The role of psychology students' motivational profiles in a problem-based learning curriculum

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The Role of Psychology Students' Motivational Profiles in a Problem-Based Learning Curriculum

Abstract (118 words)

This study investigated the effect of individual differences in students' motivational profiles for going to college on their subsequent experiences in a problem-based learning (PBL) curriculum (*N* = 736). Our results identified five motivational profiles: low-quantity, poor-quality, moderate, good-quality, and high-quantity profile. These profiles were similar to prior research investigating motivational profiles in non-PBL settings. We further found that students' motivational profiles were associated with their experience of positive affect, their engagement in class, and their academic achievement. Overall, the results indicated that students with low-quantity motivational profiles experienced less positive affect, were less engaged, and performed worse in a PBL setting. These results highlight the importance of considering prior individual differences when examining the effectiveness of PBL.

Objective (1991 words)

Student-centered learning environments such as problem-based learning (PBL) are often implemented to promote students' intrinsic motivation for studying (Barrows, 1986; Norman & Schmidt, 1992; Hmelo-Silver, 2004). Especially, learning in the context of meaningful problems, the opportunity to self-direct one's learning, and collaboration with fellow students are believed to be motivating factors in PBL (e.g., Wijnia et al., 2011). Nevertheless, research has shown that implementing PBL will not necessarily result in highly motivated students. For example, some studies report on motivational problems that occur in PBL environments (Dolmans & Schmidt, 2006). Furthermore, several comparative studies have shown that PBL curricula are not more motivating than lecture-based environments (e.g., Galand et al., 2010; Wijnen et al., 2018; Wijnia et al., 2011).

One factor that could determine the effectiveness of a PBL environment are individual differences between students when they enter a PBL curriculum (Dolmans & Gijbels, 2013). For example, students' motivation for going to college can differ before they have experienced the PBL method. A previous study has shown that individual differences in motivation can affect how students view certain aspects of the PBL environment, such as the quality of the problem (Noordzij & Wijnia, 2020). The current study examines if individual differences in students' motivation to go to college can affect their subsequent engagement in PBL meetings, their mood, and academic achievement.

Motivational Profiles

In this study, motivation is viewed from a self-determination theory (SDT) perspective (Deci & Ryan, 2000). According to SDT, the quality of a learner's motivation, determined by the reasons driving their behavior, can affect several student outcomes (e.g., Howard et al., 2021). In SDT, several types of intrinsic and extrinsic types of motivation have been distinguished that lie on a self-determination continuum (see Figure 1, Deci & Ryan, 2000; Ryan & Deci, 2020). Autonomous motivation types are considered to be good in quality as these students experience volition and psychological freedom in the activities they undertake. Autonomous motivation can be further subdivided into intrinsic motivation types (i.e., studying out of interest) and identified motivation (i.e., studying because it helps you to achieve personal growth or life goals).

Poor-quality motivation types are controlling and lead to the experience of pressure (Deci & Ryan, 2000). This pressure can come from within, such as feelings of guilt (i.e., introjected motivation) or external sources (i.e., external motivation). Lastly, students can experience amotivation, for example, when they see no reason for engaging in an activity (Deci & Ryan, 2000).

Good-quality and poor-quality motivational reasons can co-occur within the same person. For example, students can think learning is fun (i.e., intrinsic) *and* feel like they must go to college because their parents expect it from them (i.e., external). Prior research has revealed that students can fall into distinct subgroups of motivational profiles that differ in the configuration of the reasons that drive their behavior (e.g., Vansteenkiste et al., 2009). Typically, between 3-6 subgroups of motivational profiles are identified (see Wijnia & Baars, 2021). The most commonly identified profiles are the high-quantity, low-quantity, good-quality, poor-quality, and moderate profiles. The high- and low-quantity profiles are mirror images of each other. Students with high-quantity profiles score high on all SDT-motives expect amotivation, whereas students with a low-quantity profile score low on these constructs. Students with a good-quality profile have relatively higher levels of autonomous motivation than controlled motivation and amotivation. Students with a poor-quality profile experience higher levels of controlled motivation and low levels of autonomous motivation. Moderate profiles fall in between these profiles and are characterized by moderate/average scores on all constructs. There is some discussion about which motivational profile is most optimal. Some studies indicate that good-quality profiles will result in the most optimal student outcomes (Vansteenkiste et al., 20090, whereas some other studies have found that the high-quantity and good-quality profiles are equally effective (e.g., Gillet et al., 2017).

Prior research has mainly focused on motivational profiles that can be identified in non-PBL, teacher-centered settings; it is unclear if similar motivational profiles can be identified in a PBL-setting and which motivational profile is optimal for student outcomes. We expected to find between 3-5 motivational profiles, similar to prior research. We further expected that individual differences in students' motivational profiles for going to college could affect their subsequent experiences in a PBL-setting. To this end, we examined the effects of motivational profiles on students' subsequent positive and negative affect. The presence of positive affect and the absence of negative affect are often measured as indicators of student well-being (Diener et al., 1999). We further examined effects on tutor-rated professional behavior in group meetings (Loyens et al., 2007). This professional behavior scale consists of items about students' level of active participation and preparation for group meetings and can be seen as a measure of engagement. Finally, we examined differences between motivational profiles on academic achievement.

Method

In this PBL curriculum, the first-year psychology program consists of seven (out of eight) PBL-courses in which the Seven-Jump method is applied (Schmidt, 1983). Students work on problems in groups of maximally 13 students under the guidance of a tutor. All first-year (N = 881) psychology students of three cohorts were invited to participate in the study. Participation was voluntary; 736 students (74% female, M_{age} = 19.70, SD_{age} = 2.79) filled out the motivation-survey at the start of the year (the first 3-8 weeks of the academic year), and 321 students filled out the affect-survey near the end of the academic year.

Motivation was measured with the academic motivation scale (AMS; Vallerand et al., 1992). The scale consists of 28 items that reflect possible answers to the question, "Why do you go to college?" divided over seven subscales. Responses are measured on a 7-point Likert-type scale ranging from 1 (*does not correspond at all*) to 7 (*corresponds exactly*). See Table 2 for example items and reliability (i.e., McDonald's omega). The psychometric properties of the motivation scale were investigated with confirmatory factor analysis in Mplus 8.4 (Muthén & Muthén 2017) and showed acceptable fit, $\chi^2(329) = 1286.32$, $p < .001$, CFI = .92, TLI = .90, RMSEA = .06, SRMR = .07. Standardized factor scores were saved and used in the subsequent analyses

We measured students' experience of positive (McDonald's ω =.82) and negative affect (McDonald's ω =.87; Watson et al., 1988), teacher-rated professional behavior in PBL-meetings (score from 0-10; Loyens et al., 2007), and weighted average grades (based on credits) on assignments and exams as outcome measures during the first year.

Results

Latent profile analysis (LPA) was performed in Mplus 8.4 to identify PBL-students' motivational profiles for going to college. In LPA, individual students are assigned to subgroups based on their scores on the AMS-subscales. Based on the number of profiles identified in prior research, we evaluated models including 1-10 latent profiles using 5,000 random sets of start values and 1,000 iterations. The 200 best solutions were retained for final stage optimization (Gillet et al., 2017). The means of the seven motivation subscales were freely estimated in all profiles (Wang et al., 2016).

We used multiple statistical indicators to compare models with different numbers of profiles (Nylund et al., 2007). Lower values of the Akaike information criterion (AIC), the consistent AIC (CAIC), the Bayesian information criterion (BIC), and the sample-adjusted BIC (ABIC) indicate better-fitting models. The adjusted Lo, Mendell, and Rubin's (2001) likelihood ratio test (aLMR) and the bootstrap likelihood ratio test (BLRT) are tests that compare a k profile model with a k-1 profile model. A significant p-value indicates that the model with k profiles fits the data better than the more parsimonious model with one fewer profile (k-1).

Simulation studies have shown that the CAIC, BIC, ABIC, and BLRT are particularly effective in choosing a model, whereas the AIC over-extracts and the aLMR under-extracts the number of profiles (Morin & Wang 2016; Nylund et al., 2007; Peugh & Fan 2013; Yang, 2006). Entropy is a summary measure for the classification quality in an LPA-model, where a cut-off of > .80 is considered good (Clark & Muthén, 2009). To have an acceptable minimum number of individuals in each profile, we required the smallest profile to include at least 5% of the sample's individuals (Nylund et al., 2007).

Table 2 presents the results of our LPA. In line with previous studies, all indicators, except for aLMR after the 4-profile solution, kept improving when adding additional profiles to the model (Gillet et al., 2017). We, therefore, examined the elbow plots of the information criterion indicators (see Figure 2). The point after which the slope flattens suggests the optimal number of profiles (Morin et al., 2011). Based on all indicators, we selected the 5-profile model. Differences between the five profiles on the motivation subscales were tested with ANOVAs with the Games-Howell procedure to correct for Type I error (see Table 2). Figure 3 illustrates the standardized mean scores of the four profiles. Scores below -1 indicate low scores, whereas scores above 1 indicate high scores.

Profile 1 (n = 68, 9.24%) is characterized by high scores on amotivation and the lowest scores on all other motivation constructs compared to the other profiles. We, therefore, labeled this profile as low-quantity. Profile 2 (n = 130, 17.66%) is characterized by moderate-low scores on intrinsic motivation and moderate, but relatively higher scores on external motivation and amotivation. We classified this as a poor-quality profile. Profile 3 (n = 298, 40.49%), the moderate profile, was the largest group and consisted of moderate scores. Profile 4 (n = 76, 10.33%) was characterized as a good-quality profile, with low scores on introjected and external motivation and moderate but relatively higher scores on intrinsic motivation to know and to experience stimulation. The fifth profile (n = 164, 22.28%) was labeled high-quantity. It was characterized by the lowest score on amotivation, and moderate-high scores on other motivation constructs.

We further examined whether differences in students' motivational profiles for going to college at the start of the first year could affect their experiences and performance in a PBL environment (see Table 4). We found statistically significant differences for positive affect, engagement in PBL meetings (i.e., professional behavior), and academic achievement. The low-quantity group indicated that they experienced the lowest levels of positive affect and differed significantly from the moderate, good-quality, and high-quantity profile groups, but not from the poor-quality group. The low-quantity group also obtained a significantly lower weighted average on assignments and examinations than the four other profile groups. The good-quality group obtained the highest scores on teacher-rated professional behavior/engagement. These scores were significantly higher than the teacher-rated professional behavior scores of the low-quantity and poor-quality groups.

Discussion

This study examined if individual differences in students' motivational profiles for going to college could affect their subsequent experiences in a PBL-setting later that year. This study is part of a larger project in which we investigate the stability and change in students' motivation profiles during a three-year PBL-program with the overall goal of investiging how motivation develops within PBL and how it affects learning.

In this study, we first examined if similar motivational profiles were found as in previous research conducted in non-PBL, teacher-centered environments. In line with previous research, we identified five profiles. The profiles were similar to the profiles found in prior research; however, in our study, the poor-quality and good-quality profiles were less pronounced in that all scores were more or less moderate (between -1 and 1). It is unclear if the PBL-environment influenced this or if there are other factors at play.

Our study further showed that differences in motivational profiles at the start of the academic year could affect students later experiences in the PBL environment. Especially, students with a low-quantity motivation profile experienced lower positive affect and obtained significantly lower grades. The good-quality motivational profile group obtained the highest scores from their tutor's on professional behavior in group meeting, which can be seen as an indicator of engagement. These results highlight the importance of considering prior individual differences when examining the effectiveness of PBL.

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Table 1

Example Items and Reliablity of the Academic Motivation Scale

Scale	Example item	McDonald's ω
Intrinsic motivation (IM) to know	Because I experience pleasure and satisfaction while learning new things.	.88
IM to experience stimulation	For the intense feelings I experience when I am communicating my own ideas to others.	.81
IM to accomplish things	For the experience when I discover new things never seen before.	.83
Identified motivation	Because I think that a college education will help me better prepare for the career I have chosen.	.62
Introjected motivation	To prove to myself that I am capable of completing my college degree.	.87
External motivation	Because with only a high-school degree, I would not find a high-paying job later on.	.77
Amotivation	Honestly, I don't know; I really feel that I am wasting my time in school.	.90

Table 2

Results from the Latent Profile Analyses

											Smallest profile	
k	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy	aLMR	BLRT	*n*	%
1	-6986.61	14	1.22	14001.22	14079.63	14065.63	14021.18	-	-	-	736	100.00
2	-6162.44	22	1.69	12368.88	12492.11	12470.11	12400.25	.90	.0020	< .0001	208	28.26
3	-5758.57	30	1.52	11577.14	11745.18	11715.18	11619.92	.88	.0001	< .0001	79	10.73
4	-5534.20	38	1.57	11144.39	11357.24	11319.24	11198.58	.89	.0095	< .0001	80	10.87
5	-5375.01	46	1.82	10842.01	11099.67	11053.67	10907.60	.87	.3136	< .0001	68	9.24
6	-5255.24	54	1.92	10618.48	10920.94	10866.94	10695.48	.89	.3603	< .0001	18	2.45
7	-5129.55	62	2.01	10383.10	10730.38	10668.38	10471.50	.90	.5357	< .0001	19	2.58
8	-5038.43	70	1.65	10216.86	10608.95	10538.95	10316.68	.90	.2256	< .0001	12	1.63
9	-4967.03	78	1.68	10090.06	10526.95	10448.95	10201.28	.90	.4488	< .0001	9	1.22
10	-4904.55	86	1.64	9981.10	10453.81	10376.81	10103.73	.90	.4042	< .0001	8	1.09

Note. LL = Model log-likelihood; #fp = number of free parameters; AIC = Akaike information criterion; CAIC = consistent AIC; BIC = Bayesian information criterion; ABIC = sample size-adjusted BIC; aLMR = adjusted Lo–Mendell–Rubin likelihood ratio test; BLRT = bootstrap likelihood ratio test.

Table 3

Mean Motivation Scores for the Five Motivational Profiles

	Low Quantity (n = 68)		Poor Quality (n = 130)		Moderate (n = 298)		Good Quality (n = 76)		High Quantity (n = 164)			
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	$F(4, 731)$	η^2_p
IM know	4.30_a	0.81	5.03_b	0.54	5.90_c	0.43	6.19_d	0.50	6.65_e	0.34	383.09***	.677
IM stimulation	3.79_a	0.91	3.94_a	0.68	5.00_b	0.60	5.22_b	0.77	6.05_c	0.55	247.29***	.575
IM accomplishment	3.72_a	0.80	4.09_b	0.77	5.16_c	0.58	4.47_d	1.03	6.16_e	0.58	240.39***	.568
Identified	4.14_a	0.66	5.18_b	0.62	5.66_c	0.60	4.93_b	0.75	6.09_d	0.67	138.26***	.431
Introjected	3.92_a	1.06	4.52_b	1.10	5.38_c	0.82	2.86_d	1.06	5.57_c	1.20	131.79***	.419
External	4.15_a	1.09	5.24_b	0.89	5.43_b	0.85	3.11_c	1.04	5.53_b	0.96	124.64***	.405
Amotivation	3.63_a	0.94	1.72_b	0.68	1.39_c	0.59	1.33_c	0.59	1.11_d	0.42	222.01***	.548

Note. Scale range = 1-7. IM = intrinsic motivation. Mean scores are statistically significantly different based on the Games-Howell procedure post hoc test if they have different subscripts.

*** $p < .001$.

Table 4

Affect and Performance

	Low Quantity		Poor Quality		Moderate		Good Quality		High Quantity			
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	$F(4, 316)$	η^2_p
Positive affect (*n* = 321)	3.14_a	0.48	$3.30_{a,b}$	0.58	$3.59_{b,c}$	0.52	$3.56_{b,c,d}$	0.53	$3.85_{b,d}$	0.54	12.76***	.139
Negative affect (*n* = 321)	2.15	0.82	1.97	0.61	2.13	0.72	1.92	0.60	1.96	0.76	1.20	.015
Professional behavior (*n* = 639)	7.10_a	0.77	7.46_b	0.70	$7.59_{b,c}$	0.70	7.78_c	0.72	$7.57_{b,c}$	0.77	7.00***	.042
Academid achievement (*n* = 732)	6.26_a	0.82	$6.53_{a,b}$	0.82	6.73_b	0.79	6.79_b	0.96	6.62_b	0.78	5.68***	.030

Note. Affect measures are on a scale from 1-5. Professional behavior is on a scale from 0-10, and academic achievement on a scale from 1-10. Mean scores are statistically significantly different based on the Games-Howell procedure post hoc test if they have different subscripts.

*** $p < .001$.

Figure 1

Self-Determination Continuum

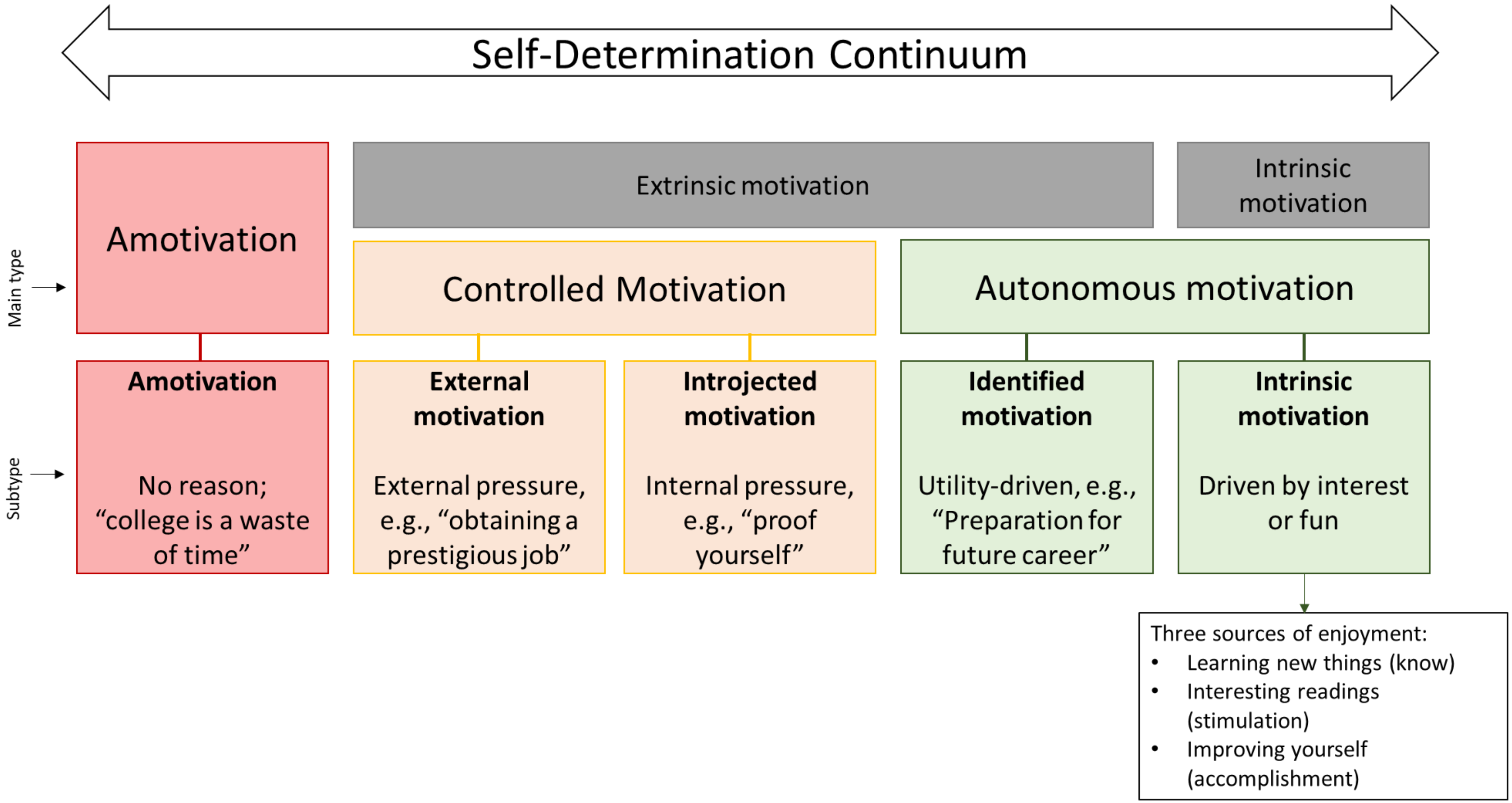
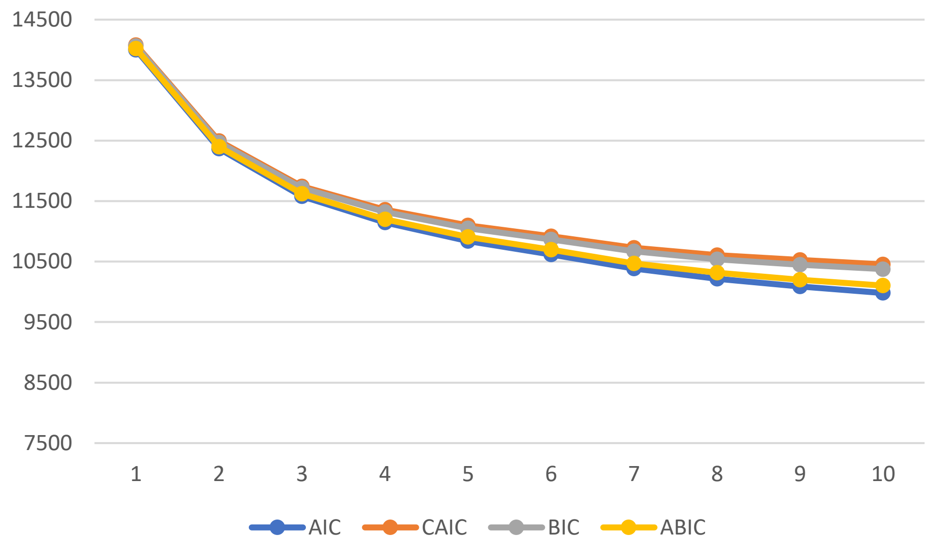


Figure 2

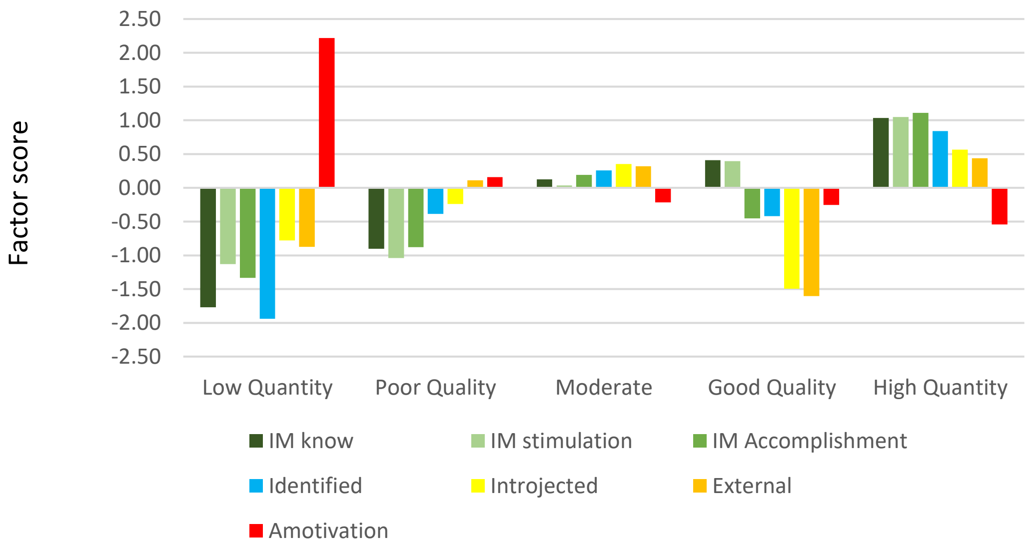
Elbow Plots



Note. AIC = Akaike information criterion; CAIC = consistent AIC; BIC = Bayesian information criterion; ABIC = sample size-adjusted BIC.

Figure 3

Motivational Profiles with Standardized Factor Scores (M = 0, SD = 1)



Note. IM = intrinsic motivation.