non- or minimal self-regulators* showed the lowest values on all parameters. *Forethought-endorsing self-regulators* were particularly strong in the planning phase, such as goal setting and organizing their learning environment. *Performance/reflection self-regulators*, on the other hand, showed strengths in the action and reflection phases of SRL.

In summary, these findings emphasize that (a) university students, including those in teacher education, exhibit substantial quantitative and qualitative heterogeneity in their SRL competencies. The differences in LPA models across studies are primarily due to variation in parameter selection, stemming from the inherent complexity of the SRL construct and contextual differences in study design. (b) The existing body of person-centered research on SRL in preservice teachers is still limited, but current findings underscore the relevance of exploring this heterogeneity in greater depth. (c) Across all disciplines, only one study has attempted to replicate its SRL profiles in a separate sample, pointing to a significant gap in replication research. There is a clear need for further studies that replicate and validate SRL profiles across contexts and populations to empirically strengthen their validity and applicability.

2.2. Stability of self-regulated learning profiles in higher education

Longitudinal studies have generally shown that students' SRL competencies tend to increase over the course of their studies (Higgins et al., 2023). This development has been attributed to students' adaptation to the demands of the higher education environment (e.g., autonomous preparation, critical thinking) as well as to increasing cognitive differentiation regarding academic content. Such positive trends in SRL development can be further enhanced through targeted interventions (e.g., Wibrowski et al., 2017). Person-centered analyses across multiple time points within the same sample can provide insights into both the natural stability of latent profile models and their sensitivity to interventions.

However, research on SRL profile stability suggests that students from different profiles may show varying developmental trajectories. Li et al. (2020), using longitudinal cluster analysis, identified three distinct SRL development patterns based on task-related regulation: *minimally engaged* learners (stable, focused on observation), *reflective-oriented* learners (stable, focused on evaluation), and *adaptive* learners (variable, demonstrating a balance between observation and evaluation).

Fryer and Vermunt (2018) investigated the stability of four SRL profiles in a sample of 933 Japanese students using latent transition analysis over an eight-month period. Their results revealed substantial differences in profile stability: *low quality* learners remained the most stable (90%), followed by *average* (93%), *high quantity* (72%), and *low quantity* (40%). Notably, the most deficient profile (*low quality*) proved particularly stable, while students in the *low quantity* profile demonstrated the greatest variability. This instability may reflect an initial orientation phase during the transition to the demands of higher education. Interestingly, no profile characterized by high-quality strategy use emerged in their sample, and only a small number of students ($n =$ 47) moved into more sophisticated SRL profiles, while 69 students regressed to profiles with fewer learning strategies. The authors attribute this to the lack of structured support for SRL in university environments.

Jeong and Feldon (2023) examined SRL profile stability in the context of an SRL intervention during one academic semester. They found that *competent regulators*, who already had high SRL competencies, remained most stable, whereas *self-confident regulators* and especially *goal-oriented regulators* showed greater variability. The latter group, particularly those with strong learning goal orientations, demonstrated the most significant SRL improvement. Similarly, Dörrenbächer and Perels (2016) found that students with moderate SRL competencies but high motivation benefited the most from SRL interventions.

These findings underscore the importance of differentiated SRL support, as profiles vary in their sensitivity to such measures. Interventions that include individualized feedback have proven particularly effective in addressing specific weaknesses within SRL profiles and supporting transitions into more competent learner profiles (e.g., Esnaashari et al., 2023; Lau et al., 2017).

In summary, students assigned to different SRL profiles demonstrate distinct developmental patterns, both naturally and in response to interventions. A minimum level of SRL competence, along with sufficient motivation, appears to be necessary for students to benefit meaningfully from academic experiences and SRL training programs. To date, no studies have been found that specifically investigate the natural development of SRL profiles among preservice teachers, despite the fact that their curriculum often includes explicit content on SRL. However, Barz et al. (2024) explored the development of SRL competencies in preservice teachers across different SRL profiles as a function of interventions in different learning environments (synchronous vs. asynchronous), as outlined in the following section.

2.3. Self-regulated learning in different instructional contexts (online vs. face-to-face learning)

Self-regulated learning (SRL) has been consistently identified as a significant predictor of academic success in both face-to-face and online learning environments (e.g., Hemmler & Ifenthaler, 2024; Xu et al., 2022; Zhao et al., 2025). However, SRL competencies are considered particularly critical in online settings, where learning environments are typically less structured by instructors and direct interactions are limited or entirely absent. In such contexts, students are required to take greater personal responsibility for managing their learning processes (Kizilcec et al., 2017; Xu et al., 2022). As a result, learners in online settings rely more heavily on the proactive application of learning strategies.

Consistent with this assumption, Broadbent (2017) found that students used self-regulated learning strategies more frequently in online learning environments than in blended learning settings. Exceptions to this pattern were the strategies of help-seeking and peer learning, which were employed less frequently in online contexts due to restricted opportunities for interpersonal interaction. In both environments, elaboration strategies and time management emerged as particularly important predictors of academic success, while repetition-based strategies were found to be least effective, similar to findings from purely face-to-face contexts.

In a study by Barz et al. (2024), a targeted SRL intervention among preservice teachers was found to be equally effective in promoting the use of learning strategies in both synchronous (face-to-face) and asynchronous (online) formats. Specifically, preservice teachers with low or moderate SRL competencies benefited most from the intervention. However, the learning environment had a differential impact on gains in declarative knowledge about SRL, with students in asynchronous formats demonstrating significantly higher improvement. The authors attributed this finding to the greater flexibility of asynchronous learning, which allowed students more time to engage with the content in depth. In particular, preservice teachers with moderate to high SRL competencies benefited most from asynchronous instruction, as these learners were better equipped to independently acquire knowledge.

Despite these promising results, there remains a notable lack of studies that systematically examine SRL profiles across different learning environments (Vanslambrouck et al., 2019).

2.4. Profiles of preservice teachers' self-regulated learning in the present study

The present study investigates profiles of preservice teachers' self-regulated learning (SRL) using latent profile analysis (LPA). The analysis incorporated parameters from all three phases (preaction, action, and postaction) of the process model of SRL proposed by Schmitz and Schmidt (2007), which extends Zimmerman's (2000) model. The identified learning profiles were previously validated in relation to learning achievement and goal orientations among $N = 240$ preservice teachers (Schel & Drechsel, 2025b). For the LPA, 12 parameters were selected to capture SRL competencies as systematically and comprehensively as possible (see also Jeong & Feldon, 2023). Parameters from each phase were chosen primarily based on evidence from meta-analyses highlighting their relevance for learning success (see Table 1).

In line with Barnard-Brak et al. (2010), who also based their parameter selection on Zimmerman's (2000) process model, five distinct learning profiles emerged. These profiles showed conceptual similarities to those reported by Barnard-Brak et al. (2010; see Fig. 1). For example, Schel and Drechsel (2025b) identified a *preaction–volitional competent* profile, characterized by strong competencies in the preaction phase (goal setting and planning) and the volitional phase (self-initiated control and positive self-motivation). This profile closely resembles *forethought-endorsing regulators* and is further associated with comparatively high use of resource-oriented strategies (learning environment structuring and, in particular, concentration).

Another profile, *action–cognitive competent*, displayed pronounced competencies in cognitive learning strategies, especially deep-level strategies such as organization, elaboration, and critical evaluation, similar to *performance/reflection self-regulators*. This profile also exhibited relatively high postaction competencies (monitoring and regulation), suggesting extensive reflection on the learning process.

A third profile, labeled *process-oriented competent*, demonstrated the

Table 1
Overview of parameter selection for the present LPA (Schel & Drechsel, 2025b).

Parameter	Empirical references
Preaction	
Goals and planning Self-efficacy expectation	Zhao et al. (2025); Hemmler and Ifenthaler (2024); Qi et al. (2024); Kocsis and Molnár (2024); Theobald (2021); Donker-Bergstra et al. (2014); Sitzmann and Ely (2011)
Action	
Volitional	
Initiation control Positive self-motivation	Justus (2017); Dörrenbächer and Perels (2015); Schutte et al. (2015); Sansone et al. (2011)
Cognitive	
Organization Elaboration Critical examination Repetition	Zhao et al. (2025); Hemmler and Ifenthaler (2024); Muwonge et al. (2020); Neroni et al. (2019); Räisänen et al. (2016); Dörrenbächer and Perels (2016); Richardson et al. (2012)
Resource-oriented	
Concentration (internal) Learning environment (external)	Zhao et al. (2025); Hemmler and Ifenthaler (2024); Preböck and Annen (2021); Lörz et al. (2020); Aeppli (2005); Boerner et al. (2005)
Postaction	
Control Regulation	Zhao et al. (2025); Hemmler and Ifenthaler (2024); Guo (2022); Theobald (2021); Donker-Bergstra et al. (2014); Glogger et al. (2012)

highest scores across all assessed parameters, comparable to *super* or *competent self-regulators*. In contrast, the profile of *non-/minimal self-regulators* differentiated into two qualitatively distinct, lower-performing profiles: *avoiding–unreflective* and *repetitive–low reflective*. The latter group reported frequent use of repetition as a cognitive strategy, whereas the former, showing the lowest scores across all parameters, reported isolated competence in deriving connections (elaboration strategy).

Validation results indicate that *process-oriented competent* learners achieve the highest learning success and exhibit the most favorable goal orientations, followed by *preaction–volitional competent*, *action–cognitive competent*, *repetitive–low reflective*, and finally *avoiding–unreflective* learners. More competent profiles were associated with higher mastery and performance goal orientations, whereas less competent profiles tended toward performance-avoidance orientations (Schel & Drechsel, 2025b).

Compared to the LPA findings of Heikkilä et al. (2012), *process-oriented competent* learners resemble *self-directed learners*, who also display high achievement, strong self-regulation, and extensive use of deep-level cognitive strategies. *Non-regulating learners* share characteristics with *avoiding–unreflective* learners, including avoidance of engagement with the learning process, generally low SRL competencies, and low interest in their studies (comparable to low mastery orientation). *Non-reflective learners*, characterized by reliance on surface-level cognitive strategies, show parallels to *repetitive–low reflective* learners.

Consistent with Barz et al. (2024) and Muwonge et al. (2020), the present study differentiates profiles with low (*avoiding–unreflective*, *repetitive–low reflective*), moderate (*action–cognitive competent*, *preaction–volitional competent*), and high SRL competencies (*process-oriented competent*). However, these profiles also differ qualitatively in their competencies and developmental potential.

As in Barnard-Brak et al. (2010), data for the present LPA were collected in the context of purely online teaching. Open questions remain regarding whether these SRL profiles can be replicated in a more recent sample of preservice teachers in face-to-face teaching contexts, and the extent to which they remain stable over time (see also Bettis et al., 2016).

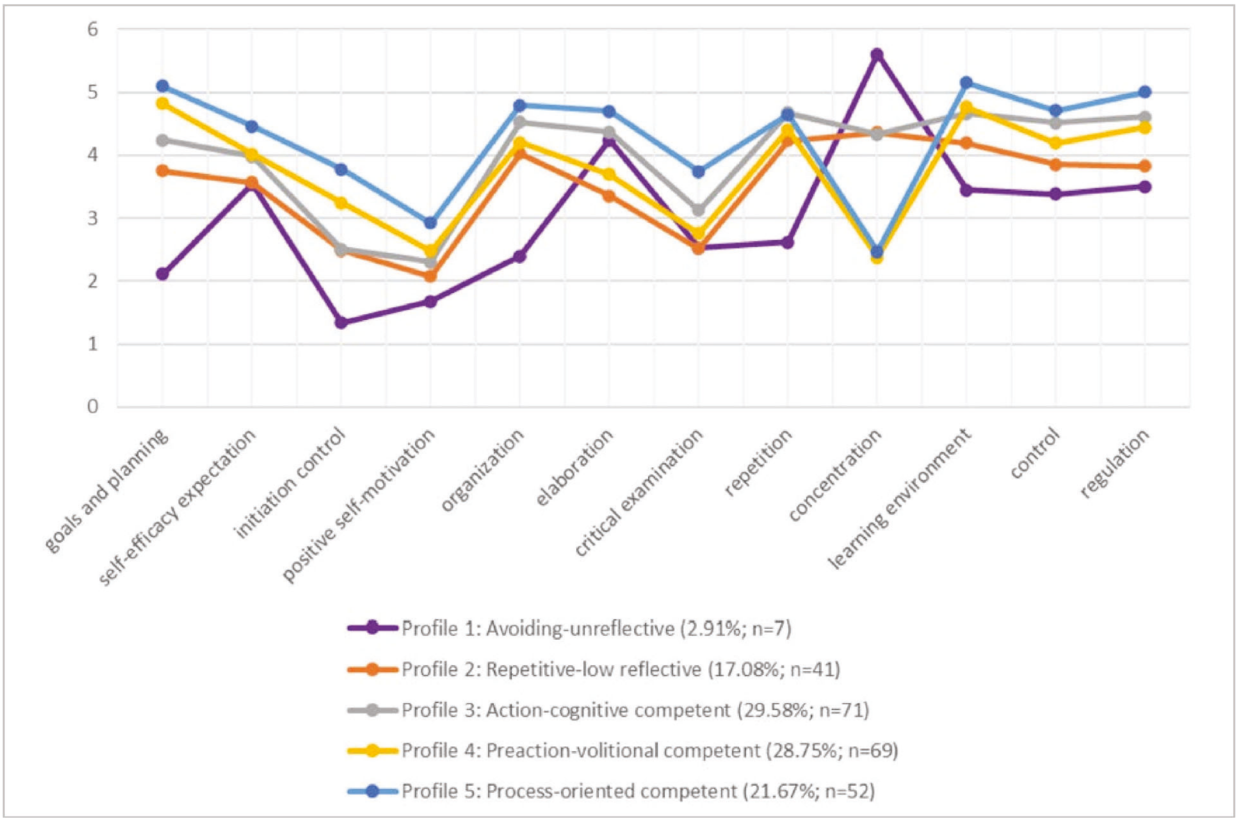

Fig. 1. Mean parameter values of the five self-regulated learning profiles in the original study. *Notes:* The "Concentration" scale is reverse-coded. The scales goals and planning, organization, elaboration, critical examination, repetition, concentration, learning environment, control, and regulation were measured on a 6-point Likert scale, whereas self-efficacy expectation, initiation control, and positive self-motivation were measured on a 5-point Likert scale.

2.5. Aims of the present study

The present study aims to replicate the self-regulated learning (SRL) profiles of preservice teachers that were identified during the Winter semester 2021/2022 in the context of pandemic-related online teaching, using a current sample of preservice teachers in mainly face-to-face instruction. A successful replication would provide evidence for the validity of these profiles across different learning environments within teacher education (see also Bettis et al., 2016). Given the limited knowledge regarding the replicability of SRL profiles in different learning contexts, the following exploratory research question is specified:

(a) Can the SRL profiles of preservice teachers identified in purely online teaching be replicated in a mainly face-to-face learning environment?

To the authors' knowledge, no studies employing person-centered approaches have yet examined the natural development or stability of SRL profiles of preservice teachers within the course of their university studies. Such development is of particular importance for this group, as enhancing their SRL competencies is essential for effectively fostering SRL in their future pupils (e.g., Vanslambrouck et al., 2019). Evidence from person-centered longitudinal studies on higher education students in general suggests that stability and developmental trajectories may vary between learning profiles (e.g., Esnaashari et al., 2023; Fryer & Vermunt, 2018). This leads to the second research question:

(b) How stable are the identified SRL profiles of preservice teachers over the course of one semester?

Although previous findings on SRL profile stability are inconclusive (e.g., Fryer & Vermunt, 2018), the general trend points toward the further development of SRL competencies during university studies, even in the absence of targeted interventions (Higgins et al., 2023). Consequently, it is assumed that the identified SRL profiles will either remain stable over the course of one semester or, if changes occur, these will primarily involve shifts toward more competent profiles. For preservice teachers in particular, reflecting on and further developing their SRL competencies constitutes valuable preparation for their future professional practice (see also Barz et al., 2024; Kramarski & Michalsky, 2009; Michalsky & Schechter, 2013; Shahmohammadi, 2014).

3. Method

3.1. Sample description

In the winter semester 2023/2024, data were collected from $N = 383$ preservice teachers via an online survey administered during the first lecture session of an educational psychology course at the University of Bamberg. It is important to emphasize that the lecture was not delivered exclusively in a face-to-face format. Although the core content was conveyed and further explored during regular in-person sessions, students were additionally provided with access to recorded lecture slides via Panopto, as well as supplementary learning materials (e.g., academic literature, links to in-depth explanatory videos) made available through Moodle. The sample consisted of 301 (78.6%) female, 77 (20.1%) male, and 5 (1.3%) non-binary participants. The mean age was $M = 21.07$ years ($SD = 3.09$), ranging from 17 to 40 years. Regarding teacher education programs, 145 participants (37.9%) were enrolled in primary school education, 144 (37.6%) in vocational education, 67 (17.5%) in secondary school education (Gymnasium), 19 (5.0%) in intermediate school education (Realschule), and 8 (2.1%) in lower secondary education (Mittelschule). On average, participants were in their second semester ($M = 2.17$, $SD = 2.56$).

From this initial sample, $N = 90$ preservice teachers participated in a follow-up survey in the summer semester 2024. Data were again collected via an online survey during the first lecture session of an advanced educational psychology course. This subsample included 75 (83.3%) female, 13 (14.4%) male, and 2 (2.2%) non-binary participants. The mean age was $M = 20.31$ years ($SD = 1.67$), ranging from 18 to 26 years. Distribution across teacher education programs was as follows: 34 (37.8%) in primary school education, 33 (36.7%) in vocational education, 18 (20.0%) in secondary school education (Gymnasium), 3 (3.3%) in intermediate school education (Realschule), and 2 (2.2%) in lower secondary education (Mittelschule). On average, participants were in their third semester ($M = 2.68$, $SD = 1.70$).

3.2. Measures

To replicate the SRL profiles from the winter semester 2021/2022 (Schel & Drechsel, 2025b) and examine their stability, the same 12 parameters were included in the LPA at both measurement points (winter semester 2023/2024 and summer semester 2024). Most survey items were drawn from the LIST (Wild & Schiefele, 1994), a widely used German questionnaire assessing learning strategies in higher education. The following LIST subscales were used: *Goals and planning* (6 items), *repetition* (7 items), *organization* (8 items), *elaboration* (8 items), *critical examination* (8 items), *concentration* (6 items), *learning environment* (6 items), *control* (6 items), and *regulation* (7 items). Cronbach's α values for these scales in validation studies range from 0.82 to 0.92 (Boerner et al., 2005), indicating high to excellent reliability, except for *repetition* (α = 0.72; Wild & Schiefele, 1994) and *control* (α = 0.73; Boerner et al., 2005), which are considered acceptable. All items were rated on a 5-point Likert scale. The *Concentration* scale was reverse-coded, with higher scores reflecting lower levels of concentration.

Self-efficacy expectation in higher education was assessed using the SESW (Petri, 2020), which comprises three subscales: *Deadlines and strategies* (8 items), *motivation and cognition* (3 items), and *cognitive challenges* (2 items). The scale shows high reliability (Cronbach's α = 0.88; Petri, 2020). Items were rated on a 5-point Likert scale.

Volitional learning strategies were measured with adapted versions (Justus, 2017) of the *initiation control* scale (4 items; Wild et al., 1995) and the *positive self-motivation* scale (5 items; Kuhl & Fuhrmann, 1998). Reliability coefficients were high for both scales (positive self-motivation: α = 0.82; initiation control: α = 0.80–0.86; Justus, 2017). Table 2 presents all scales along with illustrative item examples.

Table 2
Overview of scales and example items.

Scale	Item
Goals and planning	I formulate learning objectives that I then align my learning with.
Self-efficacy expectation	Please indicate to what extent you feel confident in organizing your exam preparations independently and responsibly.
Initiation control	When I have decided to study, I start as soon as possible.
Positive self-motivation	When processing learning content, I usually know exactly how to increase my interest in the subject when my perseverance diminishes.
Repetition	I read through my notes several times in a row.
Organization	I create tables, diagrams, or visual representations to have the learning material presented in a more structured manner.
Elaboration	When faced with new concepts, I envision practical applications.
Critical examination	I compare the advantages and disadvantages of different theoretical concepts.
Concentration	While studying, I notice that my thoughts wander.
Learning environment	I arrange my learning environment to minimize distractions while studying.
Control	I narrate the key contents to myself to identify any gaps in my understanding.
Regulation	I change my learning technique when I encounter difficulties.

3.3. Procedure

Data collection took place during the first session of the psychology lecture in each semester. Participants had 30 min to complete the online survey. Data from the winter semester 2023/2024 (T1) and summer semester 2024 (T2) were matched using anonymized participant codes, resulting in a time interval of approximately six months between measurements. Participation in both surveys was voluntary; informed consent and data protection procedures were observed, and only data from consenting participants were analyzed.

The data collection procedures in winter 2023/2024 and summer 2024 were identical. Compared to the original data collection in winter 2021/2022 (Schel & Drechsel, 2025b), there were two differences: (1) in 2021/2022, data were collected at three measurement points within the first two weeks of lectures as part of a larger online survey, whereas the current study collected data at a single time point per semester; (2) in 2021/2022, some parameters were measured on a 6-point scale, while in the current study all parameters were measured on a 5-point scale to ensure comparability. The psychometric quality of the data in the present study was largely comparable to that of the original study (see next section).

3.4. Parameter analysis for LPA

To assess the quality of the LPA parameters in the present sample, Cronbach's α and McDonald's ω coefficients were computed at both time points (winter semester 2023/2024 and summer semester 2024): *Goals and planning* (T1: $\alpha = 0.80$, $\omega = 0.80$; T2: $\alpha = 0.80$, $\omega = 0.80$), *self-efficacy expectation* (T1: $\alpha = 0.82$, $\omega = 0.82$; T2: $\alpha = 0.83$, $\omega = 0.82$), *initiation control* (T1: $\alpha = 0.89$, $\omega = 0.89$; T2: $\alpha = 0.86$, $\omega = 0.86$), *positive self-motivation* (T1: $\alpha = 0.83$, $\omega = 0.83$; T2: $\alpha = 0.87$, $\omega = 0.87$), *organization* (T1: $\alpha = 0.73$, $\omega = 0.73$; T2: $\alpha = 0.78$, $\omega = 0.77$), *elaboration* (T1: $\alpha = 0.81$, $\omega = 0.81$; T2: $\alpha = 0.83$, $\omega = 0.83$), *critical examination* (T1: $\alpha = 0.86$, $\omega = 0.85$; T2: $\alpha = 0.83$, $\omega = 0.83$), *repetition* (T1: $\alpha = 0.73$, $\omega = 0.73$; T2: $\alpha = 0.76$, $\omega = 0.75$), *concentration* (T1: $\alpha = 0.94$, $\omega = 0.94$; T2: $\alpha = 0.96$, $\omega = 0.96$), *learning environment* (T1: $\alpha = 0.80$, $\omega = 0.80$; T2: $\alpha = 0.83$, $\omega = 0.84$), *control* (T1: $\alpha = 0.68$, $\omega = 0.66$; T2: $\alpha = 0.79$, $\omega = 0.77$), and *regulation* (T1: $\alpha = 0.77$, $\omega = 0.78$; T2: $\alpha = 0.79$, $\omega = 0.80$). The nearly identical reliability estimates obtained from Cronbach's α and McDonald's ω support the essential tau-equivalence of the items within the respective scales. These reliabilities closely match those reported in the original study (Schel & Drechsel, 2025b) and validation studies (Boerner et al., 2005; Justus, 2017; Petri, 2020; Wild & Schiefele, 1994) and can be interpreted as acceptable to excellent (with the exception of *control* at T1, which falls slightly below acceptable levels). The exceptionally high internal consistency of the *concentration* scale, reflecting a highly homogeneous construct, appears plausible given the more heterogeneous nature of other parameters (see also Habók & Magyar, 2018). A confirmatory factor analysis including all 12 LPA parameters yielded an acceptable model fit, with a low CFI but good SRMR and RMSEA values: CFI = 0.802; SRMR = 0.065; RMSEA = 0.045.

3.5. Latent profile analysis

Latent Profile Analysis (LPA) was considered appropriate because the aim of the study was to identify qualitatively distinct patterns of SRL characteristics among preservice teachers rather than examining isolated variable relations. As SRL is conceptualized as a multidimensional construct, a person-centered approach enables the identification of subgroups of students with similar SRL profiles. Furthermore, the use of LPA ensures comparability with the original study conducted in the online learning context. The size of the present sample falls within the recommended range for sufficient statistical power and robust results (Nylund et al., 2007). Prior to the analyses, indicator distributions and intercorrelations were inspected. No severe violations regarding normality or multicollinearity (see Section 4.1) were observed. Profile solutions were evaluated using established fit indices, entropy, theoretical interpretability, and profile sizes. Analyses were performed in MPlus (Muthén & Muthén, 2017) using the Maximum Likelihood Estimation method. Multiple LPAs with increasing numbers of classes were estimated in an iterative process.

Model fit was assessed using both absolute and relative criteria. Absolute fit was evaluated using the Bayesian Information Criterion (BIC), sample-size adjusted BIC (SABIC), and Akaike Information Criterion (AIC), with lower values indicating better fit (Masyn, 2013; Tein et al., 2013). Relative fit was assessed by comparing each k-class model to the corresponding k–1-class model using the Vuong–Lo–Mendell–Rubin Likelihood Ratio Test (VLMR) and the Bootstrap Likelihood Ratio Test (BLRT), with significant p-values indicating superior fit for the k-class solution (Ferguson et al., 2020).

Classification accuracy was evaluated using entropy values (>0.80 indicating good classification; Clark, 2010) and average latent class posterior probabilities (>0.70 considered acceptable; Nagin, 2005). For each semester, the best-fitting model was selected based on these criteria.

To examine stability, a Latent Transition Analysis (LTA) was conducted to track participants' profile membership across the two measurement points. The same 12 parameters were used at both time points as in the original study (Schel & Drechsel, 2025b): *Goals and planning*, *self-efficacy expectation*, *initiation control*, *repetition*, *organization*, *elaboration*, *critical examination*, *concentration*, *learning environment*, *control*, and *regulation.*

4. Results

4.1. Descriptive statistics

The descriptive statistics of the scales and the correlations between the parameters of the LPA are summarized in Table 3. All correlations are clearly below 0.80, indicating that multicollinearity can be ruled out.

4.2. Research question (a): replication of preservice teachers' self-regulated learning profiles in mainly face-to-face instruction

As shown in Table 4, the information criteria for estimating relative model fit yielded inconsistent results: While the Vuong–Lo–Mendell–Rubin likelihood ratio test (VLMR) identified only the two-class model as significantly better than the one-class model, the bootstrap likelihood ratio test (BLRT) found all examined k-class models to be significantly better than their respective k–*1*-class model (see also Schel & Drechsel, 2025b; Muwonge et al., 2020). Table 4 also presents the results for absolute model fit. Overall, model fit improved with an increasing number of classes. According to the Bayesian Information Criterion (BIC), the five-class model provided the best fit, whereas the Akaike Information Criterion (AIC) and the sample-size adjusted BIC (SABIC) favored a six-class model. This pattern mirrors that of the LPA in the original study (Schel & Drechsel, 2025b). Consistent with that study, we relied on the BIC as the most conservative and parsimonious estimate of absolute model fit, which is often preferred over AIC and SABIC (Nylund et al., 2007). In terms of entropy, the six-class model slightly outperformed the five-class model (see Table 4).

However, inspection of absolute and relative manifest class sizes revealed that the six-class model included sparsely populated classes (see Table 5). Following recommendations for LPAs (Ferguson et al., 2020), that models should be parsimonious, yield interpretable profiles, and avoid extremely small class sizes, the five-class model was selected for further analysis.

The five-class model had an entropy value of 0.77, slightly below the 0.80 cutoff for good classification (Clark, 2010). However, average posterior probabilities for correct class assignment ranged from 0.845 to 0.916, well above the 0.70 cutoff (Nagin, 2005), suggesting reliable

Table 3
Descriptive statistics and correlations of the LPA parameters (T1).

Parameter	*M*	*SD*	GP	SE	IC	PS	RP	OG	EL	CE	CC	LE	CT
Goals and planning	3.49	0.66											
Self-efficacy expectation	3.83	0.24	0.36**										
Initiation control	2.89	1.21	0.39**	0.42**									
Positive self-motivation	2.89	0.58	0.33**	0.47**	0.43**								
Repetition	3.83	0.48	0.22**	0.08	0.19**	0.13*							
Organization	3.71	0.45	0.37**	0.28*	0.26**	0.28**	0.34**						
Elaboration	3.62	0.46	0.24**	0.34**	0.11*	0.19**	−0.04	0.24**					
Critical examination	2.81	0.56	0.20**	0.34**	0.13**	0.37**	−0.03	0.22**	0.49**				
Concentration	3.24	1.02	−0.41**	−0.54**	−0.53**	−0.54**	−0.13*	−0.19**	−0.14**	−0.17**			
Learning environment	3.89	0.53	0.30**	0.23**	0.38**	0.26**	0.28**	0.30**	0.11*	0.02	−0.28**		
Control	3.72	0.47	0.33**	0.30**	0.26**	0.30**	0.27**	0.29**	0.25**	0.18**	−0.26**	0.27**	
Regulation	3.32	0.23	0.28**	0.26**	0.27**	0.24**	0.24**	0.31**	0.22**	0.16**	−0.15**	0.27**	0.27**

Notes: GP = goals and planning; SE = self-efficacy expectation; IC = initiation control; PS = positive self-motivation; RP = repetition; OG = organization; EL = elaboration; CE = critical examination; CC = concentration (inverted); LE = learning environment; CT = control.
* $p < .05$.
** $p < .01$.

Table 4
Estimation of relative and absolute model fit.

Information criteria	2 classes	3 classes (vs. 2 classes)	4 classes (vs. 3 classes)	5 classes (vs. 4 classes)	6 classes (vs. 5 classes)
VLMR	<0.001	0.718	0.091	0.315	0.263
BLRT	<0.001	<0.001	<0.001	<0.001	<0.001
AIC	9376.56	9247.11	9187.66	9122.72	9092.28
BIC	9522.63	9444.51	9436.39	9422.77	9443.66
SABIC	9405.24	9285.87	9236.50	9181.63	9161.27
Entropy	0.80	0.76	0.75	0.77	0.81

Notes: VLMR = Vuong-Lo-Mendell-Rubin Likelihood Ratio Test; BLRT = Bootstrap Likelihood Ratio Test; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; SABIC = Sample Size Adjusted BIC.

Table 5
Comparison of the manifest absolute and relative class sizes of a five-class versus a six-class model.

	Five-class model *n* absolute (relative)	Six-class model *n* absolute (relative)
Class 1	23 (6.01%)	3 (0.78%)
Class 2	84 (21.93%)	21 (5.48%)
Class 3	128 (33.42%)	85 (22.19%)
Class 4	86 (22.45%)	90 (23.50%)
Class 5	62 (16.19%)	120 (31.33%)
Class 6		64 (16.71%)

classification for all profiles. Fig. 2 presents the mean parameter values for the five identified profiles.

The five profiles showed strong conceptual similarity to those in the original study. One profile demonstrated the highest competencies across all parameters and was comparable to the *process-oriented competent* learners. Compared to the original study, this profile displayed higher positive self-motivation, deeper cognitive strategies, and postaction control, but lower postaction regulation (see Fig. 3). Two profiles were identified as more deficit-oriented, aligning with the *avoiding–unreflective* and *repetitive–low reflective* learners. The avoiding–unreflective learners again exhibited the lowest competencies across parameters, with elaboration as a remaining strength. Most parameter scores were higher than in the original profile, particularly in *goals and planning*, *initiation control*, *positive self-motivation*, *elaboration*, and *critical evaluation* (see Fig. 4).

The *repetitive–low reflective* profile closely resembled its counterpart from the original study, characterized by strong reliance on the surface-level cognitive strategy of *repetition* and comparatively low postaction competencies, though with slightly higher parameter scores in the online learning context (winter semester 2021/2022; see Fig. 5).

Two additional profiles exhibited complementary strengths. One, comparable to the *action–cognitive competent* profile, showed the highest competencies in the action phase cognitive learning strategies (especially deep strategies). Compared to the original study, this profile had higher *positive self-motivation*, *elaboration*, and *critical examination* scores in the action phase, but lower postaction regulation (see Fig. 6). The other, similar to the *preaction–volitional competent* profile, demonstrated strengths primarily in the preaction and volitional phases. Most competencies in this profile were higher than in the original study, except for *goals and planning*, *self-efficacy expectation*, and particularly *regulation* (see Fig. 7).

Because the winter semester 2021/2022 study partly used a 6-point scale rather than the uniform 5-point scale employed in winter semester 2023/2024, Figs. 3–7 display relative mean scores for better comparability.

Consistent with the original findings, the five profiles differed most strongly in *concentration*. Across profiles, the greatest overall deficit appeared in *initiation control* (except for the preaction–volitional competent learners). The most frequent profile in the sample was again the action–cognitive competent learners, and the least frequent was the avoiding–unreflective learners. Overall, deficit-oriented profiles were slightly more prevalent than competent profiles, mirroring, but also extending, the original study's pattern. Taken together, these findings support a successful replication of the self-regulated learning profiles identified during online instruction in a face-to-face teaching context.

4.3. *Research question (b): stability of the identified self-regulated learning profiles*

Following the replication analysis, stability over one semester (approximately six months) was examined in a subsample ($N = 90$) matched with the T1 sample (winter semester 2023/2024). Model fit was first tested in the full sample of $N = 436$ preservice teachers. Once again, the information criteria—particularly the BIC—indicated the five-class model as the best-fitting solution (see Table 6). The five profiles could again be interpreted similarly to those from winter semesters 2021/2022 and 2023/2024 (see Fig. 8).

The transition model showed that most participants ($N = 46$; 51.11%) moved to a more competent profile over the semester, $N = 30$ (33.33%) remained stable, and $N = 14$ (15.56%) transitioned to a less competent profile (see Fig. 9). The most common transition ($n = 20$) was from the action–cognitive competent profile (the largest group at T1, $N = 30$; 33.33%) to the preaction–volitional competent profile. An upward transition, as this profile has been associated with higher learning success and more favorable goal orientations in previous research (Schel & Drechsel, 2025b).

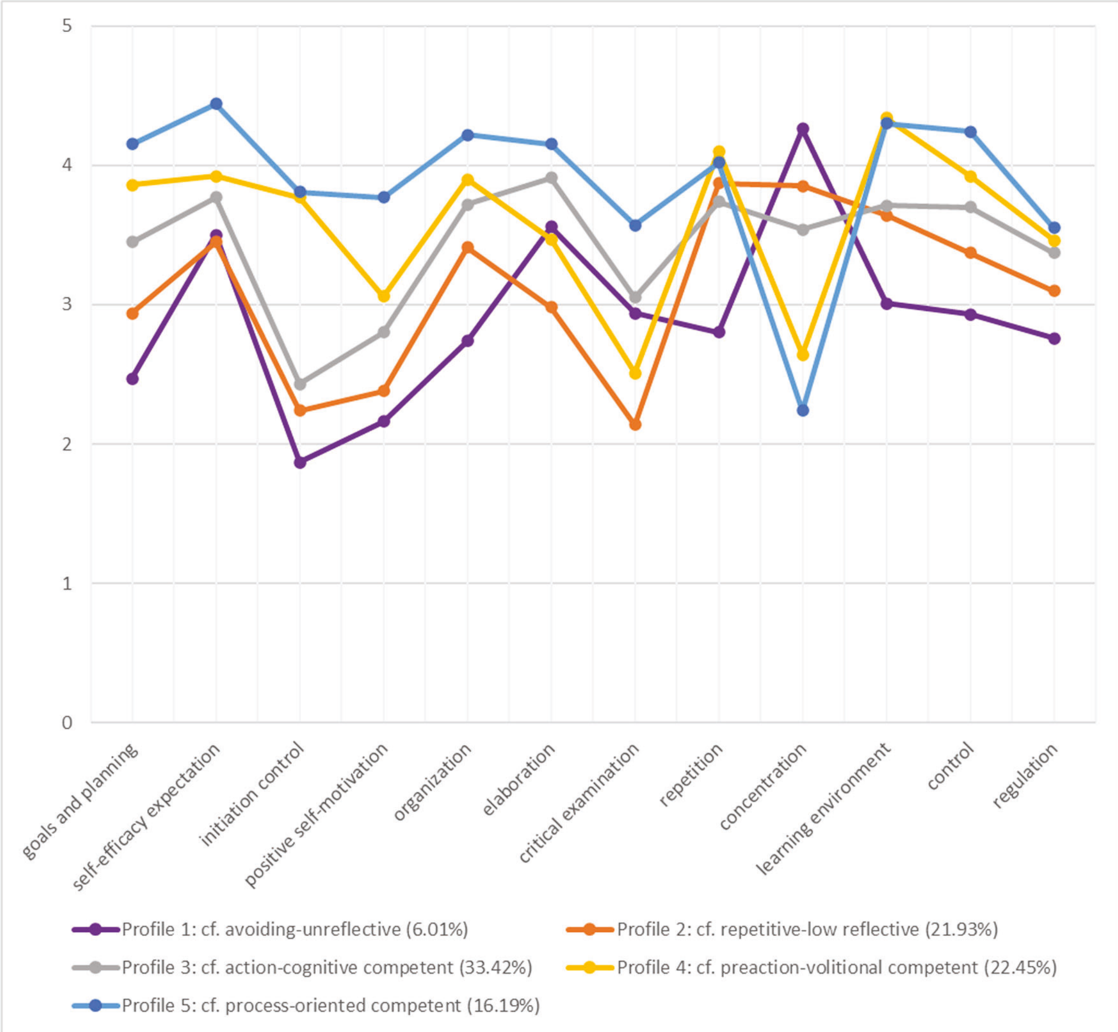

Fig. 2. Mean parameter values of the five learning profiles in the present replication study. *Notes:* The scale "Concentration" is reverse-coded. All parameters were measured on 5-point Likert scales.

The highest stability was observed among process-oriented competent learners, with $N = 10$ (58.82%) of $N = 17$ remaining in the same profile. Avoiding–unreflective learners transitioned only to the repetitive–low reflective profile, which is also deficit-oriented. Repetitive–low reflective and action–cognitive competent learners transitioned into all other profiles, with upward transitions outnumbering downward ones. The most competent profiles, preaction–volitional competent and process-oriented competent, never transitioned into the most deficit-oriented profile (avoidant–unreflective). Likewise, process-oriented competent learners never moved into the repetitive–low reflective profile.

Overall, the competent profiles (preaction–volitional competent and process-oriented competent) were more frequent at T2 than at T1, whereas the deficit-oriented profiles (avoiding–unreflective and repetitive–low reflective), as well as the action–cognitive competent profile, showed a decrease. These findings indicate an overall increase in preservice teachers' self-regulated learning competencies over the course of a semester.

5. Discussion

Although competencies in self-regulated learning (SRL) can be considered particularly important for preservice teachers (e.g., Michalsky & Schechter, 2013; Muwonge et al., 2020; Vanslambrouck et al., 2019), only few studies have examined them from a person-centered perspective. Latent profile analyses are particularly well suited to provide a systematic overview of competencies and developmental potentials, which can then serve as a basis for differentiated support approaches (e.g., Barz et al., 2024). However, only a small number of person-centered studies are replicated, even though replication is essential for validating the interpretability of learning profiles across contexts (via replication in different samples) and their stability (via replication within the same sample).

The present study therefore investigated SRL learning profiles, previously validated with regard to learning success and goal orientations in the context of online teaching (Schel & Drechsel, 2025b), in a new sample of preservice teachers in the context of mainly face-to-face instruction across two measurement points one semester apart (approximately six months). Findings indicate (a) that the SRL profiles of preservice teachers identified in winter semester 2021/2022 during online teaching could successfully be replicated in winter semester 2023/2024 under face-to-face conditions. Again, a five-profile solution demonstrated the best model fit. Both the quantitative and qualitative manifestations of the profiles were nearly identical to the original ones, allowing the use of the same labels: process-oriented competent, preaction–volitional competent, action–cognitive competent, repetitive–low reflective, and avoiding–unreflective. Overall, these results highlight the heterogeneity of preservice teachers in their competencies

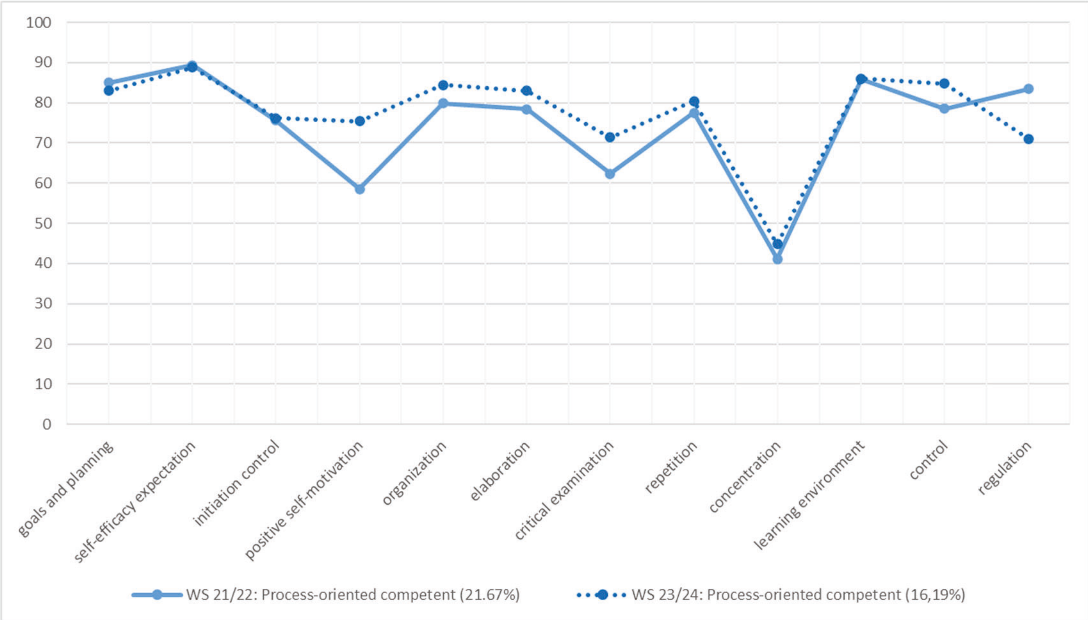

Fig. 3. Relative parameter values of the learning profile "process-oriented competent" in the winter semester 2021/2022 (online teaching) compared to the winter semester 2023/2024 (face-to-face teaching). *Notes:* The scale "Concentration" is reverse-coded.

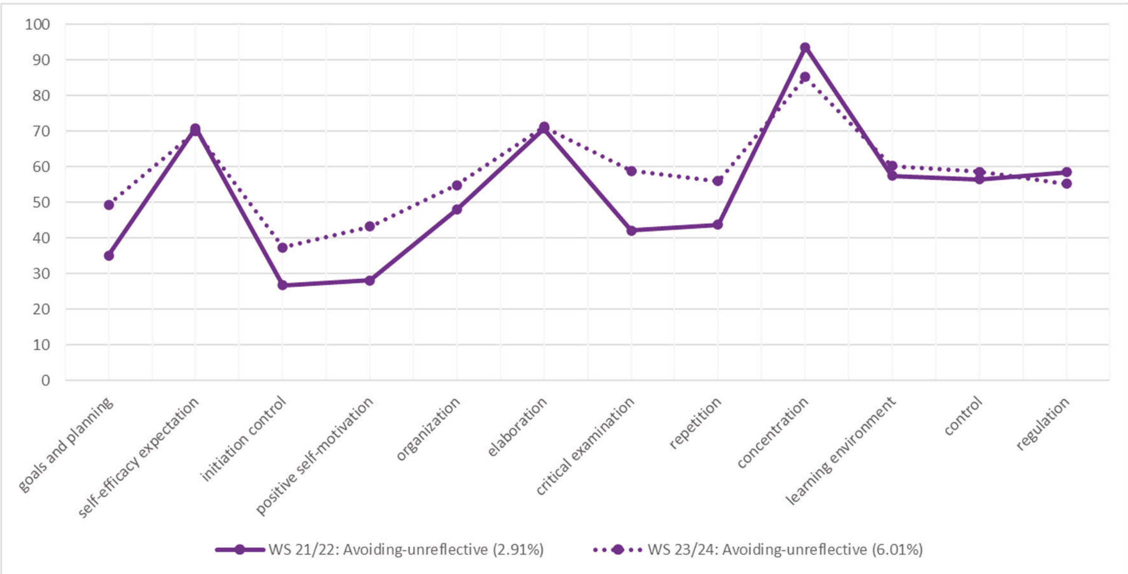

Fig. 4. Relative parameter values of the learning profile "avoiding-unreflective" in the winter semester 2021/2022 (online teaching) compared to the winter semester 2023/2024 (face-to-face teaching). *Notes:* The scale "Concentration" is reverse-coded.

and developmental potentials for SRL, which manifest both in online and in face-to-face learning contexts. The findings further show (b) that preservice teachers' SRL competencies tend to increase over the course of a semester, with most participants transitioning to a more competent profile by the second measurement point. Only a small proportion shifted into less competent profiles. This short-term development of SRL competencies appears particularly desirable given preservice teachers' professionalization as future educators (see also Barz et al., 2024).

The profiles identified in this study are consistent with findings from other person-centered research that grounds parameter selection in process models of SRL (Schel & Drechsel, 2025b; Barnard-Brak et al., 2010). While prior studies have focused on online learning contexts, the present study also identified a five-profile solution for face-to-face teaching, with competencies systematically aligning with phases of the SRL process. Content-wise, the identified profiles proved nearly identical across online and face-to-face modalities. Fundamentally, the results do not contradict profiles of SRL among preservice teachers reported by Barz et al. (2024), Muwonge et al. (2020), or Heikkilä et al. (2012). Similarly, the profiles found here correspond to learners with generally low (avoiding–unreflective, repetitive–low reflective), moderate (action–cognitive competent, preaction–volitional competent), and high (process-oriented competent) SRL competencies. Beyond quantitative distinctions, the broad set of parameters assessed along the SRL process also revealed qualitative differences between the profiles. These qualitative distinctions in face-to-face learning mirrored those previously identified in online contexts, showing parallels to Heikkilä et al.'s (2012) classification: *self-directed learners* resemble process-oriented competent students, *non-reflective learners* resemble

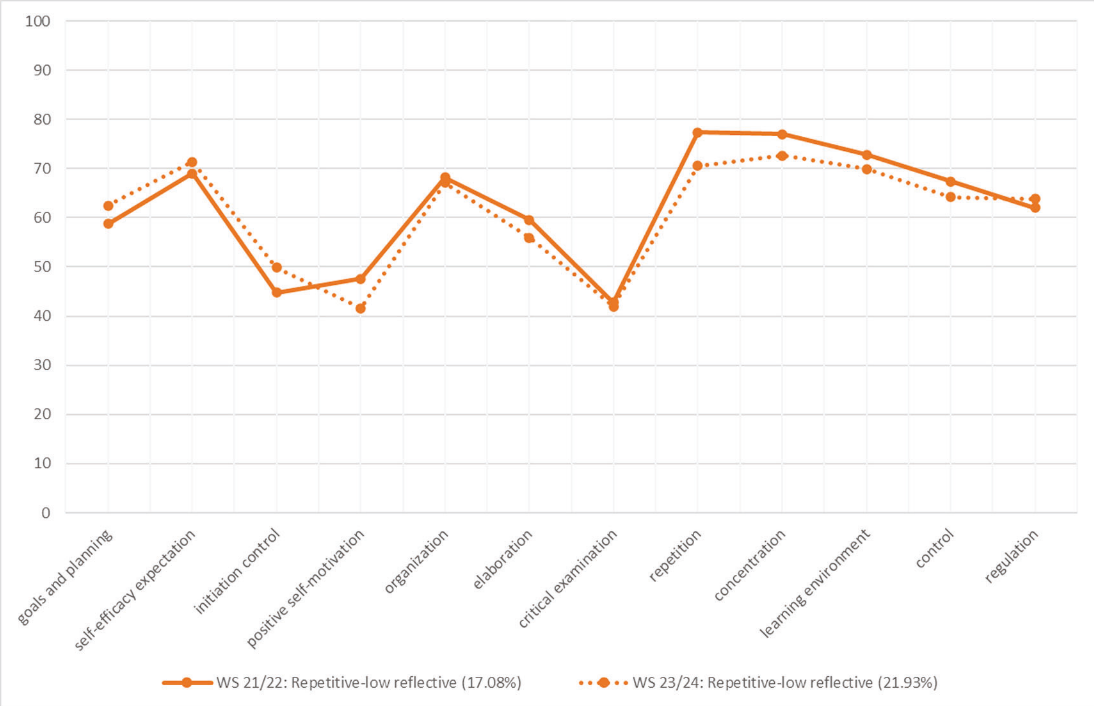

Fig. 5. Relative parameter values of the learning profile "repetitive-low reflective" in the winter semester 2021/2022 (online teaching) compared to the winter semester 2023/2024 (face-to-face teaching). *Notes:* The scale "Concentration" is reverse-coded.

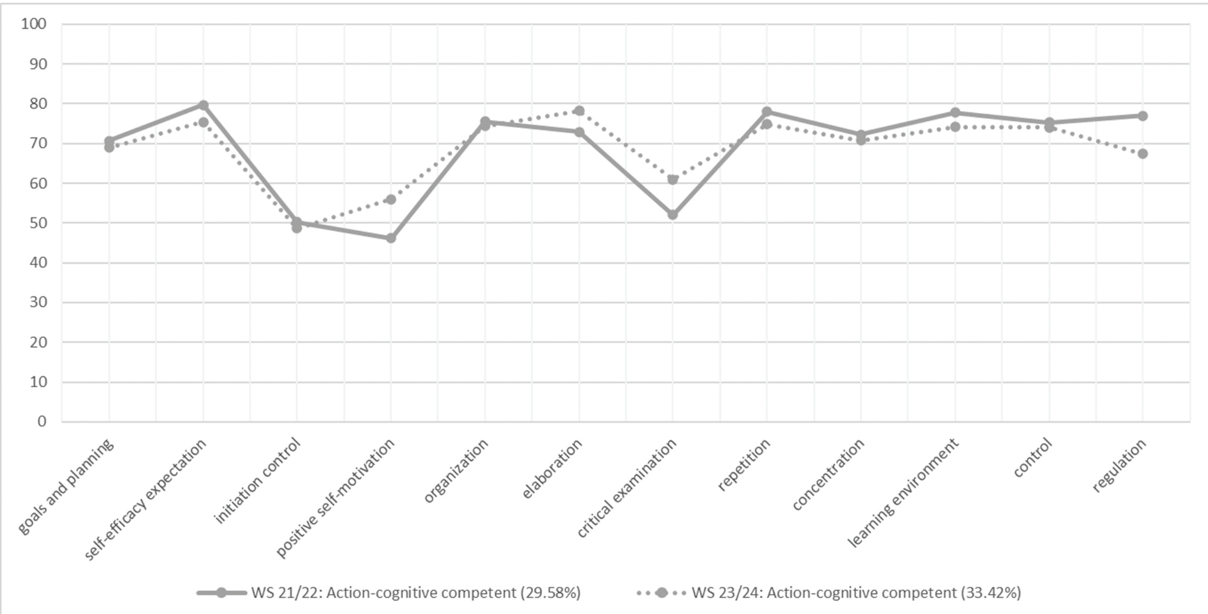

Fig. 6. Relative parameter values of the learning profile "action-cognitive competent" in the winter semester 2021/2022 (online teaching) compared to the winter semester 2023/2024 (face-to-face teaching). *Notes:* The scale "Concentration" is reverse-coded.

repetitive–low reflective students, and *non-regulating learners* resemble avoiding–unreflective students.

More fine-grained differences across profiles in the face-to-face context indicate an overall increase in reported SRL competencies, particularly in the volitional domain (initiation control and positive self-motivation) and in the cognitive domain of deep-level strategies (organization, elaboration, and especially critical evaluation). This pattern may be explained by greater structure and more interaction opportunities in face-to-face teaching, which facilitate the use of SRL strategies (e.g., Kizilcec et al., 2017). At the same time, moderately (action–cognitive competent, preaction–volitional competent) and highly competent (process-oriented competent) learners tended to report stronger regulation of learning processes in online contexts. Given the higher degree of learner responsibility in online environments (e.g., Kizilcec et al., 2017; Xu et al., 2022), metacognitive regulation strategies may be particularly activated among learners with sufficient prerequisites (see also Barz et al., 2024). The strongest gains from online to face-to-face teaching were observed for preaction–volitional

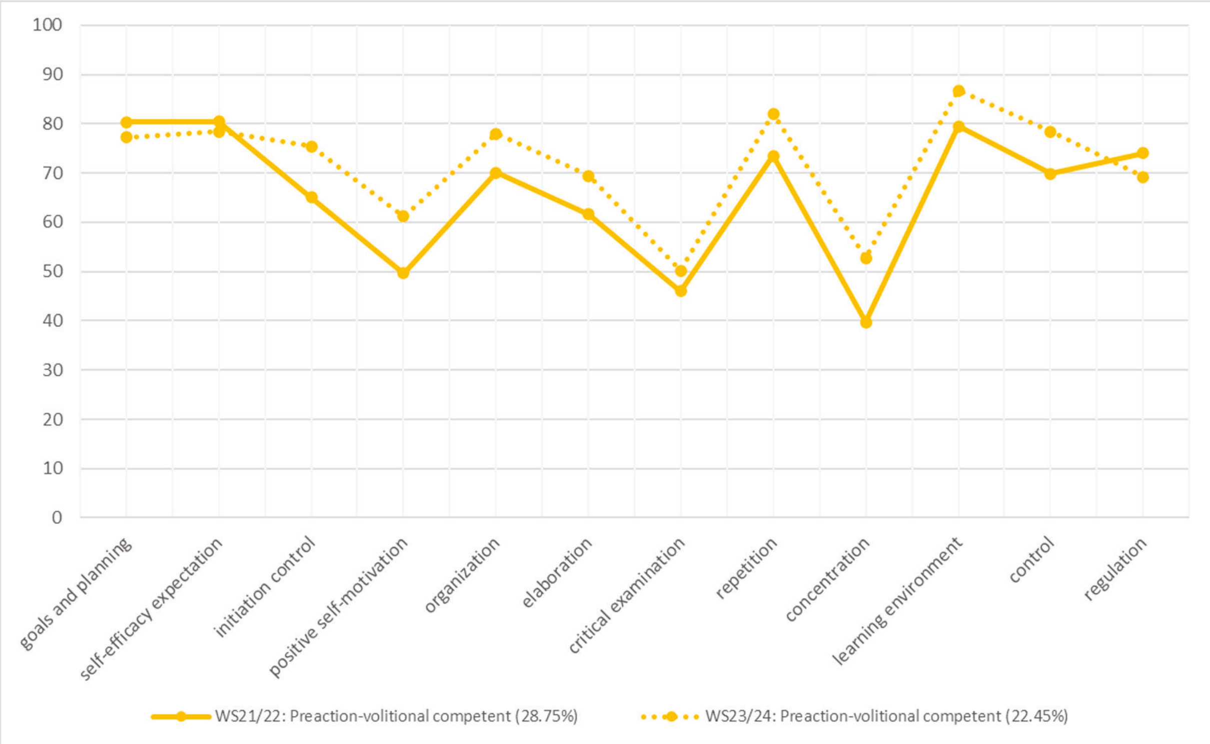

Fig. 7. Relative parameter values of the learning profile "preaction-volitional competent" in the winter semester 2021/2022 (online teaching) compared to the winter semester 2023/2024 (face-to-face teaching). *Notes:* The scale "Concentration" is reverse-coded.

Table 6
Estimation of relative and absolute model fit.

Information criteria	2 classes	3 classes (vs. 2 classes)	4 classes (vs. 3 classes)	5 classes (vs. 4 classes)	6 classes (vs. 5 classes)
VLMR	<0.001	<0.001	0.437	0.644	0.429
BLRT	<0.001	<0.001	<0.001	<0.001	<0.001
AIC	10,376.69	10,153.37	10,094.11	10,037.42	10,005.79
BIC	10,527.57	10,357.25	10,351.00	10,347.32	10,368.70
SABIC	10,410.15	10,198.58	10,151.08	10,106.13	10,086.26
Entropy	0.81	0.81	0.78	0.81	0.82

Notes: VLMR = Vuong-Lo-Mendell-Rubin Likelihood Ratio Test; BLRT = Bootstrap Likelihood Ratio Test; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; SABIC = Sample Size Adjusted BIC.

competent learners. Assuming that online environments place particular demands on preaction (planning) and volitional (persistence and motivation) competencies (e.g., Seiberling & Kauffeld, 2025), the transition to face-to-face learning may have led these learners to evaluate their competencies more positively.

Across the one-semester observation period (∼6 months), most preservice teachers in the sample transitioned into a more competent SRL profile. This aligns with findings by Higgins et al. (2023), who reported increases in SRL competencies over the course of students' studies. At the same time, the observed positive development contrasts with studies such as Fryer and Vermunt (2018), who found declining SRL competencies and high stability of deficient profiles, attributing this to insufficient SRL support in higher education. Here, a differentiated consideration of study programs may be particularly relevant. SRL processes may be more explicitly addressed in teacher education than in other disciplines, and preservice teachers may also be more motivated to develop SRL competencies. Such professionalization is of special importance given their future role in diagnosing and fostering SRL among their pupils (e.g., Barz et al., 2024; Kramarski & Michalsky, 2009; Michalsky & Schechter, 2013; Shahmohammadi, 2014). Accordingly, a positive development of SRL competencies appears especially desirable in teacher education.

Apart from avoiding–unreflective learners, who represented only a small subgroup, learners with moderate SRL competencies (action–cognitive competent) showed the greatest variability and were most likely to transition into more competent profiles (see also Dörrenbächer & Perels, 2016; Jeong & Feldon, 2023). Learners with moderate competencies may already possess the basic prerequisites for successful SRL development, while still having sufficient potential for growth, making them especially likely to progress. Moreover, action–cognitive competent learners generally demonstrate more adaptive goal orientations than the two less competent profiles (Schel & Drechsel, 2025b), which further supports positive SRL development (Jeong & Feldon, 2023). Preservice teachers in the most competent profile (process-oriented competent) displayed the highest stability (see also Barz et al., 2024). Given the high level of SRL competencies across all phases, combined with strong learning outcomes and favorable goal orientations, this stability is regarded as highly desirable (Schel & Drechsel, 2025b).

Closer inspection shows that profile transitions were also plausible in content terms, as they mainly occurred toward "neighboring" profiles. For example, learners in the most deficient profile

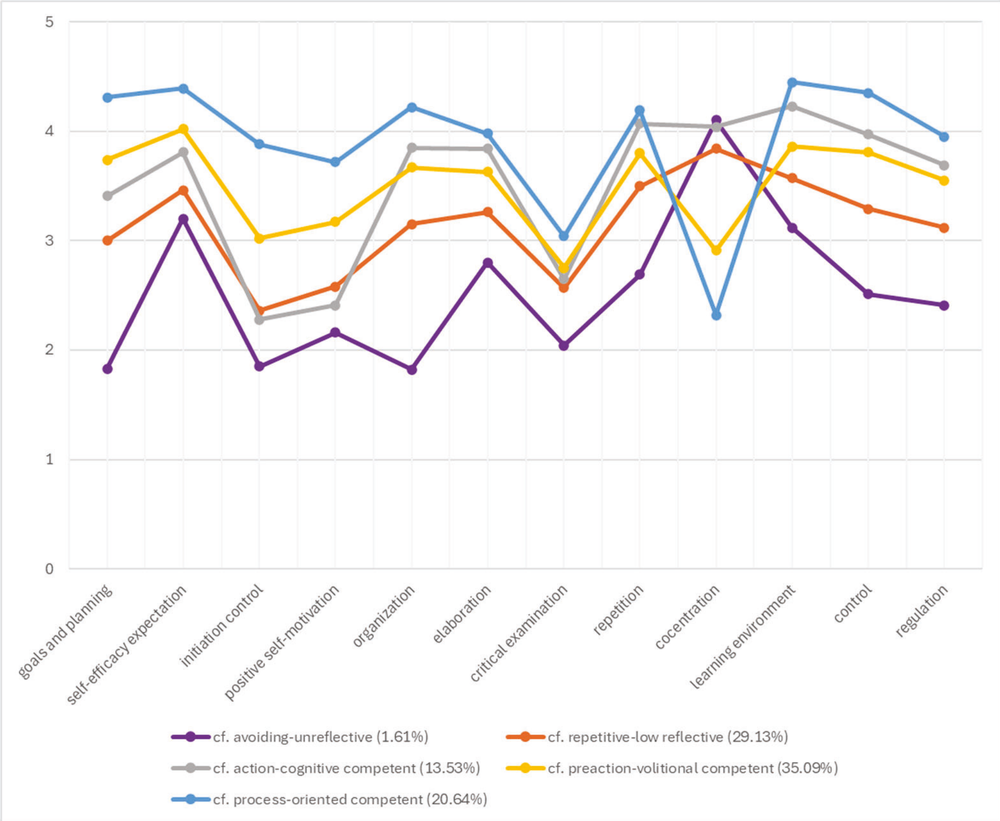

Fig. 8. Mean parameter values of the five learning profiles in the summer semester 2024. *Notes:* The scale "Concentration" is reverse-coded. All parameters were measured on 5-point Likert scales.

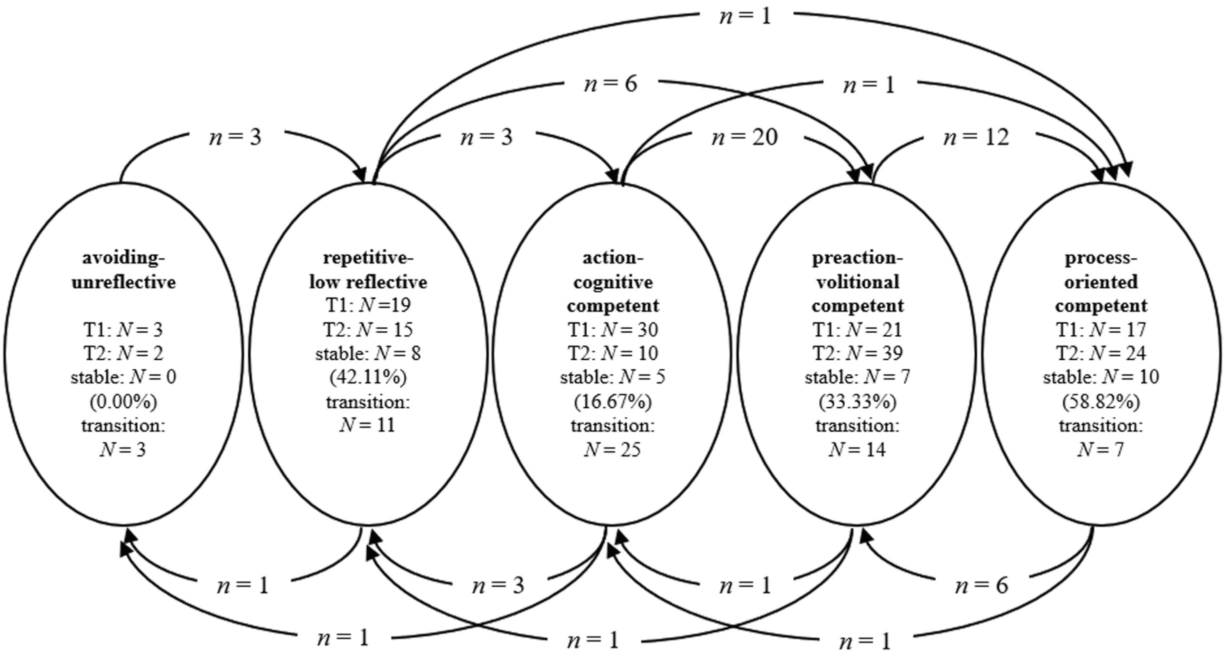

Fig. 9. Transition model on the stability of and shifts between learning profiles. *Notes:* T1 = Data collection in winter semester 2023/2024; T2 = Data collection in summer semester 2024.

(avoiding–unreflective) transitioned exclusively to the repetitive–low reflective profile, while learners in the most competent profiles (preaction–volitional competent and process-oriented competent) did not transition into the most deficient profile. Likewise, process-oriented competent learners did not move into the repetitive–low reflective profile.

In sum, while the findings indicate an overall positive trajectory of SRL competencies among preservice teachers during their studies, they also underscore, together with other person-centered research, the pronounced heterogeneity of these competencies and developmental potentials.

5.1. Practical implications

For all preservice teachers, reflective engagement with their own self-regulated learning (SRL) is crucial for competently supporting learners' SRL in their future profession. In particular, preservice teachers with low and moderate SRL competencies demonstrate considerable potential for optimization. In the present study, this includes the learning profiles avoiding–unreflective, repetitive–low reflective, action–cognitive competent, and preaction–volitional competent, which together constitute the majority of the sample. Similar patterns have been observed in studies by Muwonge et al. (2020) and Barz et al. (2024), where a substantial portion of preservice teachers exhibited developmental potential in SRL competencies. Empirical research indicates that learners with different profiles benefit differently from SRL interventions (e.g., Barz et al., 2024; Dörrenbächer & Perels, 2016). Consequently, and to avoid overloading learners while ensuring interventions are both effective and efficient (see Günther, 2021), differentiated intervention approaches based on learning profiles are advisable (e.g., Tetzlaff et al., 2023).

For differentiated yet economically feasible support, especially in large cohorts typical of teacher education, prompt-based interventions can be particularly suitable (Theobald, 2021). The qualitative differences in SRL observed across the learning profiles in the present study can guide the selection of tailored prompts for learners in each profile. At the University of Bamberg, a corresponding project to support preservice teachers' exam preparation was implemented in the summer semester of 2024 (Schel & Drechsel, 2025a). Within this project, at the beginning of the semester, learners are assigned to one of the learning profiles identified in the present study, based on diagnostic results from the questionnaire used in the preceding studies. Throughout the semester, students have the opportunity to produce short weekly summaries of the lecture content, which are then allowed as aids in the final exam. This incentive system promotes volitional components of SRL, such as early and continuous preparation throughout the semester (Herrmann, 2024). This general support approach is relevant for most learners in the identified profiles, as volitional competencies are relatively low across nearly all profiles. The creation of lecture summaries is additionally supported by differentiated cognitive prompts (see also Glogger et al., 2012; Hübner et al., 2010; Saks & Leijen, 2019). Learners with deficient profiles (avoiding–unreflective and repetitive–low reflective) receive prompts targeting organization strategies as fundamental deep-learning techniques, whereas cognitively competent profiles (action–cognitive competent and process-oriented competent) are provided prompts aimed at critically examining the content as a highly demanding deep-learning strategy. These cognitive prompts are complemented by metacognitive prompts designed to encourage individual reflection and regulation of exam preparation. Evidence supports the combined promotion of cognitive and metacognitive strategies to enhance intervention success (e.g., Donker-Bergstra et al., 2014; Theobald, 2021).

Targeted support for different competencies and developmental potentials of preservice teachers can foster and accelerate their professionalization within teacher education (see also Ganda & Boruchovitch, 2018) and contribute to their ability to design learning environments for their future students that, in turn, positively influence the students' SRL development (Perry et al., 2006).

5.2. Limitations

In contrast to the data collection procedure in the original LPA, data for the replication study were collected at a single measurement point during the winter semester 2023/2024, whereas the original parameters (winter semester 2021/2022) were collected across three measurement points during the lecture sessions within the first two weeks of the semester. This earlier procedure resulted in a substantial dropout rate, as participants who did not attend all three measurement points could not be assigned to a learning profile. Consequently, only 240 complete datasets were available. Both samples are selective, primarily due to the voluntary nature of participation in both the course and the study. However, the issue of selectivity is somewhat less pronounced in the present study due to the one-time measurement, which is reflected in a larger overall sample and, notably, in a relatively higher proportion of students assigned to deficient learning profiles, and conversely, a lower proportion in more competent profiles. For example, the avoiding-unreflective learning profile accounted for only 2.91% ($n = 7$) of the original sample (Schel & Drechsel, 2025b), whereas in the current study, this profile increased to 6.01% ($n = 28$). Despite the relatively small proportion, we argue against the exclusion of the avoiding-unreflective profile. As postulated in the original validation study, this profile is more prevalent in a less selective sample (Schel & Drechsel, 2025b). Additionally, qualitative distinctions between the deficient profiles, namely, avoiding-unreflective and repetitive-low reflective learners, enable meaningful substantive interpretation of both profiles. Statistical model fit indicators also support the five-profile solution (see also Ferguson et al., 2020).

The sample size in the present study falls within the recommended range of 300 to 500 participants for latent profile analyses to ensure sufficient statistical power and robustness (Nylund et al., 2007). However, the differing representativeness of the 2021/2022 and 2023/2024 samples should be considered when interpreting the influence of the learning environment (online vs. face-to-face instruction). If the higher selectivity in the 2021/2022 sample led to a significantly more engaged participant group compared to the 2023/2024 sample, the observed relatively small differences between learning profiles across learning environments may not be generalizable. The sample drawn in the summer semester 2024 may also be considered more selective. Only approximately one-quarter of the winter semester 2023/2024 sample could be matched for this follow-up. Thus, the subsample consists of students who voluntarily participated in both online surveys during the respective lecture sessions and who immediately continued with the advanced lecture in the semester following the introductory psychology course. It is therefore likely that these students are characterized by particularly high engagement and goal orientation in their studies. Consequently, the predominantly upward development toward more competent learning profiles observed in this subsample may not be representative of the general population of preservice teachers. Although the overall sample of pre-service teachers enrolled in the advanced lecture course, on the basis of which the learning profiles in the summer semester of 2024 were analyzed, suggests in cross-sectional comparison an overall increase in competent learning profiles (preaction-volitional competent and process-oriented competent) and a decrease in deficient learning profiles (avoiding-unreflective) compared to pre-service teachers enrolled in the introductory lecture course (winter semesters 2021/2022 and 2023/2024), this observation nevertheless requires further investigation. To more accurately examine the development of self-regulated learning (SRL) competencies in preservice teachers, multiple measurement points over an extended period using a longitudinal design would be preferable (e.g., Wibrowski et al., 2017). The samples also exhibit a recurring overrepresentation of female participants within the learning profiles, which reflects the gender distribution in the general preservice teacher population at the University of Bamberg (as of 2021). However, since some studies suggest gender differences in SRL (e.g., Liu et al., 2021), the validity of the present learning profiles should not be interpreted as universally generalizable in this regard.

Both the original and replicated learning profiles are based solely on self-report data, which are subject to methodological biases. For instance, questionnaires cannot adequately capture the actual use of learning strategies (Rovers et al., 2019). As a result, recent studies increasingly emphasize multi-method approaches that balance the methodological strengths and limitations of different assessment tools for SRL (Dörrenbächer-Ulrich et al., 2021). Similar to other studies that assess self-regulated learning using questionnaires (e.g., Schel & Drechsel, 2025b; Muwonge et al., 2020; Habók & Magyar, 2018), the present study also reveals limitations in data quality (e.g., low reliability of the "control" scale at T1) despite the use of standardized measurement instruments. This may be attributable to the fact that items in many self-regulated learning scales encompass heterogeneous learning activities. Multi-method approaches may also help to overcome these methodological limitations in the quality of assessing self-regulated learning via questionnaires. To enhance the validity of self-report data, behavior-proximal methods such as trace data (Bernacki, 2018) or learning product analyses (Schel et al., 2023) are promising alternatives. For example, it could be examined whether learners in profiles characterized by stronger cognitive learning strategies actually apply these more frequently in the production of learning materials (e.g., lecture summaries). Investigating the current learning profiles using behaviorally anchored methods would allow conclusions about their ecological validity, indicating whether differences in SRL across profiles are also reflected in actual learning behaviors.

5.3. *Future research*

Given the assumption underlying this study that preservice teachers may differ in their self-regulated learning (SRL) from students in other fields of study, future research employing person-centered approaches should investigate to what extent students from various disciplines differ in their SRL competencies and developmental potentials (see also Parpala et al., 2022). The current state of research in this area is still rather limited. A systematic sampling strategy should be applied when comparing learning profiles across different study programs. For instance, most teacher education programs at the University of Bamberg are not subject to admission restrictions (i.e., NC-free), potentially leading to greater heterogeneity in SRL compared to students in numerus clausus (NC)-restricted programs, such as psychology. In the latter case, a model with fewer learning profiles, potentially characterized by overall higher SRL competencies, might exhibit better fit. Moreover, it may be assumed that student teachers are more interested in developing their SRL competencies and that SRL is more explicitly embedded in their curriculum. Accordingly, longitudinal research designs spanning longer periods of study may reveal more pronounced differences in the dynamic development of SRL competencies between teacher education students and those in other disciplines (see also Hailikari et al., 2020). Students of economics, for example, could serve as a suitable comparison group, as their curricula do not explicitly address SRL and these programs are also generally NC-free. In this context, gender differences observed in SRL should also be taken into account (e.g., Liu et al., 2021), as gender imbalances are typically reflected in the composition of student populations across different study programs. Accordingly, future research needs to more systematically include and examine underrepresented groups within specific study programs in order to validate the generalizability of learning profiles across genders and across different academic disciplines.

In the context of longitudinal studies, the learning profiles of participants who continuously take part in the assessments should be systematically compared with those of participants who discontinue participation. This is particularly important because associations between SRL profiles and motivational indicators have been found, suggesting potential systematic biases in study participation. Students with more favorable SRL profiles generally also exhibit higher levels of motivation, which may lead to an overestimation of the development of SRL competencies over time (e.g., Schel & Drechsel, 2025b; Muwonge et al., 2020; Heikkilä et al., 2012). Such analyses could enable more accurate conclusions regarding the development of SRL competencies among preservice teachers (and students from other academic disciplines).

To promote the self-regulated learning processes of student teachers beyond the university learning environment, prompt-based interventions appear promising (Schel & Drechsel, 2025a). Prompts can be used to support a wide range of SRL components and thus offer opportunities for differentiated interventions (e.g., Daumiller & Dresel, 2019). Further research should explore how such interventions can be effectively integrated into teacher education programs, e.g., during exam preparation, in order to support SRL processes in a targeted and efficient manner. However, methodological limitations are inherent in such approaches, particularly regarding the quasi-experimental design: in the context of university exam preparation, interventions often cannot be randomized, and participants typically self-select into intervention groups. Consequently, no causal conclusions can be drawn about the effectiveness of these interventions. Therefore, future studies should aim to integrate prompt-based interventions into regular courses, using evaluated portfolio assignments throughout the semester. For instance, learners could be assigned to a waitlist control group, receive randomly assigned prompts, or be provided with prompts tailored to their learning profile.

In addition, both the learning profiles themselves and the effects of potential interventions should be examined using behaviorally anchored methods (Theobald, 2021), such as learning product analyses (Schel et al., 2023) or in-depth cognitive interviews (e.g., Karaca et al., 2023). Learning products created during the semester, especially in the context of exam preparation, could be compared interindividually between cohorts receiving prompt-based interventions and those preparing independently. Experimental studies could also compare learning products generated under randomly assigned or profile-specific prompts. Intraindividual comparisons could further be made between spontaneously produced learning products (without prompts) and those developed within a prompt-based intervention tailored to the learner's profile. The effectiveness of such interventions should manifest not only in exam performance but also in the quality of the learning products, which should increasingly reflect elaborated and diverse cognitive learning strategies. Learning products are thus particularly suitable for capturing the active and context-specific use of cognitive learning strategies (e.g., Dmoshinskaia et al., 2021). Studies employing multi-method approaches should also incorporate methods to assess metacognitive data. For example, interviews (e.g., Karaca et al., 2023) could be conducted in which learners are asked to actively report their learning strategies, providing insights into their conscious reflection on and regulation of SRL, especially in the context of exam preparation (e.g., the deliberate modification of strategies during the ongoing development of lecture summaries).

5.4. *Conclusion*

In the present study, the self-regulated learning (SRL) profiles of preservice teachers originally identified in the context of online instruction (Schel & Drechsel, 2025b) were successfully replicated in a face-to-face teaching environment. The findings suggest that SRL competencies and developmental potentials of preservice teachers can be systematically categorized into five distinct learning profiles, based on the phases of the process model of self-regulated learning (Schmitz & Schmidt, 2007). This classification highlights the considerable heterogeneity among preservice teachers in terms of their SRL competencies, underscoring the need for differentiated support approaches tailored to specific learner profiles. Furthermore, the study examined the stability of the identified learning profiles over the course of one semester. The results indicate a general trend toward transitions into more competent profiles, implying an increase in SRL competencies among preservice teachers during their university studies. However, these findings should be interpreted with caution in light of the limitations discussed, including issues of sample selectivity (e.g., high dropout rates between

T1 and T2). Future research should employ multi-method study designs to validate both the identified profiles and the observed developmental trajectories of SRL competencies using behaviorally anchored data (e.g., Theobald, 2021). In addition, longitudinal, person-centered approaches are needed to analyze and compare the dynamics of learning profile development across different fields of study over extended periods (e.g., Hailikari et al., 2020; Parpala et al., 2022). Finally, the development and validation of differentiated support interventions based on learning profiles, such as prompt-based approaches, appear to be of high practical relevance, particularly for preservice teachers who will be responsible for fostering self-regulated learning processes in their future students (e. g., Schel & Drechsel, 2025a; Barz et al., 2024).

Statement on ethical approval

Completely anonymized questionnaire surveys at the Otto-Friedrich-University of Bamberg with adult subjects that address non-sensitive topics—such as, in the case of the present study, self-regulated learning—are initially coordinated only with the data protection office of the University of Bamberg. For this reason, clearance from the university's ethics committee was obtained retrospectively: To ensure that the present study complied with the ethical standards for psychological research in Germany, it was reviewed and approved by Prof. Dr. Thomas Weißer (Laubach), Chairman of the Ethics Committee of the Otto-Friedrich-University of Bamberg, with the approval number: 2025-10/86, dated 13.10.2025. All participants provided informed consent prior to participation. They were informed about the purpose of the study, the voluntary nature of participation, the pseudonymized processing and confidential handling of their data, their right to withdraw consent at any time, and their rights under the General Data Protection Regulation (GDPR). The collected data will be stored in accordance with institutional policies and the principles of good scientific practice.

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CRediT authorship contribution statement

Janina Schel: Writing – original draft, Visualization, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Barbara Drechsel:** Writing – review & editing, Supervision, Software, Resources, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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