

Perception of Assessment Tasks and Autonomous Learning Motivation in English Classes: A Latent Profile Analysis

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Abstract: This study examined how secondary vocational students perceive classroom assessment tasks in English classes and how distinct perception profiles are associated with autonomous learning motivation. Drawing on classroom assessment theory and self-determination theory, the study focused on five perceived assessment-task features: congruence with learning plans, transparency, diversity, authenticity, and student consultation. Data were collected from 281 students at a secondary vocational school in Shanghai, China. Students completed the Perception of Assessment Tasks Questionnaire and the autonomous learning motivation dimension of the Autonomous Learning Scale. Exploratory and confirmatory factor analyses supported the psychometric adequacy of the measures, and latent profile analysis was used to identify heterogeneous patterns of assessment-task perceptions. The results supported a three-profile solution: negative perception (14.6%), positive perception (49.1%), and partially positive perception (36.3%). Students in the negative perception profile reported significantly lower autonomous learning motivation than those in the positive and partially positive profiles, whereas the latter two profiles did not differ significantly. These findings suggest that students' subjective interpretations of assessment tasks are meaningfully linked to autonomous learning motivation. In particular, assessment tasks perceived as aligned with learning goals, authentic, and responsive to student consultation may support motivational conditions for self-regulated English learning in secondary vocational education.

Keywords: Assessment Tasks, Autonomous Learning Motivation, Latent Profile Analysis, English Learning, Secondary Vocational Students, Self-Regulated Learning.

1. Introduction

A self-regulated learner has the capacity to monitor their own learning, set goals, establish plans, access resources, and assess progress [1][2]. Recent research trends emphasize integrating two critical domains: self-regulated learning (SRL) and classroom assessment (CA). This integration enables educators to refine CA practices for enhancing academic performance [3], underscoring the potential of CA to cultivate self-regulated learners. The synergy between these fields offers significant insights into adapting pedagogical strategies to improve learning outcomes [3].

As an important part of CA, classroom assessment environment (CAE) should be created to develop self-regulated learners (SRLers). The theoretical model of the CAE, first proposed by Brookhart [4], establishes a conceptual framework for understanding the role of classroom assessment in motivating students. Within this theoretical model, the CAE emerges as a critical factor for students in that they tend to evaluate the effectiveness of assessments based on the psychological orientation fostered by the assessment context [5]. According to the model, students can percept the characteristics of classroom assessment tasks (CATs) which can develop CAE.

To advance SRL-focused instructional design, several studies have proposed theoretical models that integrate CAE and SRL frameworks [6][7][8]. As CAE constitute a core component of the learning ecosystem, they can be strategically designed to foster SRL [9]. Empirical evidence

reveals significant positive correlations between CAE and SRL [8], indicating that CAE and CATs may enhance students' SRL capabilities. Specifically, Zhang and Li [9] strongly advocate for additional investigations into the role of CAE in promoting SRL. As a base stone of CAE, the function of enhancing students' SRL capabilities of CATs should be focused.

2. Literature Review

2.1. CATs and Self-efficacy

The development of self-efficacy is influenced by students' perceptions of assessment tasks. McMillan and Workman [10] examined how testing-oriented assessment tasks affect self-efficacy, proposing that test characteristics significantly shape its formation. They argued that students demonstrate weaker self-efficacy when assessment tasks are perceived as overly challenging or when grading criteria remain ambiguous. A critical determinant of self-efficacy lies in understanding the nature of scoring mechanisms and evaluation standards. Their study further emphasized that assessments characterized by authenticity and transparency enhance students' self-efficacy.

Van et al. [11] empirically demonstrated that Dutch first-year university students' perceptions of formative assessment effectively predict their self-efficacy, particularly highlighting task authenticity as one of the strongest predictive factors. The research also revealed that self-efficacy predicts improvements across six competency domains, with academic performance serving as an indicator

of such competency development. These findings suggest a research pathway: since perceived assessment characteristics predict self-efficacy, which in turn influences learning motivation and outcomes, investigating the relationship between assessment perceptions and learning motivation becomes theoretically warranted.

Alkharusi [12] found that students' self-efficacy judgments in science education become more positive when they perceive high authenticity and transparency in assessment tasks. In a cross-sectional study of Omani students, Alkharusi and Al-Hosni [13] identified that secondary students exhibit stronger self-efficacy and adopt deep learning strategies when assessments are perceived as enjoyable, meaningful, and within their capability, particularly when feedback is delivered privately.

However, the effects of perceived assessment characteristics on self-efficacy are not uniform. Through path analysis of Omani primary and secondary students, Alkharusi et al. [14] revealed: (1) Perceived congruence with learning objectives, authenticity, and transparency directly enhance self-efficacy; (2) These factors also exert indirect effects through motivational pathways; (3) While student consultation and task diversity demonstrate indirect influences, their direct effects prove statistically insignificant. Zhang's [15] synthesis cautions that neglecting students' perceptions during task design may nullify assessments' efficacy-enhancing potential, emphasizing the necessity to consider learner-relevant factors such as task relevance, engagement level, and achievability.

This body of research collectively underscores the critical role of student-centered assessment design in fostering self-efficacy. The findings advocate for transparent communication of evaluation criteria, authentic task construction aligned with learning objectives, and sensitivity to learners' affective responses during assessment implementation.

2.2. Autonomous Learning Motivation (ALM)

Self-determination theory classifies intrinsic motivation, integrated motivation, and identified regulation as components of autonomous motivation [16], which manifests in students' SRL behaviors. ALM, a central concept in Self-Determination Theory (SDT) that contrasts with controlled motivation [17], has garnered increasing attention. According to SDT, autonomous motivation encompasses three forms: intrinsic motivation (engagement driven by inherent satisfaction), identified motivation (action based on personal endorsement of an activity's value), and integrated motivation (alignment of an activity with one's core values and self-concept) [18].

ALM serves as a benchmark for evaluating learning behaviors [19]; therefore, investigating the relationship between CATs and ALM may help educators better leverage assessments to promote students' learning engagement, which is good for being a SRLer finally, that is, students' perceptions of assessment tasks are related to intrinsic motivation [20]. The satisfaction of three basic psychological needs—autonomy, competence, and social relatedness—facilitates the development of ALM, which in turn promotes ALM [21].

SRL is intrinsically linked to ALM [22][23], because self-efficacy can be seen as competence which is one of three basic psychological needs and is also a part of students' learning motivation [24]. In recent years, studies have found that self-efficacy is statistically related to ALM [25][26][27][28], so

this study believes that perceived assessment task has a certain relationship with ALM, but existing researches have not directly studied it.

Ng et al. [29] classified 782 Singaporean secondary students into four clusters using five variables: deficient self-regulation, perceived task value, anxiety, self-efficacy, and learning strategies. Compared to students in the other three clusters, those in the "high-motivation cluster" exhibited the highest levels of self-regulated learning motivation (measured by intrinsic motivation and identified regulation) alongside superior self-regulation capabilities. Given that SRL fundamentally relies on learning motivation [30][31], higher motivational levels correlate with increased utilization of cognitive strategies, thereby enhancing self-learning competence [32]. Furthermore, factors such as learning adaptability [32] and technology acceptance [33] depend critically on the mediating role of self-directed learning motivation to exert their positive effects on autonomous learning outcomes.

There are some studies focusing on the relationship between the design of assessment tasks and autonomous learning. In a system that emphasizes self-assessment tasks, self-evaluation as an intermediate variable can improve the accuracy of predicting college students' use of technology for autonomous learning [34], so assessment tasks help cultivate students' characteristics of autonomous learning [35]. Practice-oriented assessment tasks can stimulate students' enthusiasm for learning and promote autonomous learning [36]. Other studies have focused on assessment in specific teaching models, such as assessment tasks based on the SPOC learning model can improve students' autonomous learning ability [37]. These studies are based on the perspective of teachers designing assessment tasks, but ignore students' views. Since most of the time in classroom teaching is spent on assessing students' learning [38], it is reasonable to carefully consider students' perceptions of the assessment process. The relationship between students' views on assessment tasks and autonomous learning should also be paid attention to.

2.3. The Study

Using a latent profile analysis, this study hopes to focus on the perception of CETs by secondary vocational students in Shanghai, China, classify students accordingly, and then investigate the relationship between students' perceptions of different types of tasks and ALM. Specific research questions are as follow:

- (1) How many types of students can be clustered based on perceptions of classroom assessment tasks?
- (2) In terms of ALM, what are the differences between different students' groups?

3. Methods

3.1. Participants

The online questionnaires were administered and completed collectively during class meeting sessions, with the entire process lasting approximately 15 minutes. Valid questionnaires of English demonstration classes are finished by 281 students (about 50% are female; the age range is 16-18 years old) coming from a secondary vocational school in Shanghai. Detailed data is shown in Table 1.

Table 1. Sample demographic variables (N=281)

Item	Category	Proportion (%)
major	flight attendant	41.3
	mechanical and electrical technology applications	36.7
	airline services	6.4
	airport security	15.7
study period	3 years	28.8
	5 years	71.2

3.2. Instrument

A questionnaire including two scales is administered in this study. All items of two scales above are scored on a 7-point Likert scale from 1 (strongly disagree) to 7 (strongly agree).

Students' perceived assessment tasks. The Perception of Assessment Tasks Questionnaire (PATI) [39] was used. The scale has 35 items and five scales: congruence with learning plans, authenticity, student consultation, transparency and diversity. According to the results of exploratory analysis, 14 items are deleted because factor loading coefficients in more than two dimensions are greater than 0.4. In this study, the CFA results show that the five-item PATI has an acceptable model fit ($\chi^2=481.40$, $df=178$, $p<.001$; RMSEA = .078, CFI = .959, TLI = .952, SRMR = .059), and the Cronbach's alpha coefficient of this scale is 0.92.

ALM. Adapted from the 7 items of the ALM dimension of the "Autonomous Learning Scale (ALS)" [40]. This

dimension reflects the sense of responsibility for learning, openness to experience and intrinsic motivation, as well as confidence in handling new activities, all of which are core elements of autonomous learning [41]. Based on the results of the exploratory analysis, one item is deleted because the factor loading coefficient is less than 0.4. In this study, the CFA results show that the one-item ALS has an acceptable model fit ($\chi^2=27.010$, $df=7$, $p<.001$; RMSEA = .101, CFI = .993, TLI = .985, SRMR = .012), and the Cronbach's alpha coefficient of this scale is .927.

3.3. Data Analysis

This paper conducts an exploratory factor analysis (EFA) using SPSS 27 to explore the latent structure of the two scales. Then, a confirmatory factor analysis (CFA) is conducted using Mplus 8.3 to verify the construct validity. Cronbach's alpha coefficient is used to test the internal consistency. Detailed data are shown in Table 2.

Descriptive statistics of variables are calculated using SPSS 27. In addition, for the core research questions, latent feature analysis (LFA) is performed using Mplus 8.3, and 6 fitting statistics are used to evaluate the profile solution: AIC, BIC, SSA-BIC, LMR, BLRT, and entropy. The Bolck-Croon-Hagenaars approach (BCH) and robust three-step method (R3STEP) are used after the optimal profile solution is determined, respectively, to test how different profiles are related to students' ALM.

Table 2. Reliability and validity test results of the two scales

Scales	CFA							Cronbach's α
	χ^2	df	p-value	RMSEA	CFI	TLI	SRMR	
PATI	481.40	178	< .001	.078	.959	.952	.059	.920
ALS	27.01	7	< .001	.101	.993	.985	.012	.927

Note. PATI = Perception of Assessment Tasks Questionnaire; ALS = Autonomous Learning Scale.

4. Results

4.1. Reliability and Validity Test of the Scales and Descriptive Statistics

Table 3. Descriptive Statistics for the Variables

	M	SD
Perceived Assessment Task	5.57	1.16
congruence	6.38	0.97
transparency	4.53	2.18
diversity	4.84	1.91
authenticity	6.46	0.95
consultation	5.64	1.54
ALS	6.36	1.01

Note. ALS = Autonomous Learning Scale.

Table 3 uses the average score of each variable and lists the descriptive statistics of the variables. It can be seen that students generally have a good perception of the assessment

task. Among the five characteristics of the assessment task, the most obvious and positive one perceived by students is authenticity, and the least obvious and negative one is transparency. The overall autonomous learning of students is close to the total score of 7 points.

4.2. Bivariate Correlational Analyses

As shown in Table 4, there is a significant positive and moderate correlation between students' perceived assessment tasks and autonomous learning ($r=.51$) and a statistically significant positive correlation between autonomous learning and the perceived assessment tasks. Among them, autonomous learning has the highest correlation with congruence ($r=.78$) and the lowest correlation with transparency ($r=.14$). Among the five attributes, except for authenticity and transparency having no statistically significant correlation, the other variables are all significantly positively correlated.

Table 4. Results of Bivariate Correlational Analyses

	asst	cong	trans	diver	auth	cons	aul
asst	1						
cong	.53**	1					
trans	.85**	.12*	1				
diver	.89**	.18**	.96**	1			
authen	.49**	.77**	.08	.13*	1		
cons	.79**	.49**	.47**	.55**	.49**	1	
aul	.51**	.78**	.14*	.21**	.77**	.48**	1

Note. asst= perceived assessment task; cong= congruence; trans= transparency; diver=diversity; authen= authenticity; cons = student consultation; aul = ALM.

* $p<0.05$. ** $p<0.01$

4.3. Latent Profile Analysis

Latent profile analysis is conducted to determine the optimal number of latent profiles among students based on their responses to the PATI. Table 5 presents the fit indices for models with different numbers of latent profiles. The information criteria (IC)-based fit statistics, including AIC, BIC, and sample-size adjusted BIC, consistently decreased from one to six profile solutions. The lowest values are observed for the five-profile model. In terms of Entropy, the

four-profile model has the highest value (Entropy = 0.962). The results of the LMR and BLRT tests indicate that the two-profile model fit the data better than the one-profile model ($p < .001$), the three-profile model fit the data better than the two-profile model ($p < .001$). However, the four-profile model does not provide a good fit compared with the three-profile model ($p > .05$), and the five-profile model does not provide a better fit compared with the four-profile model ($p > .05$). Considering the model fit indices collectively, the three-profile solution is considered as the best fitting model.

Table 5. Model Fit Indices for the Latent Profile Analysis of Perceived Assessment Task

fit indices	number of profiles				
	1Profile	2Profiles	3Profiles	4Profiles	5Profiles
AIC	5007.459	4500.610	4034.589	3804.737	3713.927
BIC	5043.842	4558.824	4114.632	3906.611	3837.631
SSA-BIC	5012.133	4508.088	4044.871	3817.824	3729.819
LMR	/	.000	.005	.181	.1244
BLRT	/	.000	.000	.000	.000
Entropy	/	0.915	.940	.962	.954
Proportion Min(%)	/	49.82	14.59	12.81	8.54

Note. The best profile scheme is generally judged based on the following criteria: AIC value, BIC value and SSA-BIC value should be lower than other profile schemes; the entropy value should be greater than other profile schemes while being greater than 0.8; LMR and BLRT should be significant ($p < .05$).

Table 6 shows the identified profiles. Profile one is the "negative perception" group. A low score relatively means that students perceive the assessment task as generally negative. The second profile is the "positive perception" group. The students in this group have a high level of overall assessment task perception, and the average scores of all items in different dimensions are close to the full score of 7, which means students perceive the assessment task as generally positive. The third profile is called the "partially perception" group. There are high scores in congruence, authenticity, and student consultation and low scores in transparency and diversity, which means students perceive the assessment task as positive in some features rather than overall. Figure 1 shows the potential feature diagrams of the three profiles.

Table 6. Characteristics of the Identified Profiles

Indicator variable	M		
	Profile 1(14.6%)	Profile 2(49.1%)	Profile 3(36.3%)
cong	4.38	6.73	6.69
trans	3.99	6.35	2.22
diver	4.14	6.43	2.91
authen	4.60	6.75	6.78
cons	3.92	6.46	5.20

Note. asst= perceived assessment task; cong= congruence; trans= transparency; diver=diversity; authen= authenticity; cons = student consultation; aul = ALM.

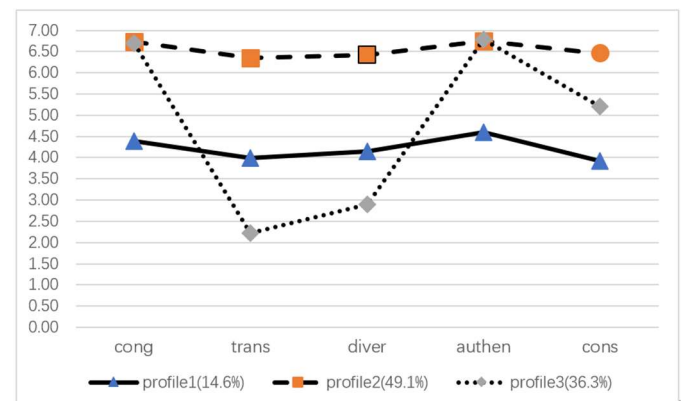


Figure 1. Latent Profile Analysis Plot of Perceived Assessment Task

Note. Profile 1 = Negative perception, Profile 2 = Positive perception, Profile 3 = Partially positive Perception. cong= congruence; trans= transparency; diver=diversity; authen= authenticity; cons = student consultation.

4.4. ALM Across Different Profiles

Table 7 shows the arithmetic series test on the means of the identified Profiles. The average scores of the three profiles of ALM are 5.39, 6.71 and 6.73 respectively. Compared with the students in positive perception and partially positive group, the overall autonomous learning level of students in the negative group is significantly lower. There is no significant difference in overall ALM between students in the partially positive group and the positive perception group.

Table 7. Equality Tests of Mean Across Profiles.

	Overall test	Profile 1 vs. 2	Profile 1 vs. 3	Profile 2 vs. 3
AutoL	49.542**	47.614**	48.658**	.167

Note. * $p < 0.05$. ** $p < 0.01$. Profile 1 = Negative perception, Profile 2 = Positive perception, Profile 3 = Partially positive Perception. AutoL= ALM.

5. Conclusion and Implications

This study involved Chinese higher vocational college students as participants and used LPA to categorize them into high, middle, and low groups based on their psychological characteristics. This result has positive implications for identifying and diagnosing the mental health status of the higher vocational college students. Additionally, the study discussed the differences among the groups in terms of learning flow, growth mindset, and meaning in life. This result is of great significance for comprehensively guiding the psychology of higher vocational college students and stimulating a more positive psychological state. The following section will analyze the two most important findings in conjunction with existing research.

5.1. Reasonable to Group Higher Vocational College Students based on Comprehensive Mental Health Indicators

This study categorized higher vocational college students into three groups using five indicators: life satisfaction, subjective well-being, depression, anxiety, and positive mental health. Students in the high-scoring group reported the highest levels of life satisfaction, subjective well-being, and positive mental health, followed by the middle-scoring group and then the low-scoring group. The pattern for depression and anxiety was reversed. These results indicate that considering positive and negative indicators together can provide a more differentiated picture of students' psychological characteristics.

The study also found positive relationships among life satisfaction, subjective well-being, and positive mental health. Students with stronger positive psychological indicators generally reported lower levels of depression and anxiety. This pattern supports the use of multiple complementary indicators when identifying students who may require psychological support.

By considering both positive and negative psychological variables, this study differentiates between students with varying psychological states. This provides a more comprehensive basis for psychological guidance and intervention.

5.2. The Psychological Differences Exhibited among Vocational College Students of Various Psychological Types.

Learning flow differed significantly across the three psychological profiles. Students with higher life satisfaction, subjective well-being, and positive mental health, together with lower anxiety and depression, reported higher levels of learning flow. The finding suggests that learning flow may be a useful indicator for evaluating students' positive psychological and learning states.

Growth mindset also differed significantly across the three psychological profiles. Students with higher life satisfaction, subjective well-being, and positive mental health, together with lower anxiety and depression, reported a stronger growth mindset. This result highlights the practical value of cultivating a growth mindset in psychological counseling and teaching.

Meaning in life differed across the three psychological profiles. Students with higher life satisfaction, subjective well-being, and positive mental health, together with lower anxiety and depression, reported a stronger sense of meaning

in life. The finding indicates that meaning in life may serve as an additional indicator when evaluating the effectiveness of psychological support.

5.3. The Significance of the Research Conclusions for the Psychological Counseling of Vocational College Students

Firstly, relevant teachers need to have a comprehensive view of students' mental health, especially in accurately identifying symptoms of depression and anxiety, as these emotions can hinder the development of positive psychological factors in students. This requires teachers to use various methods to recognize depression and anxiety during the process of counseling and teaching students. Additionally, it is necessary to categorize students based on life satisfaction, subjective well-being, and positive mental health, as these are psychological factors that can help alleviate anxiety and depression. Teachers should always keep in mind that identifying students' psychological characteristics through these three aspects can help suppress negative emotions. Finally, teachers can use learning flow, growth mindset, and Meaning in Life as indicators of the effectiveness of psychological interventions. Special attention should be given to students with high anxiety and depression, as they may try to appear as if nothing is wrong during the intervention process. If teachers can identify issues in these students' learning flow, growth mindset, and Meaning in Life, it indicates that their negative emotions have not been adequately addressed. Teachers should be vigilant to these signs and tailor their interventions to ensure that these students receive the support they need to improve their mental health.

5.4. Limitations

This study has several limitations. Firstly, the study employed a cross-sectional design, which does not allow for the establishment of causal relationships. Future research studies could use longitudinal tracking methods to further explore the causal relationships between college students with different psychological characteristics and learning flow, growth mindset, and meaning in life. Secondly, the measurement methods in this study were based on self-reporting. Future research could attempt to collect data from multiple informants to deepen the current findings. Thirdly, the survey participants were students from a single university in China. To test the current hypotheses in cross-regional and cross-cultural studies, further investigation is needed.

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