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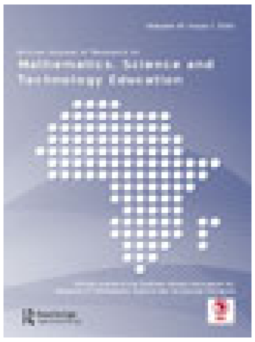

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Secondary School Students' Motivation Profiles for Physics Learning: Relations with Cognitive Learning Strategies, Gender, Attitudes and Individual Interest

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For efficient and effective pedagogical interventions to address Uganda's alarmingly poor performance in Physics, it is vital to understand students' motivation patterns for Physics learning. Latent profile analysis (LPA)—a person-centred approach—can be used to investigate these motivation patterns. Using a three-step approach to LPA, we sought to answer the following research questions: RQ1, which profiles of secondary school students exist with regards to their motivation for Physics learning; RQ2, are there differences in students' cognitive learning strategies in the identified profiles; and RQ3, does students' gender, attitudes, and individual interest predict membership in these profiles? The sample comprised 934 Grade 9 students from eight secondary schools in Uganda. Data were collected using standardised questionnaires. Six motivational profiles were identified: (i) *low-quantity* motivation profile (101 students; 10.8%); (ii) *moderate-quantity* motivation profile (246 students; 26.3%); (iii) *high-quantity* motivation profile (365 students; 39.1%); (iv) *primarily intrinsically motivated* profile (60 students, 6.4%); (v) *mostly extrinsically motivated* profile (88 students, 9.4%); and (vi) *grade-introjected* profile (74 students, 7.9%). *Low-quantity* and *grade-introjected* motivated students mostly used surface learning strategies whilst the *high-quantity* and *primarily intrinsically* motivated students used deep learning strategies. Lastly, unlike gender, individual interest and students' attitudes towards Physics learning predicted profile membership. Teachers should provide an interesting autonomous Physics classroom climate and give students clear instructions in self-reliant behaviours that promote intrinsic motivation.

Keywords: *Motivation profiles; physics learning; latent profile analysis*

For the past decade, students in Uganda have performed poorly in Science subjects, especially Physics (Uganda National Examinations Board, 2017). Consequently, the number of students willing to take Physics at advanced and tertiary levels has been rapidly decreasing (Kwarikunda et al., 2020), running counter to Uganda's projections of an accelerating need for improved Science literacy and competitiveness in Science and Technology among its citizens. Before designing any pedagogical interventions to increase the uptake of Physics, there is an urgent need to fully understand students' motivation to learn Physics in Uganda.

To fully characterise and understand the learning process, theories have emphasised the differences in learners' knowledge, beliefs, motivation, strategies and abilities at specific points in time during the learning process (Hickendorff et al., 2018). In order to account for the differences in motivation (Lazarides et al., 2016), a significant amount of research has been done (e.g.

Ardura & Pérez-Bitrián, 2019; Potvin & Hasni, 2014; Schumm & Bogner, 2016). These studies have mostly used variable-centered approaches (VCAs). VCAs assume that the relation between the constructs of motivation can be applied to all learners without catering for their individual differences (Vansteenkiste et al., 2009). They lack the ability to deal with heterogeneity within and between individuals. Specifically, numerous studies have explored students' motivation to learn Science using VCAs (e.g. Green et al., 2007). These studies have either treated Science as a whole (e.g. Zeyer, 2010) or have explored specific domains such as Chemistry (e.g. Ardura & Pérez-Bitrián, 2019) and Mathematics (Green et al., 2007). Whilst numerous studies have been conducted in developed countries and at university level, only a handful have investigated students' motivation for learning at secondary school level (e.g. Ardura & Pérez-Bitrián, 2019) in developing countries (e.g. Kwarikunda et al., 2020).

Conversely, person-centred analyses (e.g. latent profile analysis) primarily aim to categorise individuals into groups; members have similar profiles that remain concealed in VCAs. Latent profile analysis is a mixture modelling technique that employs a person-centred approach to uncover different existing but unobserved homogeneous subgroups of individuals (latent profiles) underlying a heterogeneous group (Wang & Wang, 2012). Unlike the traditional cluster analyses, e.g. K-means cluster analysis, which divide data into groups by measuring the Euclidean distance between the data points, latent profile analysis (LPA) uses probabilistic modelling to identify the likely groups and place individuals within these identified groups (Vermunt, 2010). LPA places emphasis on the individuals based on their patterns of individual characteristics, providing a moderate amount of parsimony and specificity (Muwonge et al., 2020). Latent profiles are formed such that there is much similarity within a profile, while at the same time as much difference between the profiles as possible (Hickendorff et al., 2018). Using LPA the dynamic interplay of latent profile indicator variables (in this case motivation) and covariates (like interest and attitudes) can be further studied at the individual level. Moreover, further insight into the complex ways in which other covariates interact with the motivational profiles that could have remained masked in VCA is provided by LPA (Vansteenkiste et al., 2009). Such insights not only complement existing variable-centred motivation research (e.g. Kwarikunda et al., 2020), but also provide useful heuristics for understanding how these covariates associate with these particular latent profiles.

Watt et al. (2019) suggest that targeting a well-defined profile of students is more effective compared with targeting each individual in a classroom, since feedback can be easily individualised and instructional approaches are flexibly adapted to cater for a group of similar students rather than each individual. However, little work has been devoted to the person-centred approach by motivational researchers (Chittum & Jones, 2017; Vansteenkiste et al., 2009), especially in developing countries. Equally, research investigating the relationship between secondary school students' motivation and cognitive learning strategies during Physics learning in third world countries is very scarce. Thus, there is a need for further investigation of students' motivation for Physics learning using a person-centred approach to (i) uncover the groups of students with distinct motivational profiles for Physics learning and their differing cognitive learning strategy uses that would otherwise have remained undetected in a VCA and (ii) provide further insights into possible ways in which gender, attitudes and individual interest influence membership of the disparate profiles in developing countries such as Uganda. Additionally, person-centred methods provide a more nuanced understanding of the motivational dynamics associated with particular students' profiles (Watt et al., 2019), which is currently unknown in Physics education research. In the present study, we addressed this knowledge gap by identifying secondary school students' Physics learning motivational profiles using LPA (RQ1). Further, how students in the various motivational profiles differed in their cognitive learning strategy use (RQ2) was explored. Furthermore, the factors that predicted profile membership were investigated. Specifically, we investigated whether students' gender, attitude and individual interest predict membership in the above identified profiles (RQ3). Gaining insight into students' motivational profiles for Physics learning is fundamental, so that motivational interventions can be tailored to each particular profile.

Motivation, Cognitive Strategies, Individual Interests and Attitudes towards Science Learning

The study of students' Science learning through concepts such as motivation, individual interest and attitudes has been a major concern for researchers and educational systems around the world for quite some time (Potvin & Hasni, 2014). Although students' motivation for, individual interests and attitudes towards Science are sometimes judged to be generally positive (Potvin & Hasni, 2014), there have been reports of considerable international and contextual differences (e.g. Sjøberg & Schreiner, 2010), gender differences mostly in favour of males (Meece & Jones, 1996) and subject-related differences (Green et al., 2007).

As a complex multidimensional construct, motivation interacts with cognition to influence learning Science (Glynn et al., 2011). Although different learning theorists have attempted to describe motivation and its constructs, the social cognitive perspective provides a comprehensive framework that has influenced many Science learning studies to date. In this framework, motivation for learning Science is defined as the internal state that arouses, directs and sustains Science learning behaviour (Bandura, 1986; Glynn et al., 2011). Social cognitive theory outlines four constructs of motivation: self-efficacy, self-determination, intrinsic motivation and extrinsic motivation. Students who are motivated to learn Science are self-determined, maintain their interest and pay attention during the learning process (Renninger, 2000), make an extra effort to learn (Potvin & Hasni, 2014) and use adaptive cognitive learning strategies (such as metacognition and critical thinking) that promote deep learning (Schiefele, 1991) to complete the learning task with high standards and excellence (Potvin & Hasni, 2014). Students who use maladaptive cognitive learning strategies, e.g. rehearsal (for memorisation) use strategies that result in surface learning, have low motivation for learning, and are more likely to achieve less during Physics classes (Schiefele, 1999).

On the other hand, given that individual interest is content specific, in Physics learning we refer to it as an enduring directive force that drives the ongoing feelings and deepening relations of a person to Physics (Renninger, 2000). Individual interest facilitates sustained attention and effort during learning, maintains enjoyment of focused and continued engagement in a task for the sake of the task itself and enhances the desire for mastery (Schiefele, 1999). Learners with high individual interest for learning Physics report high levels of intrinsic motivation, use a variety of adaptive cognitive learning strategies, highly endure during difficult learning tasks and are highly self-regulated compared with their counterparts with low interest (Kwarikunda et al., 2020). Individual interest increases as knowledge and the accompanying value (grade or career motivation) for the subject increase (Schiefele, 1991).

There has been little consensus in defining the term 'attitudes' among Science education researchers. However, in our study we adapted the definition offered by Kind et al. (2007), who described attitudes towards Physics as the feelings the student has about Physics learning based on their beliefs about Physics. Prior research (Potvin & Hasni, 2014) indicated that students with positive attitudes towards learning enjoy learning the subject with more confidence while using adaptive learning strategies. Attitudes have been found to greatly influence achievement. However, little is known about the relations between these variables during Physics learning in Uganda while using a person-centred approach. In the following section, we briefly provide an insight into results of studies that used a person-centred approach, in particular the LPA.

Previous Studies Using LPA of Students' Motivation

Most motivation psychologists, parents and teachers agree that students' learning behaviours in Science disciplines differ from one student to another (Hickendorff et al., 2018) and across the various Science disciplines (Glynn et al., 2011). Mostly, these differences are a result of the multiple reasons that drive students' learning behaviours. Whilst particular motives may be of great importance to some students, the same motives may be less important to others, indicating that there might exist different groups of students characterised by different motivational profiles.

Compared with cluster analyses, LPAs are based on a number of statistical indices and tests upon which the number of profiles can be identified (Muwonge et al., 2020). This reduces biases and subjectivity, which are common in cluster analyses (Wang & Wang, 2012). Despite little prior attention having been given to person-centred analyses by motivation researchers (Vansteenkiste et al., 2009), a few existing studies indicate that different profiles of students' motivation for Science learning exist. Below we summarise some of these studies.

Vansteenkiste et al. (2009) used a person-centred approach to identify motivation profiles of 881 Grade 12 students from two secondary schools in Belgium. They used autonomous motivation and controlled motivation as the LPA indicators. Four profiles (good quality, good quantity, poor quality and poor quantity) were uncovered. Students in the good quality motivation profile (i.e. high autonomous, low controlled) scored highly on cognitive processing and achievement tests, unlike their peers in the poor-quality motivation profile. Similarly, Lazarides et al. (2016) used LPA and identified four motivational profiles in Mathematics using 849 Grade 7–12 students in Berlin, Germany. The researchers named these four profiles: low motivation profile, moderate motivation profile, utility motivation profile and high motivation profile. Students within the utility- and low-motivation profiles reported lower achievement in Mathematics than the students within other profiles.

Elsewhere in USA, whilst using intrinsic and extrinsic motivation as LPA variables, Hayenga and Corpus (2010) identified four Science motivational profiles using 343 Grade 7 and 8 students from public schools. They identified these profiles as: high-quality, low-quality, high-quantity and low-quantity motivation. The high-quality motivation profile consisted of students who achieved significantly higher grades than their counterparts in the other three profiles. While using the same variables in elementary schools, Corpus and Wormington (2014) identified three profiles of motivation: primarily intrinsic, primarily extrinsic and high quantity (characterised with high levels of both motivations). Students in the primarily intrinsic cluster outperformed their peers in the other two clusters.

In a study of motivation for Science learning in 937 pre- High School students, Chittum and Jones (2017) identified five profiles: (i) low motivation; (ii) low usefulness and interest but high success; (iii) somewhat high motivation; (iv) somewhat high motivation and high success; and (v) high motivation. These profiles differed significantly in Science scores, interest and perceived usefulness of Science. Specifically, students in the high motivation profile indicated high science scores, interest and Science usefulness.

The aforementioned studies were conducted in developed countries. Low- and-middle income countries such has Uganda have secondary school Physics curricula and Physics classroom settings (characterised by inadequate laboratory space, limited teaching materials and high teacher–student ratio) that are different from those in developed countries. These factors among others have been found to affect students' motivation (Potvin, & Hasni, 2014). Thus, it may not be appropriate to generalise findings from person-centred motivation studies in developed countries to low- and-middle income countries. Moreover, most studies have explored motivation patterns in Science or Mathematics and not in Physics.

Attitudes, Individual Interest and Gender as Predictors of Profile Membership

Previous studies have noted associations between gender, attitudes, interest and motivation for Science learning. Some studies (e.g. Potvin, & Hasni, 2014) have revealed that students' attitudes predict their motivation for Science learning. Other studies indicate that interest predicts motivation for learning Physics (Kwarikunda et al., 2020). Contradictory results in prediction studies of gender on motivation exist. Whereas some studies (e.g. Glynn et al. 2011; Green et al., 2007; Sjøberg & Schreiner, 2010) indicate gender as a predictor of students' motivation for Science learning, others (e.g. Kwarikunda et al., 2020) report that gender has no influence on students' motivation for Science learning. However, there is a paucity of research on the prediction pathway of attitudes towards Physics and individual interest in Physics learning motivation profile membership, particularly in developing nations.

Methods

Participants

Participants were 523 (56%) female and 411 (44%) male Grade 9 students from eight randomly selected secondary schools in Masaka District (Central Uganda). Five female and four male students (from the initial 934 students) did not sign the consent form and were thus eliminated from data analysis. The majority of participants were aged between 14 and 15 years (mean = 14, SD = 1.51), and resided at home (n = 475, 51%).

Procedures

Ethical approval was gained from the relevant University Research Ethics Committee. With permission from the school administrators, students were contacted and briefed about the aim and purpose of the study. Students provided written consent. The questionnaires were then administered to students during a Physics class in the presence of at least one of the researchers and a research assistant. Participants used approximately 45 min to complete the questionnaire. Participation was voluntary, and anonymity of the students and schools was guaranteed.

Measures

Motivation

Students' motivation for Physics learning was assessed using a 24-item Physics version of modified Science Motivation Questionnaire II (MPMQII; Kwarikunda et al., 2020; original version by Glynn et al., 2011). Words such as 'Science' and 'grade A' were replaced with 'Physics' and 'between 75% and 100%' respectively, to fit into the context of the study. The instrument has five subscales: intrinsic motivation, grade motivation, career motivation, self-efficacy and self-determination. All of the items were answered on a five-point Likert scale ranging from 1 (never) to 5 (always). Internal consistencies as indexed by Cronbach's α were 0.66–0.78 and considered satisfactory (see Table 1). Confirmatory factor analysis (CFA) indicated that a five-factor model solution fitted with the data.

Attitudes towards Physics learning

Students' attitudes towards Physics learning were assessed using a 14-item subscale (Physics learning attitudes) of the Physics Attitude Scale (PAS; Kaur & Zhao, 2017). Items were scored on a five-point Likert scale with anchors ranging from strongly agree (5) to strongly disagree (1). An example item includes 'I wait eagerly for the Physics period'. The internal consistency of the subscale was good (α = 0.86).

Individual interest

Students' individual interest in Physics learning was assessed using the Individual Interest Questionnaire (IIQ; Rotgans, 2015). The scale consists of seven items e.g. 'I am very interested in Physics', and 'Outside of school, I read a lot about Physics' that were rated on a five-point Likert scale, ranging from 1 (not true at all) to 5 (very true for me). The reliability coefficient of the IIQ was satisfactory (α = 0.74).

Cognitive learning strategies

Different aspects of cognitive learning strategies (i.e. rehearsal, elaboration, critical thinking, organisation) and metacognition were assessed using the cognitive learning strategies section of the Motivated Strategies Learning Questionnaire (Pintrich et al., 1991). All items were answered on a seven-point Likert scale ranging from 7 (very true of me) to 1 (not at all true for me). An example of the items that assessed rehearsal use is 'When studying for Physics, I read my class notes over and over again'. Reliability coefficients were in the acceptable range (see Table 1).

Table 1. Descriptive statistics and correlations between the study variables of the overall sample

	Mean (SD)	1	2	3	4	5	6	7	8	9	10	11	12	α
Motivation														
1. IM	2.54 (0.84)	—	0.61	0.61	0.55	0.53	0.55	0.56	0.45	0.42	0.44	0.46	0.47	0.70
2. SE	2.94 (0.83)		—	0.56	0.62	0.65	0.41	0.44	0.34	0.34	0.34	0.34	0.39	0.78
3. SD	2.72 (0.76)			—	0.50	0.53	0.50	0.45	0.43	0.42	0.36	0.38	0.43	0.68
4. CM	2.94 (0.90)				—	0.57	0.41	0.47	0.36	0.30	0.32	0.33	0.38	0.72
5. GM	3.13 (0.73)					—	0.32	0.41	0.26	0.30	0.29	0.30	0.36	0.66
Prediction variables														
6. II	2.39 (0.80)						—	0.54	0.44	0.44	0.45	0.43	0.41	0.74
7. AT	3.65 (0.42)							—	0.42	0.39	0.39	0.42	0.45	0.86
Cognitive strategies														
8. RE	5.06 (1.29)								—	0.60	0.64	0.63	0.67	0.83
9. OG	5.19 (1.13)									—	0.63	0.61	0.63	0.82
10. EL	5.23 (1.25)										—	0.65	0.74	0.87
11. CT	4.74 (1.29)											—	0.64	0.79
12. MC	5.19 (0.99)												—	0.89

Note: IM, intrinsic motivation; SE, self-efficacy; SD, self-determination; CM, career motivation; GM, grade motivation; II, individual interest; AT, attitudes towards physics learning; RE, rehearsal; OG, organisation; EL, elaboration; CT critical thinking; MC, metacognition. All correlation values are significant when $p < 0.05$.

Data Analysis

Preliminary analyses

To ascertain their suitability for use in the main analyses, data were first screened for missing values, outlier, normality, sampling adequacy and sphericity. Less than 0.5% missing values were noted and handled by the full-information-maximum-likelihood method, since this method is more efficient as compared with other methods (Wang & Wang, 2012). The Shapiro–Wilk test, as a test for normality, resulted in a non-significant value ($p = 0.78$), which indicates that the distribution of our data was normal. We conducted the Kaiser–Meyer–Olkin Measure of Sampling Adequacy, and our data passed this test (KMO = 0.93). Also, Bartlett's test of sphericity indicated that the correlation matrix of items was of adequate quality ($\chi^2 = 2571.65$, d.f. = 276, $p < 0.05$). CFA was then conducted to ascertain the fit of the factors with our data. We followed Hu and Bentler's (1999) model fit criteria: comparative fit index (CFI) and Tucker–Lewis index (TLI) ≥ 0.90, standardised root mean square residual (SRMR) ≤ 0.08 and root mean square error of approximation (RMSEA) ≤ 0.06. Correlations were also done to assess the relatedness of the study variables (see Table 1).

Latent Profile Analysis

After data screening, we conducted an LPA using Mplus 8 (Muthén & Muthén, 2017). To detect and choose the correct model and number of profiles, we used six model selection criteria. These were Akaike's information criterion (AIC; Akaike, 1974), Bayesian information criterion (BIC; Schwarz, 1978), sample-size adjusted BIC (ABIC; Sclove, 1987), the Lo–Mendell–Rubin likelihood ratio test (LMR), parametric bootstrapped likelihood ratio test (BLRT) and entropy, as suggested by previous research (e.g. Morin and Wang, 2016). A model that produces lower values of AIC, BIC and ABIC has better fit (Muthén & Muthén, 2017). The LMR and BLRT compare the estimated model (k) with a model that has one profile less than the estimated model ($k - 1$). Probability values > 0.05 indicate that the $k - 1$ class model provides a significantly better fit to the data than the k class model (Wang & Wang, 2012). Entropy assesses the adequacy of profile membership classification. An entropy value greater than 0.8 indicates that the latent profiles are highly discriminating (Wang & Wang, 2012). We further examined closely the posterior classification probabilities and profile size distribution (as suggested by Wang & Wang, 2012). A model with posterior classification probability values > 0.9 for all profiles indicates adequate membership allocation. A profile with size of <5% is problematic, and thus it is recommended to reject a model with such a profile size.

Differences in Students' Cognitive Learning Strategies and Predictors of Profile Membership

We used the three-step approach as suggested by Hickendorff et al. (2018), whilst in the one-step approach, external variables are incorporated as covariates in the initial model estimation stage. In the three-step approach, the investigation of association of external variables with the assigned profiles is done after model identification. The latter approach was used since the covariates do not interfere with latent profile classification (Wang & Wang, 2012). After identifying the final model, we explored how (i) the profiles differed on use of cognitive learning strategies and (ii) profile membership was predicted by other factors (gender, individual interest and attitudes) using the *AUXILLIARY (e)* and *(r)* statements, respectively, in the LPA rerun (Wang & Wang, 2012). The inclusion of the covariates at this stage in the model helps to limit Type 1 errors (Vermunt, 2010), which are common problematic issues when using the one-step LPA approach. Chi square (χ^2) and p-values of the Equity tests were noted to describe the differences in cognitive learning strategy as a function of profile type. Probability values from the test of categorical latent variable multinomial logistic regression were noted to describe the predictions.

Results

Preliminary Results

For the CFA, the MPMQII (CFI = 0.94, TLI = 0.93, RMSEA = 0.062, SRMR = 0.041), the IIQ (CFI = 0.97, TLI = 0.95, RMSEA = 0.088, SRMR = 0.036) and PAS (CFI = 0.93, TLI = 0.92, RMSEA =

0.072, SRMR = 0.38) scales revealed acceptable fit indices, thus supporting the factor validity of the measures we used with our study population. Correlations of the study variables were all positive and significant ($p < 0.01$) ranging from 0.29 to 0.74 as indicated in Table 1.

Latent Profile Analysis of Students' Motivation for Physics learning

As presented in Table 2, the AIC and ABIC decreased as the number of the profiles increased. The BRLT improved from the four-profile model. The six-profile model was considered the best since: (i) the BLRT *p* was significant and the profiles were easily distinguished; (ii) the BIC was lowest; (iii) its entropy was higher than that of the five-profile model; and (iv) profile compositions were better for all classes unlike in the five-profile model (Table 2).

Descriptive Statistics of the Six Motivation Profiles

Two major groups of profiles were identified: the quantity and quality groups of motivation profiles (Figure 1). The quantity group comprised profiles 1, 5 and 6 with varying levels (amounts) of motivation. Profile 1 ($n = 101$, 10.8%) consisted of students characterised with the 'lowest' levels of motivation and thus was named the *low-quantity motivation* (LQM) profile. Profile 5 ($n = 246$, 26.3%) consisted of students with 'moderate' levels of motivation when compared with profiles 1 and 6. This profile was named the *moderate-quantity motivation* (MQM) profile. Profile 6 consisted of the largest student population ($n = 365$, 39.1%) with the 'highest' level of motivation when compared with profiles 1 and 5, thus it was named the *high-quantity motivation* (HQM) profile.

The quality group of profiles comprised three profiles (i.e. profiles 2–4). Profile 2 ($n = 60$, 6.4%) comprised students with the highest intrinsic motivation mean score. Given that their self-efficacy and self-determination were higher than their goal and career motivation, this profile was named the *primarily intrinsically motivated* (MPI) profile. Profile 3 ($n = 74$, 7.9%) comprised students with the highest self-efficacy and grade motivation but with very low career and intrinsic motivation. This profile was named the *grade-introjected* (GI) profile. Lastly, profile 4 ($n = 88$, 9.4%), named the *mostly extrinsically motivated* (MEM) profile, comprised students with higher scores of grade and career motivation (extrinsic) than intrinsic motivation.

Table 2. Model fit indices for the models with number of latent profiles ranging from 1 to 7

	Model						
Fit statistics	One-profile	Two-profile	Three-profile	Four-profile	Five-profile	**Six-profile**	Seven-profile
FP	10	16	22	28	34	**40**	46
Log *L*	−2,256.57	−1,911.54	−1,829.00	−1,810.85	−1,789.79	**−1,678.34**	−1,601.52
AIC	4,533.14	3,855.07	3,702.00	3,677.70	3,647.58	**3,597.35**	3,587.45
BIC	4,572.39	3,917.86	3,788.33	3,787.58	3,781.00	**3,652.32**	3,765.75
ABIC	4,540.69	3,867.10	3,718.53	3,698.75	3,673.13	**3,646.23**	3,534.98
Entropy	—	0.857	0.846	0.819	0.831	**0.91**	0.752
LMR LR	—	<0.001	0.008	0.301	0.18	**0.23**	0.33
$_{a}$LMR	—	<0.001	0.009	0.310	0.19	**0.24**	0.34
BLRT	—	<0.001	<0.001	0.02	0.04	**0.04**	0.19
Profiles with <5% composition	—	—	—	—	1	**—**	1

Note: FP, free parameters; Log *L*, model loglikelihood; AIC, Akaike's information criterion; BIC, Bayesian information criterion; ABIC, sample-size adjusted BIC; LMRLR, Lo–Mendell–Rubin likelihood ratio test; $_{a}$LMR, adjusted Lo–Mendell–and Rubin likelihood ratio test; BLRT, bootstrap likelihood ration Test. Bold indices are for the selected model.

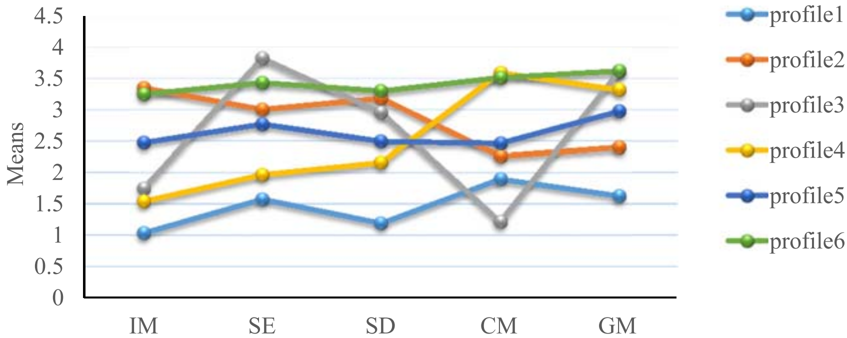

Figure 1. Graph showing variation of sample means of the different profiles with the factors of motivation. IM, intrinsic motivation; SE, self-efficacy; SD, self-determination; CM, career motivation; GM, grade motivation Class.

Differences in Students' Cognitive Learning Strategy use across the six Motivation Profiles

There were significant differences in students' cognitive strategy use across the six profiles (see Table 3). Students in the MPI profile (profile 2) scored highest on four of the five indicators of cognitive strategies. Profiles 1 (LQM), 3 (GI) and 4 (MEM) indicate that students in these profiles use less critical thinking ($\chi^2 = 0.82$, $p = 0.36$) and metacognition ($\chi^2 = 2.10$, $p = 0.44$) learning strategies during Physics learning. In contrast, students in Profiles 2 (MPI) and 6 (HQM) use organisation ($\chi^2 = 3.45$, $p = 0.23$), critical thinking ($\chi^2 = 0.94$, $p = 0.14$) and metacognition ($\chi^2 = 3.\ 84$, $p = 0.43$) learning strategies more during Physics learning.

Predictors of Profile Membership

The results of the categorical latent variable multinomial logistic regression (see Table 4) indicated that, unlike *gender*, *individual interest* and students' *attitudes* to Physics learning significantly predicted profile membership. Students with low individual interest are more likely to be placed in the LQM profile than in the MPI profile ($\beta = 0.37$, SE = 0.29, $p = 0.29$) or the HQM profile ($\beta = 0.36$, SE = 0.31, $p = 0.28$). Students with highly positive attitudes towards Physics learning are more likely to be placed in the GI and HQM profiles than in the LQM ($\beta = 0.012$, SE = 0.39, $p = 0.18$) or MEM ($\beta = 0.28$, SE = 0.31, $p = 0.38$) profiles.

Discussion

Following recommendations by Muthén and Muthén (2017) and Wang and Wang (2012), we used a person-centred approach to reveal six distinct profiles of secondary school students characterised by differing quantity and quality of motivation during Physics learning. In comparison with other studies, our findings were similar to those of Lazarides et al. (2016) in which they identified three quantity profiles (low motivation, moderate motivation and high motivation). However, their utility profile had no similarity with any of our qualitative profiles. In another study by Hayenga and Corpus (2010), although no moderate-quantity motivational profile was identified, they also identified the low- and high-quantity motivation profiles. Similarly, Corpus and Wormington (2014) identified three qualitative profiles of students with differing ratios of intrinsic to extrinsic motivation. Unlike in both studies (in Germany and USA), we identified a group of students characterised by the highest self-efficacy and grade motivation scores but with lower intrinsic motivation and lowest career motivation scores. These students have high believe that they can perform well in Physics, regardless of their low intrinsic drive and personal desire to pursue a career in Physics. Perhaps, the presence of this profile in our sample is due to the structure of secondary schools in Uganda, in which students experience increasing control and affirmation from teachers and parents that they can actually obtain good grades (Ekatushabe et al., 2021) regardless of their intrinsic motivation and value for pursuing the

Table 3. Equality tests of means across profiles using the three-step procedure

	Profile							
	LQM (1)	MPI (2)	GI (3)	MEM (4)	MQM (5)	HQM (6)	χ^2	
Cognitive learning strategy	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)		Differences between profiles
Rehearsal	4.19 (0.19)	5.21 (0.18)	6.03 (0.17)	4.98 (0.94)	4.70 (0.13)	5.56 (0.09)	50.73*	1 < 5 < 4 < 2 < 6 < 3
Organisation	4.20 (0.20)	5.76 (0.19)	4.24 (0.76)	5.09 (0.98)	4.89 (0.13)	5.69 (0.96)	55.89*	1 = 3 < 5 < 4 < 6 = 2
Elaboration	4.39 (0.19)	6.54 (0.09)	4.23 (0.98)	4.07 (0.96)	4.78 (0.12)	5.83 (0.78)	82.23*	1 = 4 < 3 < 5 < 6 < 2
Critical thinking	4.03 (0.17)	5.42 (0.18)	4.07 (0.98)	4.25 (0.96)	4.14 (0.12)	5.28 (0.96)	65.26*	1 = 3 = 4 = 5 < 6 = 2
Metacognition	4.39 (0.15)	6.35 (0.16)	4.47 (0.09)	4.53 (0.17)	4.83 (0.09)	6.10 (0.06)	94.46*	1 = 3 = 4 < 5 < 6 = 2

*Significant, $p < 0.05$.

LQM, Low-quantity motivation; MPI, primarily intrinsically motivated; GI, grade-introjected; MEM, mostly extrinsically motivated; MQM, moderate-quantity motivation; HQM, high-quantity motivation.

Table 4. Statistics from a categorical latent variable multinomial logistic regression using MPI as the reference profile

		Predictor		
Reference profile	Profile	Gende ($R^2 = 0.243$)	Individual interest ($R^2 = 0.467$*)	Attitudes ($R^2 = 0.352$*)
MPI	LQM	−0.018 (0.36)	−0.370 (0.29)*	−0.168 (0.39)*
	GI	0.420 (0.33)	0.046 (0.89)	0.350 (0.34)*
	MEM	0.012 (0.25)	0.260 (0.31)*	0.110 (0.31)
	MQM	0.280 (0.21)	0.024 (0.09)	−0.012 (0.06)*
	HQM	−0.270 (0.12)	−0.360 (0.31)*	0.360 (0.24)*

β (SE). * Significant when $p < 0.05$.

subject. Corpus and Wormington (2014) suggests that students whose ability beliefs are influenced by their peers and parents tend to largely favour their extrinsic concerns over their intrinsic motives and interests, which could undermine the development these students' intrinsic motivation.

In terms of profile prevalence, similarly to Lazarides et al.'s (2016) study, the *high-quantity motivation* profile was the most prevalent profile in our sample, a pattern of motivation that perhaps characterises high school students owing to the competitive and outcome-oriented stance common at this level of schooling (Corpus & Wormington, 2014). Given that intrinsic motivation has been found to be positively related to students' levels of performance (Vansteenkiste et al., 2009), their enduring long-term interest in learning (Kwarikunda et al., 2020) and engagement in classroom activities (Green et al., 2007), we expected more students in the *primarily intrinsic* motivation profile. However, as early as Grade 9, this profile registered the lowest membership. Wormington et al. (2012) suggest that exhibiting high or similar levels of intrinsic and extrinsic motivation is more adaptive during Science learning. Nevertheless, the results of our study provide further supportive evidence that indeed contextual, subject-specific and individual differences exist in secondary school students' motivation.

As hypothesised, students in the distinct profiles differed significantly in their cognitive learning strategy usage. Whereas LQM, GI and MQM students used more surface learning strategies, their counterparts with higher quality and quantity motivation used adaptive learning strategies more frequently. Highly motivated learners are more likely to have high academic persistence and cognitive engagement, exhibit a high sense of control of their learning beliefs and mastery goals, and tend to use adaptive cognitive learning strategies that result in deep learning to reach their learning goals compared with those with low motivation (Potvin & Hasni, 2014; Schiefele, 1999).

Concerning the prediction of latent profile membership, students' attitudes towards Physics and individual interest predicted profile membership, unlike gender. We agree with Zeyer (2010), who argued that attitudes, interest and cognitive styles might be much better predictors for explaining motivation to study Physics than gender. Studies (e.g. Kwarikunda et al., 2020; Sjøberg & Schreiner, 2010) have revealed no statistically significant gender differences in students' motivation for Physics and Science learning in developing countries. Hence Physics teachers should help students increase their motivation for learning Physics irrespective of students' gender.

Educational implications

We have demonstrated using LPA that students differ in their quality and quantity of motivation for learning Physics. Teachers should be aware that students vary in their motivation for Physics learning and that these variations are associated with their cognitive learning strategy usage, individual interest and attitudes towards Physics learning. Thus teachers need to adopt their instructional behaviours to suit the needs of the different profiles of the students if effective Physics learning is to occur.

Rather than the MPI profile, the HQM profile was much more prevalent, perhaps because teachers emphasise overall motivation for Physics learning. Although HQM students report strong performance

(Wormington et al., 2012), Corpus and Wormington (2014) found that good-quality motivated students (high intrinsic motivation relative to external regulation) obtain stronger academic performance and are lifelong learners. Much as it is important to motivate students extrinsically, teachers should note that intrinsic motivation is more advantageous to develop life learning (Hayenga & Corpus, 2010; Kwarikunda et al., 2020). To foster the development of intrinsic motivation in LQM, EM and GI profiles, firstly, teachers should provide an autonomous Physics classroom climate in which students are provided with options and opportunities to make their own decisions, as well as feeling that they have control over their environment and learning. Secondly, Physics teachers should give students instructions in self-reliant behaviours that promote self-regulation (Kwarikunda et al., 2020; Muwonge et al., 2020).

To improve students' motivation and their cognitive learning strategies, students' attitudes and individual interest should be boosted (given their predictive role on motivation). Ong and Ruthven (2009) suggested the use of inquiry-based learning with emphasis on 'hands-on' learning and laboratory work. This not only encourages student-driven discoveries and visualisations—correcting the abstract notion about the subject—but also develops their metacognitive skills. 'Hands-on' learning arouses curiosity, enthusiasm and enjoyment in Physics learning (Potvin & Hasni 2014). Rather than competitive and individualistic tasks, Shachar and Fischer (2004) advise teachers to shift to collaborative tasks since task sharing improves students' confidence, interest and attitudes. During such collaborative tasks, much attention, clear simplified instructions and constant feedback should be given to sustain students' motivation and engagement. Working in groups develops students' beliefs about their capabilities as a group, consequently improving on their motivation for learning Physics. Rather than letting students struggle with surface learning skills, Zeyer (2010) recommends that students be taught (and trained in) the various cognitive learning skills (with much focus on deep-level learning startegies) so that they can put into practice such skills during Physics learning.

Limitations

First, questionnaires were used to collect data. Such self-report measures are prone to bias and social desirability (Rotgans, 2015). To triangulate quantitative findings, future studies can employ mixed methods approaches. Secondly, some subscales had low reliabilities (below the conventional cut-off of 0.70). However, we retained these subscales following the recommendation by Vermunt (2010). Thirdly, to draw conclusions about the causal directions of the examined effects, further longitudinal studies can be designed to examine the direction of these effects as well as the trajectories of the profile membership.

Conclusion

This study confirms that individual differences with regard to motivation for Physics learning exist. Six profiles of students' motivation for Physics learning were identified. More so, the profiles differed significantly with regard to cognitive learning strategy usage. Students in the *high quantity* and *primarily intrinsically motivated* profiles used strategies that enhance deep learning as compared with their counterparts. Unlike gender, individual interest and attitudes towards Physics learning predicted profile membership. Students with low attitudes towards Physics learning and low individual interest were more likely to be placed in *low quantity* and *mostly extrinsically motivated* profiles. To improve the quality of students' motivation during Physics learning, teachers should emphasise autonomous, democratic and self-paced pedagogical settings.

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