

Article

Reexamining the Monitoring and Managing Subdimensions of the Shared Metacognition Questionnaire in Online Higher Education

Zhuo Zhang ^{1,*}  and Qian Xu ² 

¹ Department of Learning Technologies, Design & School Library Media, Towson University, Towson, MD 21252, USA

² School of Education, Iowa State University, Ames, IA 50011, USA; qxu@iastate.edu

* Correspondence: zhuozhang@towson.edu

Abstract

The Shared Metacognition Questionnaire (SMQ) is widely used to assess metacognition in collaborative online learning environments. Prior work has supported its two broad dimensions of self-regulation of cognition (SRC) and co-regulation of cognition (CRC), but the lower-order monitoring and managing subdimensions theorized within SRC and CRC have not been empirically supported. The present study used a split-sample exploratory and confirmatory factor analytic approach with graduate students ($N = 348$) enrolled in 25 fully online courses. For SRC, the results provided tentative support for a two-factor monitoring–managing structure, with the managing factor performing more strongly than the monitoring factor. For CRC, neither the theorized structure nor an empirically informed alternative reached marginally acceptable fit, and item-level diagnostics pointed to potential issues of item clarity, redundancy, and content clustering. The findings (1) provide additional validity evidence supporting the use of SMQ to measure self-monitoring and self-managing; (2) extend the original SMQ development study and broader theoretical models of self- and co-regulation; and (3) offer practical guidance on the current use of the SMQ and suggestions for refining the CRC items.

Keywords: shared metacognition; self-regulation; co-regulation; online learning; higher education; scale validation



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1. Introduction

Metacognition, broadly defined as the ability to think about and regulate one's own thinking, plays a foundational role in how individuals approach and navigate the learning process (Flavell, 1979). Since Flavell (1979) first introduced the term, metacognition has been extensively studied in educational contexts for its role in supporting learning outcomes (Marantika, 2021; Veenman et al., 2006), enhancing problem-solving (Utami et al., 2023), and promoting learner engagement (An et al., 2024). More recently, scholars have examined metacognition within online learning environments, where it has emerged as a significant factor in shaping both learner persistence and academic success. For instance, Tsai et al. (2018) found that learners' metacognitive awareness was significantly associated with their level of learning interest, which in turn positively predicted their intention to continue learning in MOOCs. Similarly, Anthonysamy (2021) found that planning, monitoring, and regulating metacognitive strategies were positively associated with students' learning performance in online learning.

With the growing emphasis on interaction and collaboration in online learning, research has increasingly extended metacognition beyond the individual level. Scholars now argue that metacognitive development often occurs through social interaction with peers and instructors (Garrison & Akyol, 2013; Halmø et al., 2022; Hadwin et al., 2018; Liu et al., 2023). One of the most comprehensive frameworks addressing this perspective was proposed by Garrison and Akyol (2013, 2015/2015), who argued that metacognition should be examined from both individual and social perspectives, incorporating processes of self-regulation and co-regulation.

Building on this view, Garrison and Akyol (2015/2015) proposed the shared metacognition construct, with self-regulation and co-regulation as broader dimensions and monitoring and managing as subdimensions within each, and developed the Shared Metacognition Questionnaire (SMQ) to measure it in online collaborative contexts. However, their sample data supported only the two broad dimensions; the theorized monitoring and managing subdimensions did not emerge clearly. Responding to calls by Garrison and Akyol (2015/2015) for further validation work on these subdimensions, the present study revisits the sub-dimensional structure of the SMQ, focusing on the monitoring and managing subprocesses theorized within self-regulation and co-regulation.

2. Literature Review

2.1. Shared Metacognition in Online Learning

Metacognition, a type of higher-order intellectual skill, emphasizes learners' ability to monitor and manage their cognitive processes (Tobias & Everson, 2009). In other words, it refers to the ability to regulate cognition. This ability is especially important in online learning environments, where greater flexibility in time and space places stronger demands on learners' regulatory skills (Cheng et al., 2025; Zhang et al., 2023a). Research has also suggested that online learners with higher levels of metacognition demonstrate stronger presence, greater use of learning strategies, and better academic achievement (e.g., Geng & Su, 2025; Ishak et al., 2025; Zhang et al., 2023b).

Early theoretical models of metacognition primarily focused on the regulation of individual learning processes in traditional learning environments (e.g., Flavell, 1979; Nelson & Narens, 1990; Pintrich et al., 2000). However, research on collaborative and online learning environments has increasingly shown that the regulation of cognition often occurs in social contexts, where learners interact with peers and instructors, exchange ideas, and influence one another's cognitive processes (e.g., Garrison, 2022; Garrison & Akyol, 2015/2015; Olesova et al., 2026; Zhang et al., 2026). In such environments, learners must regulate their own learning while also engaging in regulatory activities through online discussions and other forms of interaction that involve monitoring and responding to the work, ideas, and feedback of others. These socially situated regulatory processes are particularly important in online collaborative inquiry settings, where knowledge construction occurs through interaction.

2.2. The Shared Metacognition Construct and Questionnaire

To account for the social dimension of regulation of cognition in online learning contexts, Garrison and Akyol (2015/2015) introduced the construct of shared metacognition. Shared metacognition goes beyond monitoring and managing one's own cognition and highlights the potential social influence on one's cognitive processes during collaborative inquiry. Within this construct, regulatory processes are conceptualized as involving two related but distinct dimensions, self-regulation of cognition (SRC) and co-regulation of cognition (CRC), with each dimension further consisting of two proposed subdimensions, monitoring and managing (see Figure 1). According to Garrison and Akyol (2015/2015),

SRC refers to monitoring and managing one's own cognitive processes during learning. Monitoring refers to awareness and observation of learning processes, such as recognizing one's level of understanding, whereas managing refers to actions taken to regulate learning, such as adjusting strategies or evaluating one's approach to a task. Within SRC, monitoring strategies include awareness of one's effort, and managing strategies include assessing one's understanding. CRC refers to monitoring and managing that occur through interaction with others during collaborative inquiry. Within CRC, monitoring strategies include observing others' learning, whereas managing strategies include challenging others' perspectives. Together, these processes describe how learners regulate both their individual learning and the collaborative processes through which knowledge is constructed.

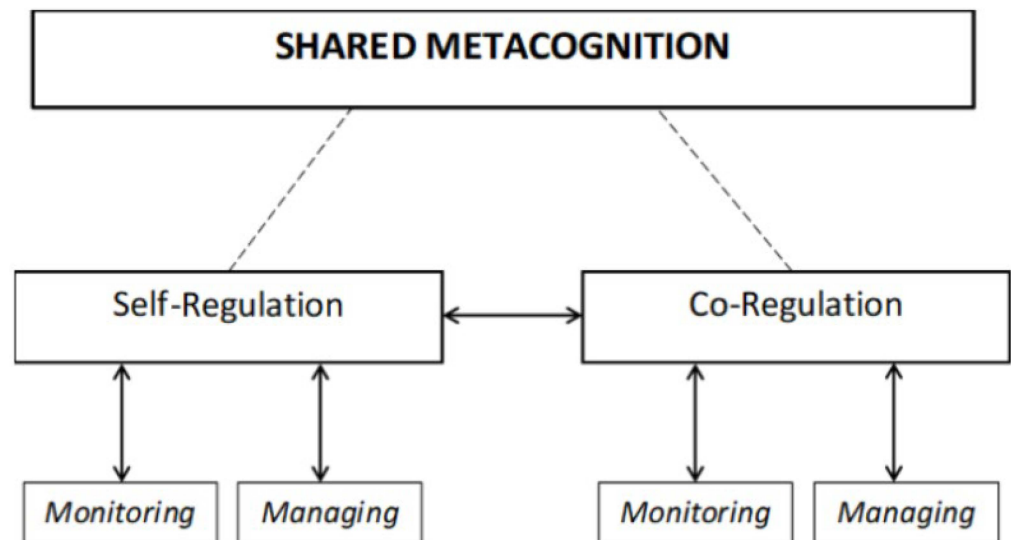


Figure 1. Shared Metacognition Construct (Garrison, 2022; Garrison & Akyol, 2015/2015).

To measure these constructs, Garrison and Akyol (2015/2015) developed the Shared Metacognition Questionnaire (SMQ; see Table 1 for item details). The instrument includes 26 items and broadly consists of two sets of items representing SRC (Items SRC1 to SRC13) and CRC (Items CRC1 to CRC13). Within SRC, Items SRC1 to SRC7 were written to reflect self-monitoring, and Items SRC8 to SRC13 were developed to measure self-managing. Within CRC, Items CRC1 to CRC6 were developed to measure co-monitoring, and Items CRC7 to CRC13 were developed to measure co-managing.

Table 1. Items of the Shared Metacognition Questionnaire (Garrison & Akyol, 2015/2015).

When I am engaged in the learning process as an individual		When I am engaged in the learning process as a member of a group	
SRC1	I am aware of my effort	CRC1	I pay attention to the ideas of others
SRC2	I am aware of my thinking	CRC2	I listen to the comments of others
SRC3	I know my level of motivation	CRC3	I consider the feedback of others
SRC4	I question my thoughts	CRC4	I reflect upon the comments of others
SRC5	I make judgments about the difficulty of a problem	CRC5	I observe the strategies of others
SRC6	I am aware of my existing knowledge	CRC6	I observe how others are doing
SRC7	I am aware of my level of learning	CRC7	I look for confirmation of my understanding from others
SRC8	I assess my understanding	CRC8	I request information from others
SRC9	I change my strategy when I need to	CRC9	I respond to the contributions that others make
SRC10	I search for new strategies when needed	CRC10	I challenge the strategies of others
SRC11	I apply strategies	CRC11	I challenge the perspectives of others
SRC12	I assess how I approach the problem	CRC12	I help the learning of others
SRC13	I assess my strategies	CRC13	I monitor the learning of others

Current validity and reliability evidence primarily supports the broad dimensions including SRC and CRC. In the original validation study, [Garrison and Akyol \(2015/2015\)](#) used a sample of 192 graduate students enrolled in fully online courses and conducted principal component analysis, which identified a two-factor structure. Items SRC1 to SRC13 loaded on one factor, and Items CRC1 to CRC13 loaded on the other. These results supported the presence of two broad dimensions corresponding to SRC and CRC and suggested a strong degree of consistency between the theoretical foundation of these two constructs and their empirical measurement. Thus, Garrison and Akyol's study provided initial support for the higher-level structure of the SMQ. [Zhang et al. \(2026\)](#) later confirmed the two-factor structure of the SMQ through confirmatory factor analysis and provided additional validity evidence, including acceptable model fit indices (e.g., root mean square error of approximation below 0.08, Tucker–Lewis index above 0.90, and comparative fit index above 0.90), as well as strong reliability evidence (Cronbach's alpha values of 0.92 for CRC and 0.94 for SRC). Together, this body of evidence suggests that the SMQ is a valid instrument for measuring shared metacognition at the broader levels of SRC and CRC.

However, existing validity evidence has not supported the proposed subdimensions of SRC and CRC, namely, monitoring and managing. In the original validation study, [Garrison and Akyol \(2015/2015\)](#) attempted to identify a four-factor structure of the SMQ, including self-monitoring, self-managing, co-monitoring, and co-managing, through principal component analysis. However, the results did not support the identification of these subdimensions within SRC and CRC. Specifically, the items did not load as hypothesized based on theory. [Garrison and Akyol \(2015/2015\)](#) offered several possible explanations for why monitoring and managing did not emerge as clearly distinct subdimensions within SRC and CRC. First, they suggested that these two concepts may be inherently difficult to disentangle in practice because learners often engage in them in a closely connected manner. Second, they noted that the wording of the questionnaire items may not have captured the distinction between monitoring and managing with sufficient clarity, which may have limited the instrument's ability to differentiate the two constructs empirically. More broadly, they acknowledged that a gap may exist between theoretical specification and empirical measurement. Therefore, in both their original validation study ([Garrison & Akyol, 2015/2015](#)) and their later discussion of the construct ([Garrison & Akyol, 2015/2015](#)), they explicitly called for more research to evaluate the subdimensions (managing and monitoring) of the SMQ.

To our knowledge, no subsequent study has directly addressed this call to reexamine the subdimensions (managing and monitoring) of the SMQ. This gap is important because the instrument has been widely used in studies of metacognitive development in collaborative learning processes in online and blended environments. Researchers often rely on the two broad subscales of SRC and CRC when examining relationships among regulatory activity, cognitive presence, and learning outcomes (e.g., [Al-Salti et al., 2025](#); [Olesova et al., 2026](#); [Zhang et al., 2026](#)). However, the extent to which the instrument captures the theoretically proposed subdimensions within the broad domains remains unclear. A closer examination of how the items function empirically can therefore provide insight into both the measurement properties of the instrument and the ways learners experience regulatory processes during collaborative inquiry.

The purpose of this study was to reexamine the proposed sub-dimensional structure of the Shared Metacognition Questionnaire (SMQ) with a specific focus on the monitoring and managing subprocesses theorized within its two broader dimensions, SRC and CRC. Although prior validation work supported the distinction between SRC and CRC, it did not find clear empirical support for the lower-order monitoring and managing subdimensions and called for further research on this issue ([Garrison & Akyol, 2015/2015](#)). Accordingly,

the present study used a split-sample exploratory and confirmatory factor analytic approach to examine whether the SRC and CRC items of the SMQ could be meaningfully differentiated into monitoring and managing subdimensions, and to identify areas where further refinement of the instrument may be needed. The research questions are:

1. To what extent do the self-regulation items of the SMQ support the theorized monitoring and managing subdimensions?
2. To what extent do the co-regulation items of the SMQ support the theorized monitoring and managing subdimensions?
3. What validity and reliability evidence supports the use of these proposed managing and monitoring subdimensions?

3. Methods

3.1. Participants and Data Collection

Following Institutional Review Board approval, graduate students enrolled in 25 fully online courses in the College of Education at a large research-intensive university in the United States were invited to participate in the study in 2023. The survey was administered online through Qualtrics, distributed to students via email or course announcements, and completed by students independently and voluntarily at the end of their enrolled courses. A total of 348 complete responses were retained after cases with missing data were excluded. Most participants identified as female (80.2%), followed by male (19.2%). Participants were drawn from a range of academic programs including Curriculum and Instruction, Special Education, Elementary Education, Learning Design and Technology, and Gifted, Creative, and Talented Studies, Teaching English Language Learners Graduate Certificate, STEM Education, Human Resource Management, and others.

3.2. Validation Procedures

To examine the psychometric properties of the subdimensions of SMQ, a series of analyses was conducted to examine evidence of construct validity (structure validity, convergent validity, discriminant validity) and reliability. SPSS Version 28 was used for the EFA and item-level diagnosis, and StataNow /SE 19.5 was used for all other analyses.

3.3. Structural Validity

The full sample of 348 participants was randomly divided into two subsamples for independent exploratory and confirmatory analyses. A larger portion ($N = 200$) was allocated to the exploratory factor analysis (EFA) to ensure stable factor extraction, as reliable identification of the underlying structure in the first stage of validation; the remaining participants ($N = 148$) were retained as an independent holdout sample for confirmatory factor analysis (CFA). This allocation strategy, prioritizing a larger sample for the exploratory stage, was applied and suggested in previous scale-validation studies (e.g., Li et al., 2025).

Exploratory Factor Analysis. EFA was conducted separately for the SRC and the CRC items. Specifically, principal axis factoring was used as the extraction method. Direct oblimin rotation was applied because the proposed dimensions and subdimensions were conceptually correlated. Sampling adequacy was evaluated using the Kaiser–Meyer–Olkin statistic and Bartlett’s test of sphericity. Decisions regarding factor retention were based on multiple criteria, including eigenvalues, scree plot inspection, factor interpretability, and theoretical alignment.

Confirmatory Factor Analysis. CFA was then conducted on the holdout subsample to evaluate competing models suggested by theory and by the EFA results. For the SRC items, CFA was used to compare a one-factor model and a theorized two-factor model representing self-monitoring and self-managing. Because the initial two-factor model did

not provide adequate fit, theoretically interpretable modification indices were reviewed alongside the EFA findings and item content to guide limited model refinement. For the CRC items, CFA was used to compare three models: a one-factor model, a theorized two-factor model representing co-monitoring and co-managing, and an empirically informed two-factor model based on the EFA results. Model fit was evaluated using the chi-square to degrees of freedom ratio (χ^2/df), root mean square error of approximation (RMSEA), comparative fit index (CFI), Tucker–Lewis index (TLI), and standardized root mean square residual (SRMR). Acceptable fit was indicated by RMSEA and SRMR values below 0.08, χ^2/df below 5.00, and CFI and TLI values above 0.90 (Browne & Cudeck, 1992; Hu & Bentler, 1999; MacCallum et al., 1996). All CFA models were estimated using maximum likelihood.

3.4. Item-Level Diagnostics

Because none of the CRC CFA models demonstrated acceptable fit, supplementary item-level diagnostics, including corrected item–total correlations and Cronbach’s alpha if an item was deleted, were conducted to identify potentially problematic items, such as those reflecting redundancy or conceptual ambiguity.

3.5. Convergent and Discriminant Validity

Convergent validity was assessed using standardized factor loadings, composite reliability, and average variance extracted (AVE). Standardized factor loading of 0.32 was considered minimally acceptable (Tabachnick & Fidell, 2001). CR values of 0.70 or higher, and AVE values of 0.50 or higher were considered indicative of adequate convergent validity (Fornell & Larcker, 1981). Discriminant validity was evaluated by examining correlations among latent factors and, when applicable, by comparing the square root of the AVE for each construct with the correlations between constructs (Fornell & Larcker, 1981).

3.6. Reliability

Reliability evidence was examined using both Cronbach’s alpha and composite reliability. Values of 0.70 or higher were considered acceptable for both indices.

4. Results

4.1. Self-Regulation of Cognition (SRC) Items

Exploratory Factor Analysis (EFA) Result for SRC

The data ($n = 200$) were well suited for factor analysis, as indicated by a KMO statistic of 0.91 and a significant Bartlett’s test of sphericity, $\chi^2(78) = 2620.46$, $p < 0.001$. The initial solution suggested a two-factor structure. The two-factor solution accounted for 69.66% of the variance, with Factor 1 accounting for 62.65% and Factor 2 accounting for an additional 7.01%. The scree plot also supported retention of two factors.

As shown in Table 2, factor loadings from the pattern matrix indicated that the two extracted factors were interpretable and broadly consistent with the theorized subdimensions of SRC. Items originally intended to reflect self-monitoring (SRC1–SRC7) tended to load on one factor, whereas items intended to reflect self-managing (SRC8–SRC13) loaded on the other. This pattern is encouraging, as it suggests that for the SRC items the hypothesized structure was more clearly interpretable than in the original study (Garrison & Akyol, 2015/2015), in which self-monitoring and self-managing did not separate clearly.

At the same time, the distinction was not entirely clean. The correlation between the two extracted factors was high ($r = -0.74$), indicating substantial shared variance and suggesting that the two subdimensions may also reflect a broader common SRC construct. In addition, one item, “I question my thoughts”, showed weaker performance than the others. It had the lowest communality among the 13 SRC items and relatively

weak loadings across factors, although its loading on the primary factor exceeded the minimum threshold of 0.32 adopted in this study (Tabachnick & Fidell, 2001). Given its theoretical relevance, the item was retained for subsequent analyses. From a metacognitive perspective, questioning one's thoughts is a strong indicator of metacognitive awareness and judgment (Pintrich et al., 2000). The discrepancy between its theoretical importance and empirical performance may suggest issues of item clarity or interpretation rather than a lack of conceptual relevance. We return to this item in the Discussion section.

Table 2. Pattern Matrix for Self-Regulation Items (n = 200).

Items	Factor 1 (Self-Managing)	Factor 2 (Self-Monitoring)
SRC 12. I assess how I approach the problem	0.96	
SRC 13. I assess my strategies	0.93	
SRC 10. I search for new strategies when needed	0.79	
SRC 9. I change my strategy when I need to	0.78	
SRC 11. I apply strategies	0.71	
SRC 8. I assess my understanding	0.60	
SRC 1. I am aware of my effort		1.01
SRC 2. I am aware of my thinking		0.93
SRC 3. I know my level of motivation		0.92
SRC 6. I am aware of my existing knowledge		0.73
SRC 5. I make judgments about the difficulty of a problem		0.45
SRC 7. I am aware of my level of learning		0.45
SRC 4. I question my thoughts	0.27	0.33

Note. Absolute values of the pattern loadings are presented for ease of interpretation.

Taken together, the EFA findings provide preliminary support for a two-factor structure of the SRC items corresponding to self-monitoring and self-managing. The strong factor correlation suggests, however, that these subdimensions are closely related and may also reflect a broader SRC construct. Accordingly, two CFA models were tested in the holdout sample: a one-factor model representing a general SRC construct and a correlated two-factor model representing self-monitoring and self-managing, with both models including all 13 items.

Confirmatory Factor Analysis (CFA) Results for SRC

As shown in Table 3, the correlated two-factor model fit the data better than the one-factor model (e.g., $\chi^2/df = 3.53$, RMSEA = 0.13). The two-factor model met suggested cutoffs for χ^2/df and SRMR, however, CFI, TLI, and RMSEA did not. The one-factor model showed poorer fit across all indices (e.g., $\chi^2/df = 4.55$, RMSEA = 0.16). These results provided support for a two-factor representation of the SRC items over a unidimensional alternative, but the two-factor solution remained suboptimal.

Table 3. Comparison of CFA Models for SRC Items.

Model	χ^2/df	CFI	TLI	RMSEA	SRMR
One-factor model	4.55	0.82	0.78	0.16	0.08
Two-factor model	3.53	0.87	0.85	0.13	0.07
Modified Two-Factor model	2.06	0.95	0.94	0.09	0.05

Modification indices (MIs) were therefore examined to identify localized misfit. Only theoretically interpretable residual covariances between items with highly similar content within the same factor were considered. First, the residuals of SRC6 ("I am aware of my existing knowledge") and SRC7 ("I am aware of my level of learning") were allowed to correlate because both items reflect awareness of one's current knowledge state

(MI = 39.93). Second, the residuals of SRC9 (“I change my strategy when I need to”) and SRC10 (“I search for new strategies when needed”) were allowed to correlate because both reflect strategic adaptation within the managing dimension (MI = 16.47). Third, the residuals of SRC4 (“I question my thoughts”) and SRC5 (“I make judgments about the difficulty of a problem”) were allowed to correlate because both capture evaluative aspects of metacognitive monitoring (MI = 40.29). The revised two-factor model showed substantially improved fit ($\chi^2/df = 2.06$, RMSEA = 0.09). Overall, these findings support a two-factor representation of SRC while indicating that several closely worded items share specific variance beyond that explained by the self-monitoring and self-managing factors. These residual covariances were identified from the modification indices after the initial two-factor model was estimated and were retained only when they were theoretically interpretable. The modifications should therefore be understood as post hoc and exploratory rather than confirmatory.

Convergent Validity, Discriminant Validity, and Reliability

As shown in Table 4, standardized factor loadings indicated that the self-managing factor was well defined, with all loadings ranging from 0.75 to 0.84. The self-monitoring factor was somewhat less consistent: most items loaded moderately to strongly, but one item showed weaker loadings, SRC4 (“I question my thoughts”; $\lambda = 0.35$), although both exceeded the 0.32 threshold (Tabachnick & Fidell, 2001).

Table 4. Factor Loadings, α , CR, and AVE for the Final Retained CFA Model of SRC Items.

Factor	Item	Standardized Loading	α	CR	AVE
Self-Monitoring	SRC1	0.76	0.83	0.85	0.47
	SRC2	0.88			
	SRC3	0.77			
	SRC4	0.35			
	SRC5	0.49			
	SRC6	0.67			
	SRC7	0.71			
Self-Managing	SRC8	0.75	0.92	0.92	0.65
	SRC9	0.83			
	SRC10	0.79			
	SRC11	0.81			
	SRC12	0.84			
	SRC13	0.81			

Reliability and convergent validity were then examined for the final retained model. The self-monitoring factor demonstrated acceptable internal consistency ($\alpha = 0.83$, CR = 0.85), but its AVE of 0.47 fell slightly below the recommended 0.50 threshold, indicating weaker convergent validity. In contrast, the self-managing factor showed strong reliability and convergent validity ($\alpha = 0.92$, CR = 0.92, AVE = 0.65).

Discriminant validity was assessed using the Fornell and Larcker criterion. The square root of the AVE was 0.68 for self-monitoring and 0.81 for self-managing, both lower than the latent factor correlation ($r = 0.85$). Thus, although the revised two-factor model fit the data better than the one-factor model, the self-monitoring and self-managing subdimensions remained highly overlapping and were not clearly distinct empirically.

4.2. Co-Regulation of Cognition (CRC) Results

Exploratory Factor Analysis (EFA) Results for CRC

Similar to the SRC items, the data were well suited for factor analysis of the CRC items, as indicated by a KMO of 0.90 and a significant Bartlett's test of sphericity, $\chi^2(78) = 2550.80$, $p < 0.001$. The initial solution suggested a two-factor structure, supported by the eigenvalues and the scree plot. The two extracted factors accounted for 70.46% of the common variance, with Factor 1 accounting for 58.02% and Factor 2 accounting for an additional 12.44%.

As shown in Table 5, the pattern matrix indicated that the two factors were interpretable but did not align with the theorized co-monitoring and co-managing subdimensions. Factor 1 appeared to reflect two complementary forms of interaction with others. Some items captured more receptive interactions, such as attending to and observing others' ideas and learning processes (CRC1–CRC6). Other items reflected more active interactions, such as seeking information or confirmation from others (CRC7–CRC9). Factor 2 was defined by two items reflecting evaluative (and critical) interactions, including challenging others' perspectives or strategies (CRC10 and CRC11), along with one item reflecting monitoring of others' learning (CRC13). CRC12 cross-loaded substantially on both factors (0.48 and 0.46). The correlation between the two factors was moderate ($r = 0.50$), suggesting that they were related but not redundant.

Table 5. Pattern Matrix for Factor Loadings for CRC Items.

Item	Factor 1	Factor 2
CRC2. I listen to the comments of others	1.02	
CRC3. I consider the feedback of others	0.97	
CRC1. I pay attention to the ideas of others	0.94	
CRC4. I reflect upon the comments of others	0.88	
CRC6. I observe how others are doing	0.75	
CRC9. I respond to the contributions that others make	0.74	
CRC5. I observe the strategies of others	0.69	
CRC7. I look for confirmation of my understanding from others	0.64	
CRC8. I request information from others	0.54	
CRC12. I help the learning of others	0.48	0.46
CRC10. I challenge the strategies of others		0.95
CRC11. I challenge the perspectives of others		0.93
CRC13. I monitor the learning of others		0.70

Two features of this pattern are important to note. First, the theorized distinction between co-monitoring (CRC1–CRC6) and co-managing (CRC7–CRC13) was not recovered. Items originally written to reflect monitoring and managing were mixed together on Factor 1, while only a subset of managing items (those involving challenging peers) separated onto Factor 2. Second, the behavior of CRC13 (“I monitor the learning of others”) is notable. Although its wording uses the term monitor, which in the original framework denotes awareness or observation, respondents appeared to interpret this item in a way that grouped it with the challenging items on Factor 2. This suggests that monitoring the learning of others may be read as a supervisory or evaluative act rather than as observation. The cross-loading of CRC12 (“I help the learning of others”) is also informative. Specifically, the term “help” is not specific, which may convey various meanings such as offering encouragement, sharing information, or correcting errors.

Confirmatory Factor Analysis (CFA) Results for CRC

Because the two-factor EFA solution was interpretable but did not closely align with the originally hypothesized co-monitoring-co-managing structure, further cross-validation was needed. CFA was therefore conducted on the holdout sample to compare three

models: (1) a one-factor model representing a strong general CRC factor, (2) a theoretically specified two-factor model based on the item structure proposed in the original scale development study (Garrison & Akyol, 2015/2015), and (3) an empirically derived two-factor model reflecting the EFA solution reported above. Relatively, as shown in Table 6, the EFA-informed two-factor model demonstrated the best fit of the three models (e.g., $\chi^2/df = 4.83$, RMSEA = 0.161). Specifically, the one-factor model showed the weakest fit. The theorized two-factor model fit slightly better. Thus, although the empirically informed two-factor model outperformed both the one-factor model and the originally hypothesized two-factor model, none of the three models reached acceptable levels of fit based on the model fit criteria defined in the study. These findings suggest that the CRC items were not well represented by either the original theoretical structure or a single general factor, and that even the empirically derived two-factor structure remained unstable at the confirmatory stage.

Table 6. Comparison of CFA Models for CRC Items.

Model	χ^2/df	CFI	TLI	RMSEA	SRMR
One-factor model	7.01	0.64	0.57	0.20	0.12
Theorized two-factor model	6.46	0.68	0.61	0.19	0.12
EFA-informed two-factor model	4.83	0.79	0.74	0.16	0.12

Item-Level Diagnosis

Because none of the CFA models demonstrated acceptable fit, supplementary item-level analyses were conducted using the full sample ($N = 348$) to identify potential sources of redundancy and conceptual ambiguity among the CRC items. To provide reliability evidence for the CRC items in response to the incomplete validity picture left by the non-fitting CFA models, both Cronbach's α and McDonald's ω were computed on the full sample. The full 13-item CRC scale showed high internal consistency ($\alpha = 0.92$, $\omega = 0.92$). Because no CFA model reached acceptable fit, composite reliability (CR) and average variance extracted (AVE) are not reported for the CRC items, as these indices are derived from an adequately fitting measurement model and would be misleading if computed from a model with unacceptable fit. As a supplementary and descriptive step, reliability was also estimated for the two item clusters that emerged in the EFA (see Table 5). The first cluster (CRC1–CRC9) showed high internal consistency ($\alpha = 0.93$, $\omega = 0.93$), as did the second cluster (CRC10, CRC11, CRC13; $\alpha = 0.86$, $\omega = 0.88$). CRC12 was not included in either cluster for reliability computation because it was cross-loaded. These clusters were derived from the exploratory analysis and were not confirmed by any acceptable CFA model; the reliability estimates are therefore reported only as descriptive information and should not be interpreted as evidence for validated subscales.

As shown in Table 7, inspection of the inter-item correlation matrix revealed several highly correlated items. The clearest example was CRC10 and CRC11, which correlated at 0.88, indicating substantial similarity and possible redundancy. A similarly tight cluster was observed among CRC1, CRC2, CRC3, and CRC4, with inter-item correlations ranging from 0.73 to 0.86. These items all reflect attention to, listening to, considering, and reflecting on others' input. Additional moderately high correlations were observed among CRC5, CRC6, CRC7, CRC8, and CRC9, indicating further clustering among items related to observing, seeking information from, and responding to others.

Table 7. Inter-Item Correlation Matrix for the Co-Regulation Items.

Item	2	3	4	5	6	7	8	9	10	11	12	13
CRC1	0.86	0.73	0.73	0.57	0.55	0.49	0.49	0.68	0.28	0.29	0.52	0.30
CRC2	1.00	0.79	0.73	0.56	0.59	0.53	0.54	0.68	0.24	0.25	0.51	0.28
CRC3	-	1.00	0.75	0.52	0.56	0.49	0.43	0.59	0.26	0.29	0.48	0.27
CRC4	-	-	1.00	0.65	0.61	0.61	0.53	0.63	0.30	0.32	0.54	0.37
CRC5	-	-	-	1.00	0.72	0.50	0.44	0.50	0.33	0.31	0.47	0.35
CRC6	-	-	-	-	1.00	0.59	0.53	0.61	0.34	0.32	0.52	0.43
CRC7	-	-	-	-	-	1.00	0.58	0.61	0.31	0.34	0.44	0.40
CRC8	-	-	-	-	-	-	1.00	0.64	0.39	0.39	0.52	0.42
CRC9	-	-	-	-	-	-	-	1.00	0.33	0.37	0.57	0.39
CRC10	-	-	-	-	-	-	-	-	1.00	0.88	0.53	0.57
CRC11	-	-	-	-	-	-	-	-	-	1.00	0.58	0.59
CRC12	-	-	-	-	-	-	-	-	-	-	1.00	0.61
CRC13	-	-	-	-	-	-	-	-	-	-	-	1.00

Item-total statistics provided a consistent picture (Table 8). Corrected item-total correlations were generally acceptable, ranging from 0.57 to 0.75, indicating that no single item was entirely disconnected from the broader CRC construct. However, CRC10, CRC11, and CRC13 showed comparatively lower corrected item-total correlations, suggesting that these items were somewhat less aligned with the dominant general factor. Cronbach's α if item deleted changed only minimally across items (0.91 to 0.92), suggesting that the poor structural fit observed in the CFA was not attributable to any single item. Rather, the issue appears to reflect broader conceptual clustering, redundancy, and mismatch between the intended monitoring/managing distinction and the way the items functioned empirically.

Table 8. Item-Total Statistics for the CRC Items.

Item	Corrected Item-Total Correlation	α If Item Deleted
CRC1	0.71	0.91
CRC2	0.71	0.91
CRC3	0.67	0.91
CRC4	0.75	0.91
CRC5	0.66	0.91
CRC6	0.72	0.91
CRC7	0.66	0.91
CRC8	0.67	0.91
CRC9	0.74	0.91
CRC10	0.57	0.92
CRC11	0.59	0.92
CRC12	0.73	0.91
CRC13	0.59	0.92

Taken together, the CFA and item-level results suggest that the CRC items are coherent as a broad measure of CRC, but their lower-order structure remains unresolved. The items appear to organize less by the theorized distinction between monitoring and managing and more by narrower content clusters, particularly a contrast between receptive engagement with others' ideas and more active or evaluative forms of regulating others' learning.

5. Discussion

The purpose of this study was to reexamine the monitoring and managing subdimensions proposed within the SRC and CRC components of the SMQ. The findings reveal a clear asymmetry between the two components. For SRC, the theorized subdimensions

were recoverable and could be modeled with marginally acceptable fit after limited, theory-guided refinements. For CRC, the lower-order structure remained unstable, and neither the original theoretical model nor an empirically informed model achieved acceptable model fit. These results advance the original validation work by moving beyond the general conclusion that monitoring and managing are hard to separate (Garrison & Akyol, 2015/2015) and by specifying where the difficulty is and how to refine the items.

5.1. Self-Regulation of Cognition (SRC)

The present SRC findings extend Garrison and Akyol's (2015/2015) original work by providing stronger evidence for a two-factor monitoring-managing structure within SRC. In the EFA, the SRC items grouped broadly in line with the hypothesized distinction: SRC1–SRC7 loaded on the self-monitoring factor and SRC8–SRC13 loaded on the self-managing factor. After theoretically justified minor modifications, the CFA model also reached marginally acceptable fit. Nevertheless, the two subdimensions remained highly correlated ($r = 0.85$), and discriminant validity was not fully supported. This pattern suggests that respondents distinguished self-monitoring and self-managing empirically, but treated them as closely related constructs. Also, this close relationship between the two SRC subdimensions was further reflected in a supplementary parallel analysis conducted on the EFA subsample. Whereas the eigenvalue, scree, interpretability, and theoretical criteria used in the primary analysis supported a two-factor solution, the parallel analysis pointed toward a single dominant dimension underlying the SRC items. Rather than contradicting the two-factor structure, this result is consistent with the strong correlation between self-monitoring and self-managing ($r = 0.85$) and the limited discriminant validity reported above. The two-factor solution was retained on the basis of the convergence of the remaining retention criteria and its superior fit relative to the one-factor model in the CFA.

This finding is theoretically plausible. Theoretical models of self-regulated learning (e.g., Pintrich, 2004; Zimmerman, 2000) and metacognition (e.g., Garrison, 2022; Pintrich et al., 2000) often conceptualize monitoring and control (or managing) as distinct yet interdependent concepts. In Pintrich's (2004) widely used framework of self-regulated learning, for example, monitoring (Phase 2, metacognitive awareness of effort and motivation) and control (Phase 3, selection and adaptation of task strategies) are described as separate and generally sequential learning phases. At the same time, Pintrich (2004) also noted that these two phases could occur simultaneously, and their order could even occasionally reverse. This dynamic and reciprocal relationship between monitoring and managing may explain the strong correlation between the two factors observed here.

The relative recoverability of the SRC subdimensions in the present study may also be understood in light of the fully online learning context. Compared with face-to-face or blended settings, fully online learning places heightened demands on learner autonomy, requiring students to direct their own learning with fewer time and space restrictions and less real-time instructor scaffolding (Cheng et al., 2025; Zhang et al., 2023a). Under these conditions, learners may need to regulate themselves more deliberately and frequently when tracking their learning progress (monitoring) and adjusting their learning strategies (managing), thereby making the two processes more cognitively distinct for fully online learners than for the mixed sample in Garrison and Akyol's (2015/2015) original study. In other words, the autonomy demands of the fully online context may partly explain why the theorized self-monitoring and self-managing structure was more clearly recoverable here, even as the two subdimensions remained highly correlated.

A second point is that the two subdimensions did not perform equally well. The self-managing items showed stronger and more consistent loadings as well as stronger convergent validity, whereas the self-monitoring factor was weaker. Within the self-monitoring

subdimension, SRC4 (“I question my thoughts”) was a particularly weak indicator. This pattern echoes Garrison and Akyol’s (2015/2015) concern that the monitoring–managing distinction may be obscured not only by conceptual overlap but also by item wording. We support retaining SRC4 in the self-monitoring subdimension because reflective appraisal of one’s own thinking is an essential part of metacognitive monitoring (Pintrich et al., 2000), but its clarity should be improved. In its current form, the item is open to multiple readings, including self-doubt, critical reflection, and cognitive checking, any of which could reduce interpretive consistency across respondents. Specific suggestions for item refinement are provided in a later section, “Implications for Item Refinement.”

5.2. Co-Regulation of Cognition (CRC)

The present EFA findings for the CRC items align closely with, and extend, the pattern reported in Garrison and Akyol’s (2015/2015) original validation study. In that study, the authors attempted to identify the theorized four-factor structure (self-monitoring, self-managing, co-monitoring, co-managing) and concluded that the monitoring and managing sub-elements could not be clearly separated. Within their co-regulation items, the same three items that emerged on Factor 2 in the present study, including “I challenge the strategies of others,” “I challenge the perspectives of others,” and “I monitor the learning of others”, also separated from the remaining CRC items. The recurrence of this specific pattern in an independent sample provides replication evidence that the separation is not sample-specific noise. Our analysis extends their finding in two ways. First, by conducting the EFA on the CRC items alone rather than forcing a four-factor solution across all 26 items, we obtained a cleaner two-factor structure that is easier to interpret. Second, our analysis shows more explicitly that the empirical structure does not correspond to the theorized monitoring–managing distinction: items originally written as monitoring (CRC1–6) and items originally written as managing (CRC7–9) grouped together on Factor 1, while only the evaluative and challenging items separated onto Factor 2. A supplementary parallel analysis supported the retention of two components for the CRC items, corroborating the two-factor structure identified in the exploratory analysis, even as that structure departed from the theorized co-monitoring/co-managing distinction.

This pattern is both theoretically interpretable and empirically supported. Theoretically, monitoring and managing in group tasks are conceptualized as highly interdependent and socially situated processes (Garrison & Akyol, 2015/2015; Hadwin et al., 2018; Hadwin & Oshige, 2011), in which strategy selection and adaptation (managing) typically depend on how learners observe and perceive the group learning environment, the difficulty of the group task, and the peers they are working with. Empirically, in online collaborative settings, attending to others, considering feedback, seeking confirmation, responding, helping peers, challenging ideas, and monitoring others’ learning tend to unfold in overlapping ways (Akyol & Garrison, 2011; Richardson et al., 2025). Additionally, co-regulation may be further shaped by the specific affordances of the asynchronous, text-based online environment in which the present data were collected. In asynchronous online discussions, interaction occurs through text-based posts rather than real-time exchange, resulting in reduced immediacy (Akyol & Garrison, 2011). Under these conditions, monitoring behaviors, such as attending to others’ ideas and feedback, and managing behaviors, such as seeking information or confirmation, may be experienced as part of a single, continuous process of engaging with peers’ and instructors’ textual input rather than as separable acts of monitoring versus managing. This may help explain why items originally written to reflect monitoring and managing behaviors (CRC1–CRC9) grouped together on a single factor. Taken together, these considerations suggest that the empirical structure of the CRC items may be partly a function of the asynchronous online modality and that respondents

in synchronous, blended, or HyFlex settings, where immediacy and real-time interaction are more feasible, might interpret and respond to these items differently. This reinforces the need for caution when applying the SMQ co-regulation items, and any prospective subdimensions, across different online and hybrid learning modalities.

Importantly, the CRC EFA pattern should not be interpreted only as a failure to recover the theorized co-monitoring/co-managing distinction. Instead, it may point to another distinction in how learners experience social regulation in online collaborative learning. The first factor (CRC 1–9) appeared to reflect receptive and responsive engagement with others' ideas, including attending to, listening to, considering, observing, seeking information from, and responding to others. The second factor (CRC 10, 11, & 13) appeared to reflect more evaluative regulation, including challenging others' strategies or perspectives and monitoring others' learning. This pattern is consistent with broader perspectives on social regulation of learning, which suggest that co-regulation and socially shared regulation emerge through interaction, discourse, and ongoing exchanges among learners rather than through isolated individual regulatory learning behaviors. Hadwin and Oshige (2011), for example, distinguished co-regulation as regulation distributed between a learner and others during interaction from socially shared regulation as the collective regulation of group activity. From this perspective, the CRC items may capture differences in the intensity and direction of social regulatory engagement, ranging from receptive or responsive participation to more active evaluation of the group's learning, rather than the intended monitoring/managing distinction alone.

Item-level diagnostics offer additional insight. Three observations help clarify why the theorized structure did not emerge. First, several item pairs were highly correlated, most notably CRC10 and CRC11, which appear to function as near-duplicates rather than distinct indicators. A further cluster (CRC1 through CRC4) reflected a narrow receptive interaction theme. Second, the wording of CRC13 ("I monitor the learning of others") appears to be read by respondents in a way that conflicts with its intended classification. Although the item uses the term "monitor", which, theoretically, associates with awareness and observation, empirically, it loaded onto factor 2 with items associated with challenging others' strategies or perspectives (CRC 10 & 11). This suggests that the term "monitor" in the context of peers' learning may be interpreted as critically evaluative rather than as awareness. Third, the cross-loading of CRC12 ("I help the learning of others") indicates that the item might be written in a way that is too general to be distinguished between managing and monitoring. Specifically, the term "help" is not specific, which may convey various meanings such as offering encouragement, sharing information, or correcting errors. Unlike more specific items such as "I respond to the contributions that others make" or "I request information from others," this item (CRC12) names an intention without specifying a behavior, which likely contributes to its ambiguous loading. Taken together, these observations suggest that refinement of the CRC items, particularly CRC12 and CRC13, may be a productive next step.

5.3. Implications for Use and Future Refinement

For researchers currently using the SMQ, the results support continued use of the full 26-item instrument to assess shared metacognition overall and the two broader dimensions of SRC and CRC. Further, our findings provide tentative and preliminary evidence for a seven-item (SRC1–7) self-monitoring subscale and a six-item (SRC8–13) self-managing subscale. Notably, although the modified two-factor model was recoverable and fit the data at a marginally acceptable level, the two subdimensions were highly correlated ($r = 0.85$) and did not satisfy the Fornell-Larcker criterion for discriminant validity. The self-monitoring and self-managing items should therefore not be treated as measuring

clearly distinct constructs, and the subscales should not be used as independent measures on the basis of the present evidence. Rather, our findings provide preliminary support that warrants further validation, ideally in independent samples and with additional discriminant validity indices such as the HTMT ratio (Henseler et al., 2015), before these subscales are applied separately. Within CRC, the items should not yet be treated as clearly validated monitoring and managing subscales. It is also worth noting that the validity and reliability evidence for the monitoring–managing subscales in the present study is specific to fully online learning contexts. As such, these subscales require further validation before being applied to other learning environments, such as blended, HyFlex, or face-to-face settings. Several directions are suggested for future item refinement.

First, for the SRC items, item SRC4 (“I question my thoughts”) may benefit from clarification to reduce ambiguity in how respondents interpret the notion of “questioning,” while preserving its focus on metacognitive evaluation. For example, the item could be rephrased as “I evaluate whether my current way of thinking is effective,” which more explicitly reflects evaluative monitoring without altering its underlying construct.

Second, for the CRC items, future refinement should prioritize item wording that describes distinct and observable co-regulatory behaviors, because broad statements about CRC may be interpreted differently by respondents depending on the specific context of their group work. Item CRC12 (“I help the learning of others”), for example, appears to lack such specificity. As currently worded, it may be perceived as including multiple forms of co-regulatory support, such as sharing information or resources, providing encouragement, asking clarifying questions, explaining ideas, or offering feedback on others’ work. To reduce construct ambiguity, this item could be rewritten or split into multiple items that target more specific and observable behaviors. For example, future items might distinguish between providing feedback on others’ work, asking questions to clarify others’ understanding, or sharing resources to support others’ learning.

Third, item CRC13 (“I monitor the learning of others”) closely reflects the general construct of monitoring and may therefore lack specificity as an observable behavior. Items that merely restate the construct label can limit interpretability and reduce measurement precision because respondents may interpret “monitoring” in different ways, such as observing, checking, documenting, or supervising others. Therefore, this item may benefit from re-specification to capture a more observable monitoring behavior, such as checking whether group members understand co-designed task strategies, tracking peers’ progress toward shared goals, or socially comparing one’s own progress with that of other group members during a collaborative project. If redundancy or ambiguity persists after refinement, the item may also be considered for removal.

Fourth, for CRC items, the distinction between receptive engagement (CRC 1–6, e.g., paying attention, listening, observation) and active regulation (CRC 7–9, e.g., seeking confirmation, requesting information, responding to contribution) could be sharpened in item wording.

Lastly, overall, the SMQ, particularly the CRC items, may benefit from an additional round of content review with members of the target population to obtain more direct feedback on item clarity and interpretation. Qualitative item development approaches, such as cognitive interviewing or think-aloud protocols, may be especially useful for identifying sources of ambiguity and improving item wording (DeVellis & Thorpe, 2021).

6. Limitations

Several limitations should be acknowledged. First, participants were graduate students enrolled in fully online courses within a single college at one U.S. research university, and the sample was predominantly female (80.2%). Although participants represented

a range of academic programs, the concentration within a single institution, discipline, degree level, and learning modality, together with the gender imbalance, limits the generalizability of the findings. Regulatory and co-regulatory processes may be experienced or reported differently across disciplines, degree levels, learner populations, and instructional modalities, and the present subscales should therefore be validated in more diverse samples before broader application.

Second, given the number of items and parameters in the CFA models, the holdout sample of $n = 148$ may limit the stability of parameter estimates and model fit conclusions.

Third, the SMQ relies on self-report data. Although theoretical frameworks conceptualize monitoring and managing as related but distinguishable regulatory processes (Pintrich, 2004), empirical work on the SMQ, including Garrison and Akyol's (2015/2015) original validation study and the present findings, suggests that these processes may be difficult to distinguish using self-report items alone, particularly within the CRC dimension. These studies suggest that alternative approaches, such as think-aloud protocols and behavioral indicators, may provide more insights. Future research should explore and validate these approaches as complementary methods to strengthen assessment through triangulation.

Fourth, for the modified SRC model, the three residual covariances that brought this model to marginally acceptable fit were identified from modification indices computed on the holdout sample ($N = 148$) rather than specified in advance. Although each was retained only where the item pair shared clearly overlapping content within the same factor, post hoc respecification of this kind is a recognized form of capitalization on chance, in which model adjustments reflect only sample-specific variation. This concern is heightened in a sample of modest size ($n = 148$). The fit of the modified SRC model should therefore be considered sample-specific and has not yet been cross-validated. Confirmation in an independent sample is needed before the modified SRC model can be fully used in practice.

Finally, the CFA models were estimated using maximum likelihood, which treats the Likert-type SMQ items as continuous. Although this is a common approach for five-point items, it does not fully account for the ordinal nature of the scale. Robust or ordinal estimators, such as robust maximum likelihood (MLR) or weighted least squares mean- and variance-adjusted estimation (WLSMV), can possibly yield different fit indices and standard errors. Future validation studies could consider re-estimating the models with such estimators.

7. Conclusions

This study reexamined the monitoring and managing subdimensions proposed within the SMQ. The results reaffirm the broader distinction between SRC and CRC, offer support for the self-monitoring and self-managing subdimensions within SRC, and indicate that the lower-order co-monitoring and co-managing distinction is not currently supported within CRC. The findings do not weaken the conceptual importance of shared metacognition. Rather, they suggest that its lower-order measurement, especially within co-regulation, requires further refinement before these subdimensions can be treated as well-established empirical structures.

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