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Use of self-regulated learning strategies Among Teacher Education students: A latent profile analysis

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ABSTRACT

In the present study, we conducted a latent profile analysis to identify three clusters of Teacher Education students based on their reported use of self-regulated learning strategies. The sample comprised 527 undergraduate Teacher Education students (*Mean age = 22 years; SD = 2.20*) randomly selected from seven universities in Uganda. Data were collected using the modified Motivated Strategies for Learning Questionnaire. These profiles included the following; (a) high self-regulated learners (*252 students; 47.8%*), (b) average self-regulated learners (*209 students; 39.7%*), and (c) low self-regulated learners (*66 students; 12.5%*) who differed significantly with respect to their motivational beliefs. Additionally, motivational beliefs significantly predicted latent profile membership. It is, therefore, important to understand such profiles' differences among Teacher Education students in order to improve on their self-regulated learning strategies. Implications of the study findings are further discussed in this paper.

The late 1970's saw a shift in pedagogical practices from teacher-centered approaches to more learner-centered approaches - in which learners were empowered to actively take control and participate in the learning process (Low & Jin, 2012). Consequently, by the early 1980's, educational researchers and psychologists focused their attention to individual self-regulatory processes (such as critical thinking, self-efficacy, planning, metacognition, self-reflection, and causal attributions) among learners (Zimmerman & Schunk, 2001). Indeed, with the growing need to train self-reliant and independent learners to meet the current job -market demands, over the previous three decades, more pedagogical research has concentrated in the field of self-regulated learning (SRL). SRL is a multi-faceted construct that refers to the process by which learners are meta-cognitively, emotionally, motivationally, and behaviourally active in their own learning (Zimmerman, 1990). SRL is a self-directed process in which learners become masters of their own learning and transform their mental skills into academic skills (Zimmerman, 1990). Highly self-regulated learners are able to understand, control their own learning environments and adapt easily to new learning situations.

SRL not only improves one's educational competences, but also prepares a life-long learner who is able to cope with the professional challenges in his career after school. In fact, in schools nowadays, contrary to what was practiced a few decades ago, learners are not taught how to assimilate knowledge from the teacher, but rather, are guided on how they may *learn to learn*, which transforms schools from *institutions of teaching* to *institutions of learning*. Moreover as Low and Jin (2012) assert, learning, "is a kind of complex human activity to be done by students rather than to be done for students" (pg. 3015).

SRL is not only needed by students, but also practising teachers and Teacher Education students, since these later act as role models from whom students can emulate how to regulate their own learning. Teachers who can ably regulate their learning exhibit better professional development within their professional communities (Michalsky & Schechter, 2011) on top of having a successful academic performance at the university (Hwang & Vrongistinos, 2002). Moreover, as Kramarski and Michalsky (2009) assert, to be effective self-regulated role models to their learners, Teacher Education students should be able to self-regulate their own learning. It is undoubtedly true that there is necessity for Teacher Education students to be adept at self-regulated learning, and hence, the urgent need to prioritise pedagogical research on SRL among such trainees.

Nevertheless, research in SRL over the past decades has focused more

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how on teachers may foster self-regulation among their own learners. Critical inquiry into SRL among Teacher Education students has not had much strides (Saariaho, Pyhältö, Toom, Pietarinen, & Soini, 2016); and especially in the Third World countries (Muwonge, Schiefele, Ssenyonga, & Kibedi, 2017, Muwonge, Schiefele, Ssenyonga, & Kibedi, 2018). There are glaring gaps in this aspect that need to be filled.

In this study, we addressed this knowledge gap by using a person-centered approach (i.e., latent profile analysis; LPA) to identify different profiles of Teacher Education students based on their SRL strategies. We also examined whether significant differences existed among the profiles identified with respect to motivational beliefs of these Teacher Education students.

A latent profile analysis is a mixture modeling technique that employs a person-centered approach to uncover different unobserved homogeneous sub-populations that may exist within a general target population, and offers a moderate amount of parsimony and specificity compared to variable-centered approaches (Howard & Hoffman, 2017). Moreover, the use of a person-centered approach in the present study will help in complementing the few variable-centered investigations (Muwonge et al., 2017, 2018) that have been conducted with Teacher Education students in Uganda, thereby broadening our understanding of the various factors related to SRL among Teacher Education students in Third World countries.

LPA aids in classification of Teacher Education students into homogenous groups, describes the characteristics of each profile, and examines the significant differences across such groups. In teacher training, LPA can assist in identification of Teacher Education students with poor learning skills/strategies and low motivation, and hence, at high risk of poor performance and dropping out from their studies. This profiling further provides an insight and understanding of the strengths, challenges and weaknesses faced in the teaching and learning among Teacher Education students in the Ugandan context. Based on the present study findings, teacher instructors and university administrators can offer prevention-oriented interventions that are consistent with the students' profile needs. The study findings will also aid university administrators in proper allocation of resources towards the learning and improvement of the motivation of Teacher Education students in Uganda.

In the next sections, we give an overview of the theoretical framework, followed by the literature review of the study variables before describing the present study.

Various models have been theorized to describe the different stages of SRL (e.g., models by Boekaerts, 1999; Pintrich, 2004; Winne & Hadwin, 1998; Zimmerman, 1990). In some of these models, SRL had been conceptualized to comprise four phases (e.g., Pintrich, 2004; Winne & Hadwin, 1998) while others conceptualize SRL as a three-phase process (e.g., Zimmerman, 1990; 2000). Although, these conceptualizations are derived from different backgrounds, their proponents agree that SRL, generally, comprise three phases including: (a) preparatory phase, (b) the performance phase and (c) the appraisal phase that follows one's performance (Zimmerman, 1990).

During the preparatory phase, learners break down learning material into smaller manageable tasks, set goals, and lay down strategies on how to achieve their goals. A number of motivational beliefs (such as self-efficacy, task value, control of learning beliefs, and goal orientations) will energize the learner in pursuit of their learning goals as well as influence the use of learning strategies and persistence during the learning process (Pintrich, 2004; Zimmerman, 2000).

In the performance phase, learners employ various strategies listed in the preparatory phase during the learning process. As Pintrich (2004) asserts, such strategies vary from surface (e.g., rehearsal and organization) to deep learning cognitive strategies (such as metacognition, critical thinking, and elaboration).

Throughout learning, one may alternate through different learning strategies to a different degree depending on the complexity of the course material and motivation of the learner. Hence, learners don't learn in an entirely deep or surface manner, but rather combine a number of strategies during the learning process. As Vanthournout, Donche, Gijbels, and Van Petegem (2014) assert

> …, one can state that the way students engage in learning is not solely the sum of the repertoire of learning strategies they have acquired, but also the interrelationship between these strategies. Consequently, it can be said that students have a relatively unique *learning profile*. Identifying typical learning profiles within a student population and investigating the relation of these subgroups and other variables such as instructional methods or learning outcomes is likely to yield valuable information that is complementary to insights gained by a variable-oriented approach (Fortunato & Goldblatt, 2006).

Moreover, using profiles to describe students' scores on various learning dimensions and their interrelation also reduces complexity, as a single (complex) construct replaces the influence of various factors and their interrelations (Von Eye & Bogat, 2006).

Lastly, during the appraisal phase, a student engages in self-judgment in which he/she compares his or her performance to that of other peers. During this phase, students also attribute factors responsible for their performance, good or poor.

Among Teacher Education students in Uganda, previous studies (e.g., (Muwonge et al., 2018)) have indicated variations in the degree of use of learning strategies during their studies. There is need to further understand whether such variations in the use of learning strategies lead to emergency of different profiles of students, and the various educational requirements of such profiles. Therefore, findings from this study will help in designing of educational interventions that are specific to the learners' SRL profile.

Based on the above background, we hypothesized that (a) there are different students' profiles based on their reported use of SRL strategies, (b) there are significant differences in the students' SRL profiles based on their motivational beliefs, and (c) students' motivational beliefs significantly predict membership in the SRL profiles.

1. Previous studies on latent profile analysis of student's self-regulated learning

Mixture modeling involves modeling of mixture outcome distributions, and as such is advantageous in clustering of individuals based on variables of interest, assessing differences across different classes, examining the effects of covariates on class membership and studying transitions of respondents between different latent classes over time (Wang & Wang, 2012). Compared to traditional cluster analyses, latent profile analysis is based on a number of statistical indices and tests upon which the number of classes can be identified (Steinley, 2003), and hence, this reduces subjectivity and bias as in the traditional cluster analysis (Aldenderfer & Blashfield, 1984). Although educational researchers agree that students differ with respect to use of SRL strategies (Abar & Loken, 2010), very few studies have tried to classify self-regulated learners based on their learning strategies (Vanthournout et al., 2014). In fact, these studies have been mainly conducted in developed countries as described below.

Ning and Downing (2015) conducted a latent profile analysis of university students' self-regulated learning strategies with a sample of 828 students in Hong Kong. Four profiles (i.e., competent profile, cognitive-oriented profile, behavioural-oriented profile and minimal profile) were identified. Compared to other profiles, the competent profile had significantly higher motivation, better study attitudes, higher academic self-concept and higher GPA's. In Finland, Räisänen, Postareff, and Lindblom-Ylänne (2016) used a person centered approach to cluster 33 university students based on their self- and co-regulation of learning. Data was collected using interviews and analyzed by inductive and deductive content analyses. Findings indicated three profiles namely (a) self-regulated students not using co-regulation (b) students with self-regulation problems relying on co-regulation and (c) actively co-regulating students with average self-regulation skills. Students with high self-regulation skills exhibited deep-level processing of study material compared to those with poor self-regulation and high co-regulation who exhibited more surface-level processing approaches to learning. This study was particularly interesting as it utilized a qualitative approach to examine individual differences among learners; something that is not very common in person-centered inquiries.

Dörrenbächer and Perels (2016) further conducted a latent profile analysis with 337 university students selected from different study subjects from a certain German university. Analysis indicated four groups of students including those with (a) low self-regulated learning and moderate motivation, (b) moderate self-regulated learning, (c) conflicting self-regulated learning and high motivation and (d) high self-regulated learning. The profile with learners of high self-regulated learning and motivation exhibited better academic achievement, low test anxiety, openness to experiences, and high extraversion. In fact, an 8-week self-regulated learning training yielded significant benefits for the group of students with moderate and motivated self-regulated learning than those with low and high self-regulatory skills. This finding implies that interventions for improving student's self-regulatory skills should be consistent with their learning profiles and needs.

Abar and Loken (2010) identified three groups of self-regulated learners (i.e., low, high, and average learners) in a sample of 205 high school students in the U.S. The high self-regulated learning profile reported high levels of mastery orientation and studying more material contrary to the low self-regulated learning profile which reported high avoidant orientations.

Barnard-Brank, Lan and Paton (2010) used a person-centered approach to identify different profiles for self-regulated learning skills among university students enrolled in online degree programs in the U. S. Five profiles of self-regulated learners were replicated in two different studies including the (a) super self-regulators, (b) competent self-regulators, (c) fore-thought endorsing self-regulators, (d) performance/reflection self-regulators, and (e) non- or minimal self-regulators. The super- and competent self-regulators had significantly higher GPA's compared to their counterparts in other profiles. In fact, super- and competent self-regulators exhibited better skills related to goal setting, time management, help seeking, environmental structuring and developing appropriate strategies to solve tasks which could have enhanced their academic performance.

Among teacher education students at the university, Heikkilä, Lonka, Niemivirta, and Nieminen (2012) identified three profiles of students (i.e., the non-regulating students, self-directed students and non-reflective students) based on their reported use of learning strategies. These three classes differed significantly with respect to their motivation, stress levels and academic achievement, with the self-directed students exhibiting higher deeper understanding of concepts, higher critical evaluation skills, and lower levels of use of surface approaches to learning.

Following the above discussions, it is evident that most of the studies have been conducted in Europe (e.g., Heikkilä et al., 2012), Asia (Ning & Downing, 2015), and the U.S. (e.g., Barnard-Brank, Lan, & Paton, 2010) – leaving a wide knowledge gap on the SRL profiles of Teacher Education students in Third World countries. Moreover, many of such studies have been conducted with other student-populations, other than Teacher Education students, thereby narrowing our understanding of the SRL profiles among Teacher Education students.

Differences in the learning contexts and curricula followed by Teacher Education students in First and Third World countries would imply that these students approach learning differently. For example, a teacher-training degree program in the U.S. will take four years instead of the 3 years as it is in Uganda. Secondly, the curricula in Uganda is more theoretical and exam-oriented with less practical experiences compared to the learning experiences in First World countries which are more practical and aimed at accumulation of skills.

Besides, universities offering Teacher Education students in First World countries are well funded compared to those in Third World countries, and as such, Teacher Education students in First World countries have access to more scholastic materials and better learning environments compared to their counterparts in Third World countries whose universities receive low funding.

Consequently, there are distinct differences in the learning patterns between Teacher Education students in First World and those in Third World countries. This explains why studies conducted with students in developed countries may not be used to inform educational practice in Third World countries. In fact, profiling of Teacher Education students will help in the development of interventions that are consistent with the students' learning profile and motivational beliefs. The present study therefore responds to the above research gaps.

2. Present study

The present study was guided by three research questions;

RQ1. Which profiles of Teacher Education students exist with regards to their use of SRL strategies? As noted above in the literature discussions, during their learning, Teacher Education students alternate through different learning strategies to a different degree, and hence, leading to existence of distinct learning profiles. Elsewhere, in developed countries, studies (e.g., Heikkilä et al., 2012) have indicated existence of such profiles, and consequently, in the present study, we hypothesize existence of different profiles of Teacher Education students with regards to their reported use of SRL strategies.

RQ2. Do motivational beliefs explain significant differences in the profiles identified above? Previous research had indicated differences in the levels of motivation among different clusters of students based on their use of learning strategies (e.g., Ning & Downing, 2015), and hence, we hypothesize significant differences in the motivational beliefs of the profiles identified above. Consistent with the literature (e.g., Heikkilä et al., 2012; Zimmerman, 1990), we expect profiles with better use of self-regulated learning strategies to exhibit higher motivational beliefs compared to their counterparts with low use of self-regulated learning strategies.

RQ3. Do motivational beliefs predict membership in the latent profiles identified above? Previous studies have indicated high correlations between motivational beliefs and use of learning strategies (Pintrich, Smith, Garcia, & McKeachie, 1993; Rotgans & Schmidt, 2010), hence, we hypothesize that motivational beliefs would predict membership of Teacher Education students in the latent profiles identified above.

3. Methods

3.1. Research design

A cross-sectional research design was adopted for the present study.

3.2. Participants

Participants were students enrolled for a Bachelor of Science with Education (BSc Ed.) degree program at undergraduate level in seven universities in Uganda. These students train to become teachers of science subjects (i.e., physics, chemistry, biology, and mathematics) at secondary school level in Uganda. The BSc Ed. Program runs for three years on full-time basis. These Teacher Education students follow a similar curriculum accredited by the National Council for Higher Education – which is a regulatory body for higher institutions of learning in Uganda. Detailed information about the composition of the BSc Ed. program in Uganda can be found elsewhere (Muwonge et al., 2018).

During their training, instructors use variety of teaching strategies including discussions, brainstorming, group work, and project work among others which provide opportunities for these Teacher Education students to use a variety of learning strategies such as critical thinking, elaboration, metacognition, peer learning, and help seeking, among others. In fact, previous studies (Muwonge et al., 2017, 2018) have indicated use of such learning strategies among Teacher Education students in universities in Uganda.

Participants were in the age range of 18–35 years with a mean age of 22 years (standard deviation [*SD*] = 2.20). The majority of the students were males (416; 78.9%), residing off-campus (65%), and were not engaged in any form of full-time or part-time employment (90%). Approximately equal numbers of students were in first and second years of study (i.e., 41% vs 34%, respectively) while the rest were in third year of study.

3.3. Instrument

A self-report questionnaire consisting of two sections was used for data collection. The first section consisted of items about the students' demographic characteristics such as age, gender, residence status, employment status, and year of study.

The second section consisted of items about students' motivational beliefs and learning strategies assessed using the Motivated Strategies for Learning Questionnaire (MSLQ; Pintrich et al., 1993) – which can be used to assess SRL in the general curriculum (Rotgans & Schmidt, 2010).

The MSLQ comprises fifteen sub-scales - with six sub-scales assessing motivational beliefs and nine sub-scales assessing learning strategies. The responses are rated on 7-point Likert scale ranging from 1 (*not at all true of me*) to 7 (*very true of me*). We excluded three sub-scales (intrinsic goal orientation, $\alpha = 0.28$; effort regulation, $\alpha = 0.28$; and help seeking, $\alpha = 0.22$) from the analysis due to extremely low reliabilities.

3.3.1. Latent profile analysis indicators

Seven sub-scales which assess the strategies that learners employ in studying their courses were used in identifying latent profiles. A confirmatory factor analysis (CFA) on this section led to an acceptable model fit (CFI = 0.921; TLI = 0.941; SRMR = 0.044; and RMSEA = 0.032). The rehearsal subscale (4 items, $\alpha = 0.69$) assessed the basic strategies that learners use to store information in the short-term/working memory (e.g., reciting or naming items from a list to be learned) rather than in the long-term memory. The elaboration subscale (5 items, $\alpha = 0.72$) examined the strategies that learners use to integrate and connect new information with prior knowledge. Such strategies as paraphrasing, summarizing and creating analogies help the learner to store information in the long term memory. The organization sub-scale (4 items, $\alpha = 0.72$) examined the students' ability to select appropriate information to be learnt and their ability to construct connections between information learnt. The critical thinking sub-scale (5 items, $\alpha = 0.76$) assessed the student's ability to apply previous knowledge to new situations in order to solve problems such as making critical evaluations and inquiries into the phenomenon under study. The meta-cognitive self-regulation sub-scale (10 items, $\alpha = 0.80$) examined the learner's awareness, knowledge and control of cognition (e.g., tracking of one's attention when reading, self-testing and questioning). The time and study management sub-scale (5 items, $\alpha = 0.68$) assessed the degree to which learners control their time and study resources. The peer learning sub-scale (3 items, $\alpha = 0.68$) examined the willingness of students to collaborate with other peers in learning.

3.3.2. Latent profile analysis covariates

We included five other variables (i.e., extrinsic goal orientation, self-efficacy, task value, test anxiety and control of learning beliefs) from the motivational beliefs section of the MSLQ as covariates. A CFA on this section led to an acceptable model fit (CFI = 0.940; TLI = 0.929; SRMR = 0.045; and RMSEA = 0.032).

The self-efficacy sub-scale (4 items, $\alpha = 0.74$) assessed the Teacher Education students' self-appraisal to master a task (i.e., self-efficacy). Teacher Education students' extrinsic motivation was assessed using the extrinsic goal orientation sub-scale (3 items, $\alpha = 0.61$). The control of learning beliefs sub scale (4 items, $\alpha = 0.53$) examined the Teacher Education students' beliefs that their academic outcomes are contingent upon their personal efforts (i.e., control of learning beliefs). The task value sub scale (5 items, $\alpha = 0.74$) assessed the Teacher Education students' evaluation of how important and useful a task is (i.e., task value) while the test anxiety scale (4 items, $\alpha = 0.63$) examined the Teacher Education students' worries and anxieties related to sitting for examinations and tests (i.e., test anxiety).

3.4. Procedure

Data were collected with the help of two trained research assistants. During questionnaire administration, the first author explained to the participants relevant details about the study. Participants were allowed to ask questions for clarity before enrolling them in the study. Participants consented to participate in the study before filling the questionnaires. Students took between twenty and 25 min to fill out the questionnaire.

3.5. Ethical considerations

Ethical clearance was obtained from the Uganda National Council for Science and Technology (SS 3908) and Mbarara University of Science and Technology Research Ethics Committee (15/05–13). All information collected was anonymous, confidential, and used for research purposes only.

3.6. Analysis

We determined the number of optimal classes by running a series of LPA models with an increasing number of latent classes and comparing *k-class* models with (*k-1*) – class models iteratively.

Selection of the best class solution was reached at using several model fit indices and test statistics which included (a) information criteria indices such as the Akaike's Information Criterion (AIC); Bayesian Information Criterion (BIC); Sample Size Adjusted BIC (SSA BIC) and (b) statistical model comparison tests which included the Lo-Mendel-Rubin Likelihood Ratio (LMR LR) test, and the Bootstrap Likelihood Ratio Test (BLRT). Smaller values on the BIC, AIC and SSA BIC indicate a better model fit (Wang & Wang, 2012).

The BLRT and LMR LR tests assess improvements in neighbouring class models (e.g; comparing models with 3 vs 4 classes, and 4 vs 5 classes etc) and statistically significant improvements after addition of one more class are assessed using the *p-values*. A significant *p-value* on the BLRT or LMR LR tests would imply a significant improvement in the *k-class* model as compared to the *(k-1)* class model (Wang & Wang, 2012) and thus accepting the k-class model and reject the k-1 model.

Simulation studies have indicated that BLRT and BIC perform better in estimating best model fits compared to other indicators (Berlin, Williams, & Parra, 2013). Hence, in choosing the best class solution in the present study, we first assessed these two values.

The quality of latent class membership classification was assessed using the posterior class membership probabilities and entropy. The entropy values range between 0.00 and 1.00 with values close to 1.00 suggesting a better classification. We also followed Clark (2010) recommendation who suggested an entropy value of > 0.80 as being high (hence good classification), 0.60 – medium and 0.40 as being low entropy (and hence an inadequate classification).

For an appropriate class solution, the correct class assignment probabilities should all be above the cut-off point of .70 (Nagin, 2005), and the size and sample proportion of each class should not be too small (Wang & Wang, 2012) for better and meaningful interpretations.

All analyses were conducted using *Mplus* 7.4 (Muthén & Muthén, 1998–2015) using the maximum likelihood estimation method which is not affected by violations of normality (Wang & Wang, 2012). Missing values were handled by mean imputations.

Mean differences and regression analyses were computed in SPSSv20 by including the socio-demographic characteristics and motivation beliefs in the regression model after conducting an unconditional latent profile analysis.

4. Results

4.1. Descriptive statistics

Descriptive statistics of the variables used in the analysis are reported in Table 1 below.

The mean scores on the motivational beliefs ranged between 4.34 and 6.15 while those of learning strategies ranged between 4.98 and 5.71. All correlations between the study variables were below 0.85, indicating lack of multicollinearity. With the exception of test anxiety, the rest of the motivational beliefs had significant positive correlations with all SRL strategies. This implies that students with such high motivational beliefs scored high on the use of learning strategies – and this is in line with previous studies (e.g., Pintrich, 2004; Zimmerman, 2000).

4.2. Latent profile analysis

Based on the results presented in Table 2, the information criteria indices reduced with increasing number of classes, indicating that increasing the number of classes produced better class solutions for the data. In fact, all information criteria indices indicated that the 5-class model provided the best solution for the data.

Although the BLRT is powerful in choosing the number of latent classes, statistical model comparisons using the BLRT was not helpful in the present study as all analyses gave *p-values* of $< .0001$, hence, the BLRT could not be used for model comparisons. Similar challenges have been reported on the use of the BLRT in other studies (e.g., Chen & Usher, 2013).

The LMR RT test was more informative and meaningful in model comparisons in our study; hence, it was used in choosing the best class solution. The *p-value* for the LMR tests for the 4-class and 5-class models were not significant indicating that addition of extra classes on the 3-class model did not provide statistically significant improvements in the model. In this case, we rejected the 4-class and 5-class models in favour of the 3-class solution - which was also more parsimonious.

The relative entropy for the 3-class model solution was above the cut-off point of .80 (see Table 2) as recommended by Clark (2010), indicating a better classification (Wang & Wang, 2012). The class counts based on the most likely posterior class membership were 66 (12.50%), 209 (39.70%), and 252 (47.8%) for profiles 1, 2 and 3 respectively. The size and proportions of students in each profile are therefore not small, and the correct class assignment probabilities are all above 0.70 (i.e., 0.93 for profile 1, 0.91 for profile 2 and 0.94 for profile 3) as recommended by Nagin (2005). Given the high relative entropy and the adequate class assignment probabilities, it is evident that the latent profile membership classification in the present study was adequate enough.

Table 2
Fit indices, statistical model comparison tests, and other characteristics for profile models with 1–5 Classes.

Fit statistics	1 Class	2 Classes	3 Classes	4 Classes	5 Classes
AIC	11585.25	10576.30	10304.38	10252.53	10184.27
BIC	11644.99	10670.18	10432.39	10414.68	10380.56
SSA-BIC	11600.55	10600.34	10337.16	10294.06	10234.55
Entropy	NA[a]	0.85	0.84	0.84	0.78
LMRT, *p-value*	NA[a]	0.00	0.00	0.16	0.30
BLRT *p-value*	NA[a]	0.00	0.00	0.00	0.00
Number of free parameters	14	22	30	38	46

Note. AIC = Akaike information criterion; BIC = Bayesian information criterion; SSA BIC = Sample size adjusted BIC; LMRT = Lo, Mendell, and Rubin likelihood ratio test, BLRT = Bootstrap likelihood ratio test; NA – Not appropriate.
[a] Entropy, LMRT and BLRT are not available for the one-class model.

The first profile comprised 66 students (12.5%; 54 males and 12 females) with low scores (mean values ranging between 3.23 and 4.17) on all the learning strategies. This profile comprised more second year students (32 students) than those of first year (17) and third year (17 students). Students in this profile demonstrated low reported use of self-regulatory learning strategies compared to the other groups, hence, this group of students was labelled the *low self-regulated learners.*

The second profile comprised 209 students (39.7%; 175 males and 34 females) with moderate scores (mean values ranging between 4.50 and 5.49) on the different learning strategies. This profile comprised more first year students (89) than those in second year (67) and third year (53). In terms of scores on the use of different learning strategies, this class was intermediate between the two other profiles; hence, it was named the *average self-regulated learners.*

The third profile comprised 252 students (47.8%; 187 males and 65 females) had high scores (all mean scores above 5.75) on all learning strategies compared to the rest of the profiles above, hence, it was named the *high self-regulated learners.* This profile comprised more first year (111) students than second year (79) and third year (62) students.

4.3. Differences between the latent profiles with respect to motivational beliefs

We noted significant differences in the profiles' extrinsic goal orientation [$F\ (2, 524) = 24.76, p < .001$], task value [$F\ (2, 524) = 48.42, p < .001$], control of learning beliefs [$F\ (2, 524) = 35.99, p < .001$], self-

Table 1
Descriptive statistics for the variables used in the analysis.

	Mean	SD	EGO	TV	CLB	SLP	TA	R	E	O	CT	MS	TS
1. EGO	*6.15*	*1.11*											
2. TV	*5.85*	*1.03*	.19**										
3. CLB	*5.13*	*1.20*	.15**	.32**									
4. SLP	*5.38*	*1.13*	.14**	.39**	.34**								
5. TA	*4.34*	*1.51*	.09*	.11**	.13**	.03							
6. R	*5.35*	*1.19*	.29**	.18**	.17**	.20**	.13**						
7. E	*5.58*	*1.05*	.21**	.39**	.31**	.41**	.05	.45**					
8. O	*5.05*	*1.30*	.15**	.30**	.25**	.30**	.06	.46**	.62**				
9. CT	*4.98*	*1.23*	.18**	.34**	.31**	.41**	.19**	.32**	.55**	.49**			
10. MS	*5.36*	*1.01*	.22**	.37**	.30**	.39**	.07	.43**	.58**	.58**	.60**		
11. TS	*5.52*	*1.11*	.28**	.35**	.21**	.33**	.03	.38**	.47**	.44**	.40**	.56**	
12. PL	*5.71*	*1.25*	.21**	.31**	.23**	.26**	.05	.32**	.44**	.38**	.36**	.47**	.45**

Note. EGO = Extrinsic goal orientation; TV = Task value; SLP = Self efficacy for learning and performance; CLB = Control of learning beliefs; TA = Test anxiety; R = Rehearsal; E = Elaboration; O = Organization; CT = Critical thinking; MS = Meta-cognitive self-regulation; TS = Time and study management; PL = Peer learning.
*$p < .01$.
**$p < .05$.

efficacy for learning and performance [F (*2, 524*) = 56.88, *p* < *.001*] and test anxiety [F (*2, 524*) = 5.13, *p* < *.001*]. As indicated in Table 3, the highly self-regulated profile exhibited high extrinsic goal orientations, task value, self-efficacy, control of learning beliefs, and test anxiety compared to the other two groups.

4.4. Predictors of latent profile membership

Motivational beliefs explained a significant proportion of variance in latent profile membership, $R^2 = 0.30$; F (*5, 521*) = 43.23, *p* < *.001*. Among the motivational beliefs, extrinsic goal orientation (β = 0.15, *p* < *.001*), task value (β = 0.21, *p* < *.001*), control of learning beliefs (β = 0.15, *p* < *.001*), self-efficacy (β = 0.26, *p* < *.001*) but not test anxiety (β = 0.05, *p* = *.20*) significantly predicted profile membership. Additionally, none of the students' demographic characteristics significantly predicted profile membership.

5. Discussion

A person-centered approach was used to examine differences in the use of self-regulated learning strategies among Teacher Education students in Uganda. A latent profile analysis identified three distinct types of students (i.e., high, average, and low self-regulated learners) who differed significantly in their motivational beliefs. Additionally, motivational beliefs significantly predicted latent profile membership.

Firstly, the presence of heterogeneous profiles of Teacher Education students, each with its own distinct mean scores on the reported learning strategies and motivational beliefs, has important revelations for researchers in the field of SRL among Teacher Education students. For example, researchers should be aware that Teacher Education students may not be homogenous with regards to the distribution of the various learning strategies used, and as such, sample statistics used to describe students' mean and variances among the different learning strategies measures may not be reflective of the whole population.

Additionally, the presence of heterogeneous populations may explain why study findings may vary. For instance, a researcher who sampled students in the high self-regulated learners' profile would obtain significantly different results from one who samples from the low self-regulated learners' profile.

Secondly, latent profile membership in the present study is a function of students' motivational beliefs; hence, students should be helped to heighten their motivational beliefs irrespective of their age and gender.

Our findings dovetail with those of Valle et al. (2008) who also identified three profiles of self-regulated learners (i.e., high, intermediate and low learners); with statistically significant differences among their self-regulation levels. Additionally, our results are consistent with those of Heikkilä et al. (2012) who also identified three profiles of student-teachers based on their approaches to learning. These profiles including the; (a) non-regulating students (106 students; 50%); (b) self-directed students (60 students, 28%) and (c) non-reflective students (46 students; 22%) differed with respect to their motivation - as it is in the present study. In fact, our high self-regulated learners' profile resemble the self-directed profile in Heikkilä et al. (2012) study - which exhibited high use of deep learning strategies.

Our results confirm earlier findings elsewhere (Heikkilä et al., 2012; Ning & Downing, 2015) which have indicated that highly self-regulated learners are highly motivated, use a variety of learning strategies, and as such have better academic performances than the low self-regulated learners. There is a clear link between students' motivational beliefs and their use of learning strategies in literature (Pintrich, 2000; 2004; Zimmerman, 1990). When learners believe that they have the abilities to succeed in their studies (i.e., high self-efficacy) or when they attach high importance to their studies (i.e., high task value), they exhibit high persistence in their studies, employ a variety of learning strategies to reach their goals, and as such are more likely to have high academic persistence compared to those with low efficacy beliefs and task value (Zimmerman, 2000). Additionally, students with a strong sense of control of learning beliefs exhibit a strong mastery goal orientation (Ng, 2012), have high efficacy beliefs, adopt different goals for learning, and as such, use a variety of learning strategies to achieve their goals.

Elsewhere (Muwonge et al., 2018), we have elaborated on the different ways of increasing Teacher Education students' self-efficacy, task value, and control of learning beliefs using approaches such as goal setting, use of learning journals, linking of learning content to learners' experience and societal problems and constant provision of feedback regarding their progress. For example, when learners set very specific and realistic goals, they are motivated to achieve such goals and are more likely to employ a variety of learning strategies to reach these goals. Previously, variable-centered analyses (Muwonge et al., 2018) have indicated that Teacher Education students with high task value and control of learning beliefs exhibited higher cognitive engagement in their studies and exhibited better performances – and this is consistent with the expectancy-value theory of achievement motivation (Wigfield & Eccles, 2000). Task value could be enhanced by allowing Teacher Education students to engage in projects that allow them to integrate knowledge from their experiences into their lesson so that they appreciate the real-life applications of the concepts they study. Also, exposing Teacher Education students to role models, especially practising teachers, will enhance their value of studying - in order to get employment later.

In the present study, students in the high self-regulated learners' profile exhibited higher test anxiety compared to other two profiles. Given that majority of previous findings have indicated low test anxiety among expert self-regulated learners, this contradicting result was indeed intriguing and surprising. This finding could be explained by the fact that because these self-regulated students are very ambitious and set high academic goals and targets for themselves (Zimmerman, 1990), coupled with the high expectations that their peers, teachers and parents may have about their future performances, it may not be surprising that these students have fears and anxieties related to passing their examinations in order to meet these expectations and their targets.

On the contrary, low self-regulated learners do not set high goals and academic targets for themselves, and hence may not have high academic expectations, thereby exhibiting low fears and worries about the likely outcomes of their test and examinations.

Contrary to our expectations, the high self-regulated learners' profile exhibited a higher extrinsic goal orientation compared to other profiles - and this finding was also not in line with previous studies which have indicated that low and poorly self-regulated learners have high extrinsic motivation. Highly self-regulated learners always have high academic targets to pursue among which include getting better grades compared to their classmates or even being recognized as being the best performers by

Table 3
Differences in the motivational beliefs of the profiles.

		Mean	SD	Minimum	Maximum
Extrinsic goal orientation	Profile 1	*5.32*	*1.42*	1.67	7.00
	Profile 2	*6.18*	*1.05*	2.00	7.00
	Profile 3	*6.35*	*0.96*	2.00	7.00
Task value	Profile 1	*5.00*	*1.20*	2.00	7.00
	Profile 2	*5.69*	*1.04*	2.20	7.00
	Profile 3	*6.21*	*0.79*	3.60	7.00
Control of learning beliefs	Profile 1	*4.40*	*1.44*	1.00	7.00
	Profile 2	*4.88*	*1.14*	2.50	7.00
	Profile 3	*5.54*	*1.03*	2.00	7.00
Self-efficacy	Profile 1	*4.42*	*1.25*	1.75	7.00
	Profile 2	*5.16*	*1.06*	2.00	7.00
	Profile 3	*5.82*	*0.93*	2.75	7.00
Test anxiety	Profile 1	*4.21*	*1.45*	1.00	6.75
	Profile 2	*4.12*	*1.54*	1.00	7.00
	Profile 3	*4.56*	*1.48*	1.00	7.00

Profile 1 = Low self-regulated learners; Profile 2 = Average self-regulated learners; Profile 3 = High self-regulated learners.

their teachers, classmates and/or parents/guardians – which tendencies predispose them to exhibit a more extrinsic goal orientation. Additionally, previous studies (e.g., Bastick, 2000) have indicated that students in developing countries join Teacher-Training institutions because of external reasons such as getting employment, failure to get tuition fees for their desired courses, among other reasons, – and as such they have low intrinsic motivation (and self-efficacy, task value and control of learning beliefs) for their program of study. Moreover, the very poor reliability of the intrinsic goal orientation sub-scale in the present study adds more evidence to the latter argument. Therefore, a combination of the above factors could explain the reason why (a) the high self-regulated learners' profile had a high extrinsic goal orientation compared to the other profiles and (b) all profiles had generally a higher extrinsic goal orientation compared to other motivational beliefs.

The low self-regulated profile in our study exhibited low task value, low self-efficacy and control of learning beliefs compared to other profiles. This profile is similar in characteristics to the (a) non-reflective profile (see study by Heikkilä et al., 2012) (b) non-academic profile (see study by Heikkilä, Niemivirta, Nieminen, & Lonka, 2011) and (c) minimal self-regulated profile (see study by Ning & Downing, 2015).

For example, the minimal self regulated profile in Ning and Downing (2015) study exhibited significantly lower motivation, low attitudes, low self concept and lower grade point averages, and although in our study, we studied slightly different constructs of motivational beliefs, these two profiles are evidently similar, as they generally exhibit low motivation. As discussed with the first profile, there is need to increase on the student-teachers' motivational beliefs using the strategies outlined above.

6. Practical implication of the study findings

In this study, we have demonstrated how latent profile analysis can be used to generate meaningful profiles of Teacher Education students based on their self-regulated learning strategies. Therefore, teacher educators should be aware that Teacher Education students vary in their approaches to learning in their studies and those variations are associated with their motivational beliefs. Additionally, some profiles of Teacher Education students with high motivation show high use of surface learning strategies such as rehearsal while others exhibit more use of deeper learning strategies (e.g., metacognition) – and this may affect the overall academic achievement of Teacher Education students in universities. Therefore, there is need for routine screening and assessment of motivation of Teacher Education students enrolled at different universities. Teacher Education students found to exhibit low motivation should be immediately refereed to the university academic counsellors, and appropriate interventions should be designed to improve on their motivation. Such interventions such as helping them to improve on goal setting, linking learning experiences to the societal needs and problems, use of learning journals, and peer learning could aid in improving on their self-efficacy beliefs, task value and control of learning beliefs. Additionally, as Ning and Downing (2015) assert, the curricula of Teacher Education students could be reviewed to include a constructivist student-centered learning environment and experiences that promote independent and active learning among Teacher Education students. A constructivist approach to learning such as problem-based learning actively involves the learner in the classroom, and as such arouses curiosity, motivation and consequently improves the learning approaches of the student. Lastly, instructors in Teacher Education universities should aid Teacher Education students in setting up learning objectives, monitoring the progress of learning and providing regular and immediate feedback to teacher education students during the learning process. Such interventions will help to improve the motivation and learning skills of teacher education students. Generally, the present study makes significant contribution to the ongoing debate regarding motivation and self-regulated learning among Teacher Education students in developing countries.

The findings above should be interpreted in light of the methodological and theoretical limitations discussed below.

First, some of the subscales used had a relatively low reliability, evidenced by the Cronbach alpha below the conventional cut-off point of 0.70. However, these subscales were retained since a lower internal consistency can still be acceptable (e.g. following a cut-off of 0.5 as suggested by Hinton, Brownlow, McMurray, & Cozen, 2004). Secondly, the current study used a cross-sectional data set, and hence, cannot be used to make causal inferences. Making causal inferences would require carefully designed longitudinal studies. Lastly, we used a self-report instrument for data collection which is subject to social-desirability, a response bias where participants respond in such a way that would be viewed favourably by others. This response bias may include over-reporting a good behaviour and under-reporting a bad or socially unacceptable behaviour, and this may affect the reliability and validity of the study findings. Future studies would employ a mixed-methods approach as a way of validating and triangulating quantitative findings with data collected from qualitative approaches such as interviews, focus group discussions and open ended questionnaires. Moreover, a mixed-methods approach provides a deeper understanding of the phenomenon under study than does a single-methods approach. For example, the high levels of test anxiety among the high self-regulated learners could have been examined further through interviews or focus group discussions.

7. Conclusion

This study has revealed that different profiles exist with respect to their reported use of learning strategies among Teacher Education students – and that there are significant differences in these profiles with regards to their motivational beliefs. The high self-regulated profile had higher motivational beliefs compared to the average and low self-regulated profiles; hence, it is important that instructors in Teacher-Training institutions design various interventions discussed above to increase the motivation of Teacher Education students. This is especially important as previous studies have indicated low motivational beliefs (especially low self-efficacy) among Teacher Education students in Uganda (Muwonge et al., 2018).

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.

CRediT authorship contribution statement

Charles Magoba Muwonge: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Funding acquisition, Resources. **Joseph Ssenyonga:** Conceptualization, Formal analysis, Resources, Supervision, Writing - original draft, Writing - review & editing. **Henry Kibedi:** Conceptualization, Supervision, Writing - original draft, Writing - review & editing. **Ulrich Schiefele:** Conceptualization, Formal analysis, Resources, Software, Supervision, Writing - original draft, Writing - review & editing.

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