A Cross-Cultural Examination of the Online Self-regulated Learning Questionnaire (OSLQ) with Korean College Students

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Abstract
The Online Self-Regulated Learning Questionnaire (OSLQ) is a widely used self-report instrument for assessing student self-regulated learning (SRL). Despite its prevalence, the dimensionality of the OSLQ is often unclear across different populations, and its item-level characteristics remain underexplored. This study investigates the psychometric properties of the OSLQ with a sample of 571 Korean college students, using both confirmatory factor analysis (CFA) and item factor analysis (IFA). CFA results supported a seven-factor model over the original six-factor version. Furthermore, IFA results revealed that the OSLQ items have high item discrimination, a wide range of item difficulties, providing strong marginal reliability for students within a latent ability (θ) range of -2.5 to 1.5. A key finding was that students with moderate to low SRL ability tend to overestimate their skills. These findings confirm the OSLQ's psychometric robustness and cultural relevance for Korean college students, particularly for assessing those with lower ability levels, while also highlighting the limitations of self-report measures.

Keywords: Online learning, self-regulated learning, online self-regulated learning questionnaire, OSLQ, item factor analysis

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Introduction

The rapid growth of online education in recent years has granted students more autonomy, but it has also placed greater demands on their ability to independently manage their learning (Broadbent & Poon, 2015; Guntur & Purnomo, 2024). As such, self-regulated learning (SRL)—a proactive process in which learners deliberately organize and manage their cognitive, motivational, and behavioral resources—has emerged as a key competence for academic success (Zimmerman, 2000). SRL involves a cyclical process of setting goals, employing strategies to attain those goals, monitoring progress, and reflecting upon the outcomes to inform future learning actions (Pintrich, 2004). As online environments often lack the external structure and supervision found in traditional classrooms, students' ability to self-regulate plays a critical role in promoting meaningful and learning experiences (Cheng et al., 2025; Dunn & Hayakawa, 2021; Hayes et al., 2015; Zhao et al., 2025).

Recent advances in data collection methods and technologies in online learning environments have focused on identifying, assessing, and diagnosing students' use of SRL strategies through multi-channel and multimodal data sources (de Mooji et al., 2025). While such innovations offer rich insights into students' SRL, self-report questionnaires remain one of the most commonly used tools. These SRL questionnaires typically ask students to reflect on their learning behaviors and indicate the extent of their strategy use using Likert-scale items. The continued popularity of self-report measures can be attributed to their ease of administration and scalability (e.g., Roth et al., 2016) and their strong alignment with theoretical frameworks (e.g., Pintrich et al., 2000). Moreover, they often complement behavioral indicators, such as clickstream measures from learning management systems (e.g., Li et al., 2020).

In online learning contexts, a growing body of research has widely used the Online Self-Regulated Learning Questionnaire (OSLQ; Barnard et al., 2009) to assess students' SRL strategies. Past research has shown that the OSLQ effectively captures students' self-regulation processes (e.g., Lai & Hwang, 2016) and helps classify their SRL levels (e.g., Na et al., 2024; Barnard-Brak et al., 2010). Despite its broad application, the OSLQ's psychometric quality remains substantially underexplored. Previous validation studies have reported inconsistent factor structures (i.e., dimensionality) across different countries and sample characteristics (e.g., Martinez-Lopez et al., 2017). Moreover, while most studies have focused on construct-level validation through exploratory or confirmatory factor analyses, few have examined item-level characteristics such as item difficulty and discrimination. This gap may lead to misinterpretation of scores, limiting the educational utility of the OSLQ.

To address these limitations, we focus on examining the dimensionality of online self-regulated learning, as measured by the OSLQ, among Korean college students, and investigating its item characteristics. As online learning has become more prevalent in the context of Korean higher education, the role of SRL has been more critical (Joo et al., 2008). However, previous studies in online learning have often adapted SRL instruments for traditional learning settings. To assess accurately students' SRL strategies in online environments, it is necessary to validate instruments that are better fit to online learning contexts. Furthermore, given the inconsistent psychometric properties found in previous studies, our research aims to provide confirmatory evidence for the OSLQ's factor structure and enhance understanding of its item-level properties. This validation is particularly significant in light of the increasing use of OSLQ across various educational settings, including culturally diverse settings. This validation study is important for SRL research. Confirming that the OSLQ is a reliable tool for Korean college students allows researchers and educators to better identify learners who struggle with self-regulation, and in turn, develop the targeted interventions needed to enhance their success in online learning environments.

Related Literature

Self-regulated Learning in Online Learning Environments

While SRL has been regarded as critical elements in educational settings, prior literature demonstrated that the role of SRL has been more emphasized in online learning environment (Bernard et al., 2009; Kizilcec et al., 2017). Unlike traditional classroom setting (e.g., face-to-face setting), online learning environments often require students to be more self-directed and responsible for their learning processes and outcomes, due to the reduced supervision and immediate feedback from instructors (Broadbent & Poon, 2015). With this high degree of autonomy, the ability to self-regulate is paramount for fostering learners' meaningful online learning experiences (e.g., Na et al., 2024; Yeh et al., 2019) and therefore achieving academic success in these settings (e.g., Broadbent & Poon, 2015; McManus, 2000). These inherent differences between traditional and online learning settings require a distinct understanding of, and approaches to measuring students' SRL that are more suitable for online learning contexts.

For example, a meta-analysis by Zhao et al. (2025) synthesizing 42 studies conducted between 2011 and 2022, revealed a modest yet positive average correlation between SRL strategy use and academic performance ($r = .14$, $p < .001$) in online and blended-learning environments. Notably, the strength of the effect sizes at the undergraduate ($r = .16$, p < .001) and graduate levels ($r = .18$, $p < .001$) was larger than that at the K–12 level ($r = -.11$, $p < .001$), indicating that the role of SRL is more critical in higher education online settings. Similarly, a synthesis by Cheng et al. (2025) of 80 correlational effect sizes from 27 reports found that SRL strategy use was positively correlated with learning performance ($r = .21$, $p < .001$) in online higher education. Interestingly, the type of instrument used to measure SRL served as a significant moderator ($Q(4) = 13.16$, $p = .01$). This suggests that different SRL instruments can significantly influence the magnitudes of the relations between SRL and academic performance, highlighting selecting and using valid and appropriate instruments are key to SRL research.

Importance of Assessing Self-regulated Learning

Over the past decade, advances in learning analytics and the emergence of AI in education have introduced novel possibilities for measuring students' SRL processes in online settings (Järvelä et al., 2023). Recent developments have enabled researchers to gather and analyze multimodal data to deepen our understanding of how students regulate their learning (de Mooji et al., 2025; Sharma et al., 2024). Frameworks like the SMA (self-regulated learning processes, multimodal data, and analysis) grid proposed by Molenaar et al. (2023), emphasize combining multiple data sources and multichannel data streams, including tracing or physiology data, to capture the complex and dynamic nature of individuals' SRL processes (Azevedo, 2015).

However, self-report surveys, which function as self-perception and outcome-oriented measurement approach, are still recognized as valid methods for detecting how students use SRL strategies during their learning. This is because they can serve as calibrators for making inferences from other data sources (Molenaar et al., 2023). In this regard, the accurate measurement of SRL behaviors is essential for understanding and improving student performance in online learning settings (Barnard et al., 2009). By identifying how well students can manage their learning processes, educators and researchers can develop targeted interventions to support those who struggle with self-regulation. Thus, having reliable tools to measure SRL is crucial for advancing educational practices and policies. Therefore, as online education continues to grow, adapting SRL measurement tools to various cultural and educational contexts becomes increasingly important (Lau, 2022). Different student populations may exhibit unique self-regulatory behaviors based on their cultural backgrounds, prior educational experiences, and the specific demands of their learning environments. Therefore, ongoing development and validation of SRL instruments across diverse settings are necessary to ensure their effectiveness and applicability.

Previous Validation Studies of OSLQ

The Online Self-Regulated Learning Questionnaire (OSLQ) was originally developed by Barnard et al. (2009) to address the need for a reliable tool to measure SRL in online environments, using a sample of U.S. college students. The OSLQ consists of 24 items that are grouped into six factors, each assessing a different aspect of SRL: Goal Setting, Environment Structuring, Task Strategies, Time Management, Help-Seeking, and Self-Evaluation. These items are rated using a 5-point Likert-type response format, with values ranging from strongly disagree (1) to strongly agree (5). The comprehensive nature of the OSLQ has made it a widely recognized and valuable tool for researchers, enabling them to gain crucial insights into students' self-regulatory behaviors and identify areas requiring intervention.

As the OSLQ has seen widespread adoption, efforts have been undertaken to validate the instrument across diverse cultural and educational settings, including the United States, Belgium, Hong Kong, Turkey, and Brazil (see Table 1). This is not surprising, as cultural differences have always been a critical concern in the SRL literature (McInerne & King, 2018; Purdie & Hattie, 1996). Indeed, previous studies conducted with Brazilian and Hong Kong students identified two- and seven-factor solutions, respectively, rather than the original six-factor structure (Lau, 2022; Rufini et al., 2021). Such variation suggests that the psychometric properties of the OSLQ may depend on cultural or educational contexts, warranting further validation studies in diverse settings.

To date, no study has yet validated the OSLQ with Korean college students. This is a noteworthy gap in the literature, especially given the traditional values of Korean culture, which are rooted in Confucianism and collectivism (Beik & Cho, 2024; Lee et al., 2017; Turingan & Yang, 2009). Beik and Cho (2024) argue that collectivism leads Korean students to be highly sensitive to others' evaluations and to focus heavily on comparisons with others. Moreover, classroom culture in Korea still remains largely instructivist rather than constructivist. For example, in their cross-cultural study, Yoo et al. (2014) found that Korea instructors preferred teacher-to-learner interactions in online learning activities, whereas U.S. instructors tended to focus on learner-to-learner interactions. Such cultural uniqueness may influence how they respond to specific OSLQ items, particularly those related to peer-based evaluations.

Methodologically, previous validation studies also have some limitations regarding their analytic approaches. Specifically, most of them have primarily adopted confirmatory factor analysis (CFA) to assess construct validity. A traditional CFA is a tool used to test whether respondents' observed responses fit an *a priori factor structure,* assuming continuous item responses and linear relationships with latent factors (Ferrando, 2009). However, the Likert scales are ordinal, not continuous, and thus it is problematic to assume linear relationships between observed and latent scores. Specifically, if the outcome responses are categorical or ordinal, the residuals cannot be normally distributed (Miles & Shevlin, 2001). In this regard, violating the assumption of normality can lead to misspecification of item parameters and standard errors. Moreover, in the context of CFA, a simulation study by Rhemtulla et al. (2012) showed that using a continuous approach with fewer than five categories can risk underestimating both factor loadings and standard errors, thereby leading to model misspecification.

However, item factor analysis (IFA), which assumes non-linear relationships between latent scores and categorical item responses (Wirth & Edwards, 2007), allows us to account for the ordinal nature of Likert scale responses and to examine item-level parameters such as item discrimination and item difficulty (i.e., thresholds). In short, IFA is an extension of CFA, but its purpose is to understand how individual items (questions) relate to a given knowledge, skill, or trait using categorical data (e.g., true/false or Likert scale).

Additionally, previous studies primarily reported internal reliability using Cronbach's alpha. Since Cronbach's alpha stems from a composite score on the test, it assumes that reliability is uniform across each person's ability (i.e., latent scores, θ). However, the degree to which the SRL measurement tool is reliable can vary depending on an individual's latent ability.

Table 1

Existing Validation Studies or Checking Dimensionality of the OSLQ

References	Participants	Factor structures	Validity	Reliability
Kilis & Yildririm (2017)	Undergraduates of public university in Turkey (N = 321)	Six-factor model (N_{item} = 24) 1. Goal Setting, 2. Environmental Structuring, 3. Time Management 4. Cognitive strategies 5. Help-Seeking 6. Self-Evaluation	Construct validity (CFA)	Internal consistency (Cronbach's α: .67 < α < .87)
Fung et al. (2018)	Study 1: Primary and Secondary students in Hong Kong (N = 412) Study 2: Mathematically talented primary and secondary students in	Six-factor model (N_{item} = 24) 1. Goal Setting, 2. Environmental structuring, 3. Time Management 4. Cognitive strategies 5. Help-Seeking 6. Self-Evaluation	Study 1: Construct validity (CFA) and Measurement Invariance by gender Study 2: Construct validity (CFA)	Study 1: Internal consistency (Cronbach's α: .75 < α < .86) Study 2: Internal consistency (Cronbach's α: .78 < α < .87)

	Hongkong (N = 374)			
Vanslambrouck et al. (2019)	Adult learners (blended learning settings) in Belgium (N = 213)	Seven-factor model (N_{item} = 24) 1. Goal Setting, 2. Environmental structuring, 3. Time Management 4. Cognitive strategies 5. Help-Seeking 6. Self-Evaluation through Strategies 7. Self-Evaluation through peers	Construct validity (CFA)	Internal consistency (Cronbach's α: .59 < α < .93)
Rufini et al. (2021)	Undergraduates who registered for online pedagogy courses in Brazil (N = 1,434)	Two-factor models (N_{item} = 19) 1. Goal Setting / Environmental Structuring / Time Management 2. Task Strategies / Help-Seeking / Self-Evaluation	EFA	Not reported
Lau (2021)	Junior secondary students in Hong Kong (N = 716)	Seven-factor model (N_{item} = 28) 1. Goal Setting, 2. Environment Structuring, 3. Time Management, 4. Effort regulation, 5. Cognitive/monitoring strategies, 6. Help-Seeking, 7. Self-Evaluation	Construct validity (CFA)	Internal consistency (Cronbach's α: .80 < α < .91)
Funa et al. (2023)	Preservice teachers (N = 301) in Philippines (10 preservice and five faculty members for interview)	Six-factor model (N_{item} = 24) 1. Goal Setting, 2. Environmental structuring, 3. Time Management 4. Cognitive strategies 5. Help-Seeking 6. Self-Evaluation	Construct validity (EFA and CFA) Content validity (Qualitative Interview)	Internal consistency (Cronbach's α:.71 < α < .91)

Note. EFA refers to exploratory factor analysis; CFA refers to confirmatory factor analysis.

Goals of Present Study

Our study aims to conduct a cross-cultural validation of the OSLQ with Korean college students, ensuring that the instrument is culturally relevant and psychometrically robust within this group. Specifically, we use both CFA and IFA to determine the dimensionality of the OSLQ and to investigate item characteristics. This work is guided by the following research questions:

Research Question 1: What underlying factor structure (i.e., dimensionality) of the OSLQ best fits the responses of Korean college students?

Research Question 2: What are the item characteristics, specifically item difficulty and item discrimination, of the OSLQ as demonstrated by Korean college students?

Methods

Participants and Procedures

A total of 750 college students were initially recruited for this study. Participants were from an online introductory mathematics course at a public university in South Korea. The course was designed for first-year students to learn undergraduate-level mathematical concepts. At the beginning of the semester, participants completed a demographic survey, which included questions about gender and academic majors (categorized as STEM or non-STEM). At the end of the semester, they completed the OSLQ survey. The final analytic sample (n = 571; M_{age} = 19.4 years; 60.7% female) was selected based on two criteria: (a) voluntary consent to participate and (b) enrollment in academically oriented majors. Students in career-oriented majors, such as veterinary medicine or nursing, were excluded in the analyses due to potential differences in motivation and response patterns on the OSLQ instrument, relative to students in other fields. Among the valid respondents, 72.5% were majoring in STEM fields (n = 414), whereas 27.5% were in non-STEM majors (n = 157). The survey system was configured to prevent participants from proceeding without completing each page, resulting in no missing data. Given the asynchronous and self-paced nature of the online course, all survey administration process was conducted through the course learning management system.

Measures

The original OSLQ (Barnard et al., 2009) consists of six factors: Goal Setting (five items), Environment Structuring (four items), Task Strategies (four items), Time Management (three items), Help-Seeking (four items), and Self-Evaluation (four items). The items use a five-point self-report format from (1) strongly disagree to (5) strongly agree. To avoid potential loss of meaning in the items, we conducted a translation and back-translation process (Brislin, 1970). The internal reliability of this study ranged from .77 to .93 (see Table 2 for all items with their descriptive statistics and internal consistency based on the current sample).

Analytical Strategies

First, we conducted CFAs to examine the dimensionality of the OSLQ. Specifically, we built two competing models—original six-factor model (Barnard et al., 2009) and seven-factor model by splitting Self-Evaluation into two subfactors (Vanslambrouck et al., 2019). Although both constructs have traditionally been categorized under the broader concept of self-evaluation in OSLQ, several studies have demonstrated that Self-Evaluation against Peers and Self-Evaluation using Strategies are distinct (Vanslambrouck et al., 2019). According to Topping (2009), peer assessment refers to a structured process in which students assessed, or are assessed by, their peers or classmates in the online courses. In this regard, Self-Evaluation against Peers involves students assessing their own learning by comparing it to the progress and activities of their peers. In this case, the primary reference point for self-evaluation is external and the perceived performance or learning behaviors of others.

In contrast, Self-Evaluation using Strategies refers to students reflecting on their own learning progress by evaluating the effectiveness of the strategies and techniques they have used. In this case, a key indicator to self-evaluation is internal, with students monitoring and making judgments about their learning based on how well their chosen strategies have been useful to support effective and meaningful learning. Based on this rationale, we therefore split Self-Evaluation into two factors, Self-Evaluation using Strategies and Self-Evaluation against Peers, in the seven-factor model.

We evaluated these two CFA models using model χ^2 test, Comparative fit index (CFI), Tucker–Lewis index (TLI), root-mean-square error of approximation (RMSEA), and standardized root-mean-square residual (SRMR). We regarded a non-significant χ^2 test, TLI and CFI $\geq .90$, RMSEA $\leq .06$, and SRMR $\leq .08$ as acceptable model fit (Hu & Bentler, 1999). We also checked linear relationships between observed item response patterns and latent ability. To address non-normal distributions at the item levels, MLR estimator was used to estimate all CFA models. The Satorra-Bentler scaled chi-square difference test (Satorra & Bentler, 2010) were used to conduct model comparisons.

We next conducted IFAs to understand the item characteristics of the OSLQ using WLSMV estimation with THETA parameterization. We evaluated the global model fit using the same criteria as in CFA. Unlike CFA, IFA does not assume linear relationships between factor scores and observed response patterns (Wirth & Edward, 2009). We estimated two types of parameters from IFAs: factor loadings and thresholds corresponding to response options. These two types of parameters in IFA can be directly transformed to two types of parameters—item discriminations (a, how well an item can differentiate between individuals who have different levels of latent ability) and difficulties (b_i, transition points between ordered response options)—in the graded response model of the polytomous IRT model (Samejima, 2016). From these item parameters, test information, and marginal reliability, we can evaluate how reliably and well each item functions according to respondents' latent abilities. CFA and IFA analyses were conducted in *Mplus* version 8.8 (Muthén & Muthén, 1998–2017) and all other analyses were conducted with *Jamovi* (The jamovi project, 2024).

Table 2
Descriptive Statistics for OSLQ Item Response Patterns

SRL subconstructs	*Item descriptions*	*M*	*Med*	*SD*	*Response Patterns (%)*				
					1 (%)	*2 (%)*	*3 (%)*	*4 (%)*	*5 (%)*
Goal Setting (α = .88)	Q1. I set standards for my assignments in online courses.	4.07	4.00	0.86	1.2	3.0	17.5	44.5	33.8
	Q2. I set short-term (daily or weekly) goals as well as long-term goals (monthly or for the semester).	3.96	4.00	0.95	1.2	6.3	21.4	37.7	33.5
	Q3. I keep a high standard for my learning in my online courses.	3.37	3.00	1.13	5.3	17.0	32.2	26.4	19.1
	Q4. I set goals to help me manage studying time for my online courses.	3.73	4.00	1.00	1.9	9.6	26.1	37.8	24.5
	Q5. I don't compromise the quality of my work because it is online.	3.68	4.00	1.03	1.6	13.1	25.2	36.1	24.0
Environment Structuring (α = .86)	Q6. I choose the location where I study to avoid too much distraction.	4.14	4.00	0.82	0.7	2.8	14.9	45.2	36.4
	Q7. I found a comfortable place to study.	4.24	4.00	0.75	0.4	1.9	11.2	46.1	40.5
	Q8. I know where I can study most efficiently for online courses.	3.97	4.00	0.94	1.6	4.7	21.7	39.2	32.7
	Q9. I choose a time with few distractions for studying for my online courses.	4.09	4.00	0.86	0.9	4.2	15.1	44.8	35.0
Task Strategies (α = .77)	Q10. I try to take more thorough notes for my online courses because notes are even more important for learning online than in a regular classroom.	3.69	4.00	1.11	4.6	10.7	21.9	36.6	26.3
	Q11. I read aloud instructional materials posted online to fight against distractions.	2.93	3.00	1.27	13.0	29.8	23.3	18.9	15.1
	Q12. I prepare my questions before joining in the chat room and discussion.	3.35	3.00	1.14	5.8	17.3	30.8	27.8	18.2
	Q13. I work extra problems in my online courses in addition to the assigned ones to master the course content.	3.63	4.00	0.99	2.1	10.3	31.2	35.7	20.7
Time Management	Q14. I allocate extra studying time for my online courses because I know it is time demanding.	3.65	4.00	0.99	1.9	10.3	29.9	35.9	21.9

(α = .80)	Q15. I try to schedule the same time every day or every week to study for my online courses, and I observe the schedule.	3.66	4.00	1.11	4.4	11.7	22.8	35.4	25.7
	Q16. Although we don't have to attend daily classes, I still try to distribute my studying time evenly across days.	3.60	4.00	1.04	2.8	11.7	29.8	33.6	22.1
Help-Seeking (α = .77)	Q17. I find someone who is knowledgeable in course content so that I can consult with him or her when I need help.	3.62	4.00	1.10	5.8	9.8	21.9	41.3	21.2
	Q18. I share my problems with my classmates online, so we know what we are struggling with and how to solve our problems.	3.51	4.00	1.13	5.6	14.4	24.2	35.6	20.3
	Q19. If needed, I try to meet my classmates face-to-face.	3.73	4.00	1.09	4.4	8.2	24.9	34.9	27.7
	Q20. I am persistent in getting help from the instructor through e-mail.	3.45	3.00	1.05	3.5	14.2	34.5	29.4	18.4
Self-Evaluation (α = .89)	Q21. I summarize my learning in online courses to examine my understanding of what I have learned.	3.70	4.00	0.98	2.5	7.4	31.3	35.9	22.9
	Q22. I ask myself a lot of questions about the course material when studying for an online course.	3.55	4.00	1.00	2.6	10.9	34.3	33.1	19.1
	Q23. I communicate with my classmates to find out how I am doing in my online classes.	3.45	4.00	1.15	6.5	14.4	26.8	32.6	19.8
	Q24. I communicate with my classmates to find out what I am learning that is different from what they are learning.	3.37	3.00	1.18	7.7	15.9	26.6	31.5	18.2

Note. M = Mean, Med = Median, and SD = Standard deviation. In the seven-factor model, the internal reliability of Self-Evaluation using Strategies is α = .84, and Self-Evaluation against Peers is α = .93.

Results

Research Question 1: Dimensionality of OSLQ

Descriptive statistics and response patterns for all items are presented in Table 2. First, the comparison of global model fit between the two CFA models (see Table 3) indicated that the seven-factor model had a better fit. The Satorra-Bentler scaled chi-square difference test (Satorra & Bentler, 2010) confirmed that the seven-factor model fit the data significantly better than the six-factor model, $\chi^2(6) = 208.91$, $p < .001$. The standardized factor loadings of the seven-factor model ranged from .52 to .93, all of which are acceptable (see Table A1 in Appendix A).

Table 3

A comparison of CFA Model Fit between Six- and Seven-Factor Models

	χ^2	*df*	CFI	TLI	RMSEA	SRMR
Seven-factor	586.052	231	.940	.928	.052, 90% CI [.047, .057]	.046
Six-factor	819.561	237	.901	.885	.066, 90% CI [.061, .071]	.064

Note. CFI = Comparative fit index, TLI = Tucker–Lewis index, RMASEA = Root-mean-square Error of Approximation estimate, and SRMR = Standardized Root-Mean-square Residual.

Despite the acceptable model fit, we did not find a linear relationship between the latent scores estimated by CFA and the observed item responses. Figure 1 shows the item responses predicted by CFA for latent scores within ±3.5 SDs of the mean of 0. We found that linear slopes did not function well for many items because some predicted item responses were not located within the possible range of item responses (i.e., below 1 or above 5). For example, some predicted item responses in Task Strategies were close to 0. To address this issue and to examine the item characteristics of the OSLQ, we ran the IFA—assuming nonlinear relationships between observed and latent scores—with the seven-factor model.

Research Question 2: Item Characteristics of OSLQ

The IFA model showed a good fit for the seven-factor model: $\chi^2(231) = 1129.478$, $p < .001$, CFI = .964, TLI = .957, RMSEA = .083, SRMR = .036. Figure 2 shows the discrimination estimates for each item (see the upper section in Figure 2), along with the range of item difficulty estimates and their thresholds (see the lower section in Figure 2). All item parameters are fully reported in Table A2 in Appendix A.

Item discrimination parameters ranged from .73 (for Q19) to 2.87 (for Q23), and each SRL substructure showed similar levels of item discrimination. Interestingly, items related to Self-Evaluation against Peers were significantly more discriminating than items related to Self-Evaluation using Strategies. This supports our hypothesis of the seven-factor model that Self-Evaluation using Strategies is psychometrically distinct from Self-Evaluation against Peers.

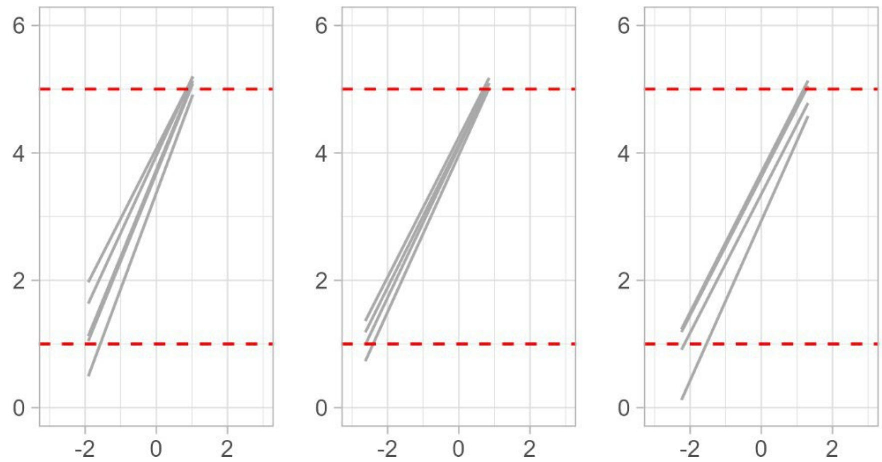
The OSLQ items showed a wide range of item difficulties. Reporting frequent uses of SRL strategies (i.e., selecting "5. Strongly agree") required a latent SRL ability level of more than 0.5 to 1.0 SD above average (i.e., b_4). On the other hand, the first, second, and third threshold parameters (b_1, b_2, and b_3) were negative, meaning that students with below-average SRL ability (i.e., $\theta < 0$ on the Y-axis in Figure 2) can use SRL strategies to some extent. Finally, test information functions (see Figure 3) for each SRL subcomponent indicated that the OSLQ provided the most information for students with latent abilities approximately 2.5 SD below and 1.5 SD above the mean. In other words, the OSLQ items can provide the most information about the latent SRL ability for students within this range ($-2.5 < \theta < 1.5$).

Specifically, based on the test information functions (see Figure 4), the items in the Environmental Structuring -construct (blue line) were more informative for students with lower levels of the latent trait ($-3.6 < \theta < -1.0$), whereas the items in the Self-Evaluation against Peers sub-construct (light green line) were more effective in measuring students with higher levels of the latent trait ($-2.0 < \theta < 1.5$). Moreover, the estimated latent ability of students is most reliably measured within this same range, although there is some variation within constructs (see Figure 4). All item parameters, including item discrimination and item difficulty (i.e., threshold, b_1, b_2, b_3, and b_4), are reported in Table A2 in Appendix A.

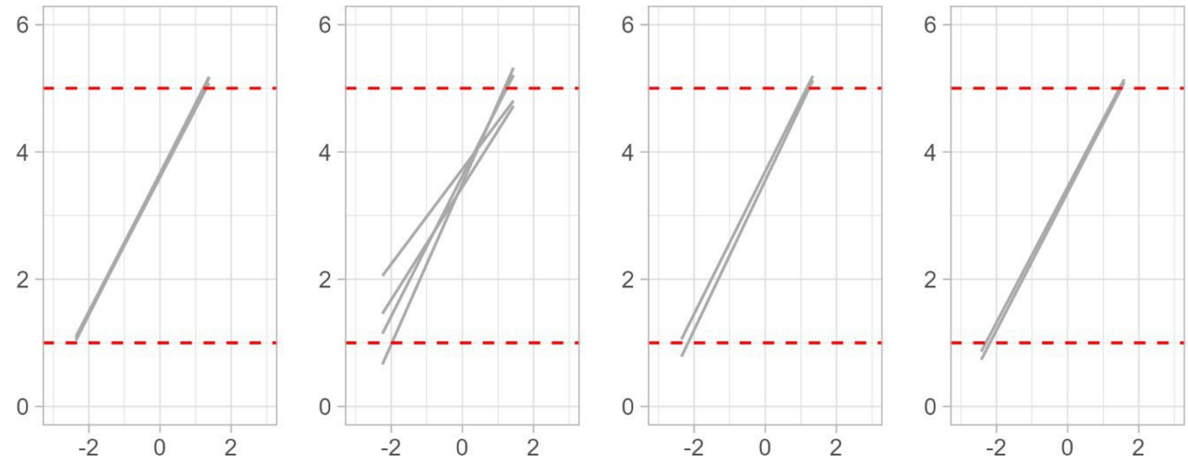
Figure 1

Linear Relationships Between Observed Response Patterns and Latent Abilities (i.e., Latent Scores)

Goal Setting	Environment Structuring	Task Strategies	



Time Management	Help-Seeking	Self-Evaluation using Strategies	Self-Evaluation against Peers



Note. X-axis refers to the latent scores (i.e., students' latent ability of SRL, θ) and y-axis refers to the observed response patterns. Each regression line depicts a linear relationship between observed response patterns (y-axis) and factor scores (x-axis). Red dotted lines in the graphs mean a possible range of observed response patterns, ranging from 1 (totally disagree) to 5 (totally agree).

Figure 2

Item Discriminations (Upper) and Item Difficulties and Thresholds (Lower) of OSLQ items

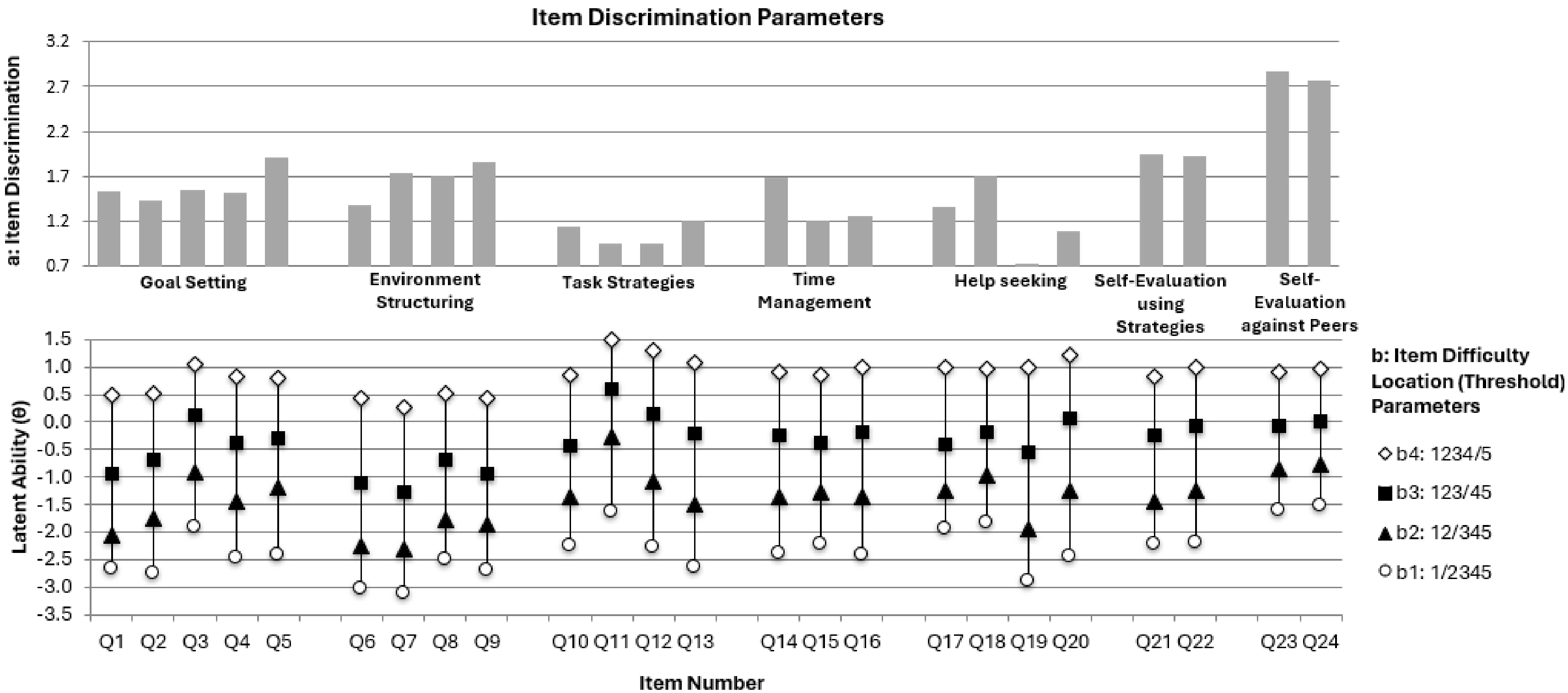
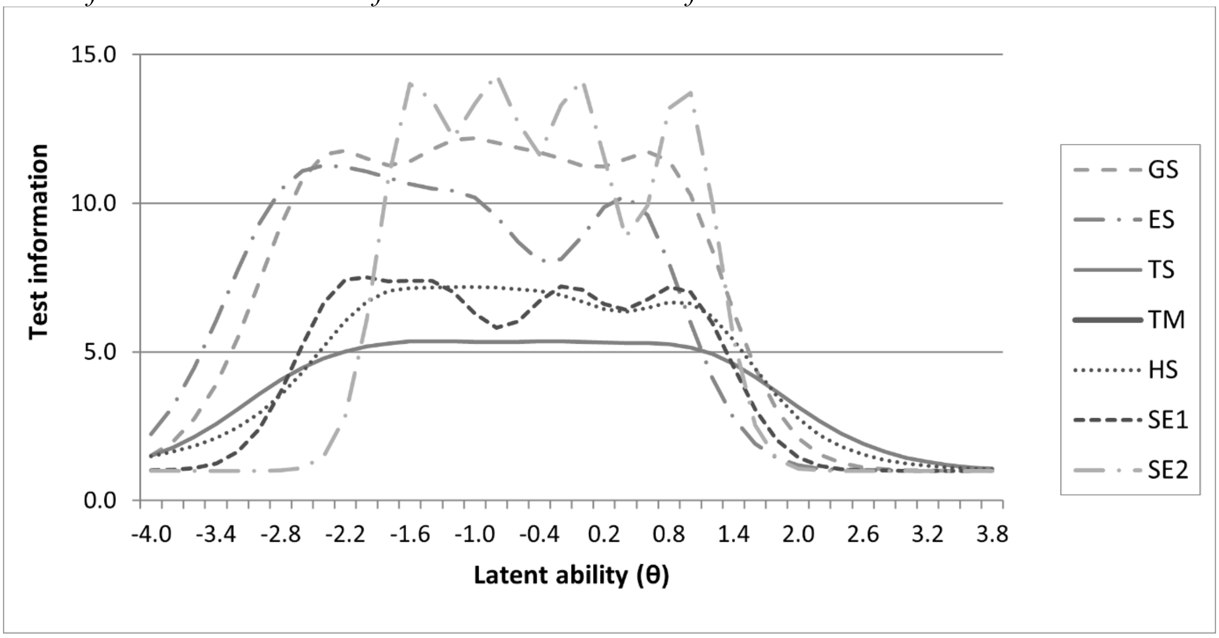
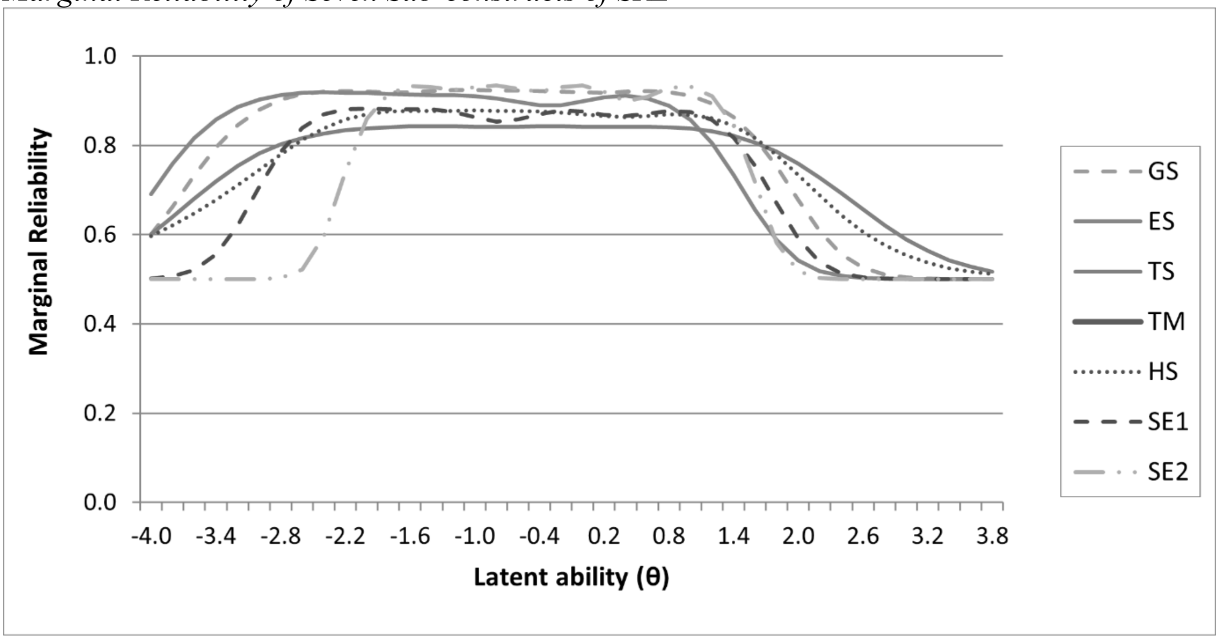


Figure 3
Test Information Functions of Seven Sub-constructs of SRL



Note. GS = Goal Setting, ES = Environmental Structuring, TS = Task Strategies, TM = Time Management, HS = Help-Seeking, SE1 = Self-Evaluation using Strategies, and SE2 = Self-Evaluation against Peers. X axis refers to latent ability (θ) of SRL, and Y-axis refers to test information estimated from item factor analyses.

Figure 4
Marginal Reliability of Seven Sub-constructs of SRL



Note. GS = Goal Setting, ES = Environmental Structuring, TS = Task Strategies, TM = Time Management, HS = Help-Seeking, SE1 = Self-Evaluation using Strategies, and SE2 = Self-Evaluation against Peers. X axis refers to latent ability (θ) of SRL, and Y-axis refers to marginal reliability (r_{xx}) estimated from item factor analyses.

Discussion

The OSLQ has been widely recognized as a useful instrument for assessing students' use of self-regulatory strategies in online learning environments (Roth et al., 2016).

Originally developed in the United States, the instrument has since been validated in various cultural contexts, such as Hong Kong (Fung et al., 2018; Lau, 2021), Turkey (Kilis & Yıldırım, 2018), Singapore (Lin et al., 2023), and Brazil (Rufini et al., 2021), consistently demonstrating its reliability and cross-cultural applicability. Since how well a measurement instrument works can change across different educational systems and sociocultural environments, it is essential to test and validate the instrument before using it in a new context (Cho et al., 2007). As such, this study aimed to examine the dimensionality and item characteristics of the OSLQ for Korean students. Overall, the results underscore the psychometric soundness and cultural relevance of the OSLQ for assessing SRL among Korean college students, supporting its utility across varying levels of SRL abilities. The main findings and implications are outlined below.

First, the CFA results provided empirical support for a seven-factor structure of the OSLQ, offering a better fit than the original six-factor structure. This is consistent with Lau's (2022) recent validation study, which also questioned the unidimensionality of certain factors. The result is also corroborated by application studies, such as Vanslambrouck et al. (2019). These findings suggest that a refined seven-factor model may better capture the underlying dimensions of online SRL, particularly by distinguishing between different modes of Self-Evaluation.

Specifically, the IFA results indicated that the items loaded onto Self-Evaluation using Strategies had different psychometric features (i.e., item discriminations) from those loaded onto Self-Evaluation against Peers. This suggests that these two constructs may represent distinct dimensions of Self-Evaluation, each with unique characteristics and implications for students' SRL processes, especially within the Korean context. These findings might be attributed to the cultural characteristics of Korean higher education. Beik and Cho (2024) point out that Korean students tend to be highly sensitive to others' evaluations and rely heavily on social comparison. As they suggest, even though items fall under the same self-evaluation construct, students may perceive those involving peer comparison as fundamentally different in nature. This could explain why the factor split into two separate constructs. Another explanation is that online courses in this context tend to be designed to be individual-centric, which naturally reduces opportunities to engage in communication, peer feedback, or group-based activities (Yoo et al., 2014). Such instructional design also inadvertently limits the social aspects of self-evaluation, such as peer comparison. Consequently, students are more likely to depend on personal cognitive strategies, such as summarization and self-questioning, for evaluating their learning progress.

Next, the item-level analyses demonstrated that the OSLQ features high item discrimination across its components (see Figure 2). This indicates that individual items are effective in distinguishing between students with differing levels of SRL abilities. This finding suggests that the OSLQ is not only psychometrically sound, but also well-suited for capturing a wide spectrum of SRL behaviors among Korean college students, ensuring that it is a robust tool for both research and educational practice in this context.

Given that the marginal reliability was concentrated within a broad spectrum of latent ability ($-2.5 < \theta < 1.5$), the test information in some sub-constructs of SRL was centered around lower levels of true ability (see Figure 3). This indicates that the OSLQ was particularly effective in assessing students with lower self-regulated learning abilities. Further research with diverse samples is needed to determine whether such partial functionality of the OSLQ is due to the characteristics of the Korean college sample or inherent limitations of the

OSLQ instrument itself. Further, to better capture higher levels of self-regulated learning, complementary survey items or additional measurement tools may be required.

A particularly noteworthy observation from our analysis is the pattern of responses among students with low SRL latent abilities ($\theta < 0$). Despite their lower SRL levels, a substantial number of these students reported moderate to high use of SRL strategies (i.e., selecting "3. Neutral" and "4. Agree"). This trend implies that students might generally overestimate their SRL abilities. The fact that even lower-ability students report higher-than-average use of SRL strategies indicates a possible overestimation of their SRL abilities. These results align with research on metacognition, which suggest that students often exhibit poor metacognitive calibration, meaning they struggle to accurately access their own abilities (Dunlosky & Metcalfe, 2008; Hacker & Bol, 2019). These findings are further connected to the need for more objective or performance-based measures, rather than self-reported measures, to help students accurately assess and develop their SRL abilities (Winne & Perry, 2000).

Based on the findings mentioned above, we propose several practical implications for college educators. First, instructors should recognize that online courses may include diverse subgroup students who engage in SRL differently due to their cultural backgrounds. It is important to use culturally appropriate tools to accurately identify these groups and design learning activities and environments that address their specific needs. Second, for students with low SRL abilities, tailored support should be provided to promote equitable learning outcomes.

Limitations and Future Research

The current study has some limitations. First, the goal was to investigate (a) dimensionality and (b) item characteristics (i.e., item discrimination and difficulty), both of which are fundamental aspects of validity and reliability evidence. However, we did not directly address issues of test fairness. As a key component of psychometric evidence, test fairness is critical for determining whether items function equivalently across different demographic groups (e.g., gender or age, Fung et al., 2019) or across time points (e.g., Jeong & Feldon, 2023), which allows for meaningful between and within group comparisons. Future research should systematically examine the fairness of the OSLQ by testing measurement invariance at the construct level and differential item functioning at the item level.

Next, the psychometric characteristics of the test are sample- and context-dependent (Lovett, 2023). Therefore, our findings can only be generalized to Korean higher education contexts. Furthermore, given that self-regulated learning processes vary substantially depending on context and culture (Mclnerney, 2008; Purdie et al., 1996), it is necessary to investigate the item characteristics of the OSLQ in other research contexts and to comprehensively compare these characteristics. Such efforts will enable us to develop an in-depth understanding of the SRL instruments, along with measuring students' SRL learning processes.

Furthermore, in the seven-factor model identified in this study, Self-Evaluation consists of two distinct sub-constructs: Self-Evaluation Using Strategies and Self-Evaluation against Peers (Vanslambrouck et al., 2019). In conjunction with the investigation of dimensionality, IFA analyses confirmed that these sub-constructs exhibit different psychometric characteristics. However, as each sub-construct includes only two items, they are fully identified subparts of the model, which may lead to improving global model fit. To enhance the solid and robust psychometric evidence of OSLQ, future research should develop additional items for these sub-constructs and validate them with larger and more heterogeneous samples.

As pointed out in the SMA gird framework (Molenaar et al., 2023), it cannot be disregarded that self-reported measures remain valid and meaningful resources for assessing students' SRL processes. However, this approach is more suitable for capturing SRL before or after an intervention, rather than over the SRL learning process. Furthermore, response patterns of the self-report survey may be biased and even distorted by personal beliefs, social desirability, and individual's imprecise memory (Veenman, 2011). Therefore, to address the inherent limitations of self-reported measures, the item characteristics of the OSLQ should be triangulated with other objective data sources, such as trace data (e.g., Fan et al., 2021), contextual data in technology-enhanced learning settings (Sobocinski et al., 2024), and physiological data (Malmberg et al., 2021).

Conclusion

The present study revisited the inconsistent factor structures of the OSLQ reported in previous validation studies and confirmed a seven-factor model using data from Korean higher education students. Notably, two new sub-constructs, Self-Evaluation Using Strategies and Self-Evaluation Against Peers, were identified. Item-level analyses using IFA revealed that the OSLQ items demonstrated high discrimination parameters and broad ranges of item difficulty, along with strong marginal reliability for students within a latent ability range of -2.5 to 1.5. These findings are significant in that they offer confirmatory evidence from a different academic context and strengthen prior research by providing robust reliability and validity evidence at the item level through more rigorous analytical approaches.

Conflict of Interest Statement

No conflict of interest was reported by the authors.

Ethics Statement

The study was reviewed by the Institutional Review Board at Utah State University. No violation of human research ethics was found during the study.

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Appendix

Item Parameters

Table A1

Standardized Factor Loadings of CFA model With the Seven-Factor Model

Items	Standardized Factor loadings	*SE*	*z*-scores	*p*-value
Goal Setting				
Q1	0.75	0.03	29.96	< .001
Q2	0.75	0.03	27.59	< .001
Q3	0.79	0.02	33.54	< .001
Q4	0.81	0.02	37.58	< .001
Q5	0.79	0.02	33.09	< .001
Environment Structuring				
Q6	0.79	0.04	21.43	< .001
Q7	0.83	0.03	33.98	< .001
Q8	0.75	0.03	24.54	< .001
Q9	0.78	0.03	30.60	< .001
Task Strategies				
Q10	0.67	0.03	21.21	< .001
Q11	0.66	0.03	21.62	< .001
Q12	0.64	0.03	20.27	< .001
Q13	0.74	0.03	25.68	< .001
Time Management				
Q14	0.81	0.02	34.04	< .001
Q15	0.71	0.03	23.13	< .001
Q16	0.74	0.03	26.67	< .001
Help-Seeking				
Q17	0.76	0.03	25.52	< .001
Q18	0.84	0.02	35.95	< .001
Q19	0.52	0.04	12.99	< .001
Q20	0.63	0.03	18.72	< .001
Self-Evaluation using Strategies				
Q21	0.84	0.02	45.08	< .001
Q22	0.87	0.02	44.00	< .001
Self-Evaluation against Peers				
Q23	0.93	0.01	84.79	< .001
Q24	0.93	0.01	68.10	< .001

Table A2

Item Discrimination and Item Difficulty Parameters

Item	Item Discrimination a	Item Difficulty Threshold 1 (b_1: 1/2345)	Threshold 2 (b_2: 12/345)	Threshold 3 (b_3: 123/45)	Threshold 4 (b_4: 1234/5)
Goal Setting					
Q1	1.54	-2.68	-2.06	-0.93	0.50
Q2	1.43	-2.75	-1.76	-0.68	0.52
Q3	1.54	-1.93	-0.91	0.13	1.04
Q4	1.51	-2.48	-1.44	-0.38	0.83
Q5	1.92	-2.43	-1.18	-0.29	0.80
Environment Structuring					
Q6	1.38	-3.04	-2.24	-1.11	0.43
Q7	1.74	-3.11	-2.31	-1.27	0.28
Q8	1.70	-2.50	-1.78	-0.68	0.52
Q9	1.85	-2.70	-1.86	-0.95	0.44
Task Strategies					
Q10	1.15	-2.24	-1.36	-0.44	0.84
Q11	0.96	-1.63	-0.27	0.60	1.50
Q12	0.96	-2.28	-1.06	0.14	1.31
Q13	1.20	-2.65	-1.50	-0.21	1.06
Time Management					
Q14	1.69	-2.40	-1.35	-0.23	0.90
Q15	1.21	-2.22	-1.29	-0.37	0.85
Q16	1.27	-2.43	-1.35	-0.18	0.98
Help-Seeking					
Q17	1.37	-1.95	-1.25	-0.40	0.99
Q18	1.71	-1.84	-0.98	-0.17	0.96
Q19	0.73	-2.90	-1.94	-0.54	1.01
Q20	1.09	-2.46	-1.26	0.07	1.22
Self-Evaluation using Strategies					
Q21	1.94	-2.22	-1.45	-0.25	0.83
Q22	1.92	-2.19	-1.25	-0.06	0.99
Self-Evaluation against Peers					
Q23	2.87	-1.61	-0.86	-0.06	0.90
Q24	2.76	-1.52	-0.76	0.01	0.97