

A Theoretical and Empirical Analysis of Cognitive Engagement in Self-regulated Learning

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Table of Contents

Abstract	iv
Résumé.....	v
Acknowledgments.....	vii
Dedication	ix
Preface and Contributions of Authors.....	x
List of Tables	xiii
List of Figures	xiv
List of Appendices	xv
Chapter 1. Introduction	1
Overview of the Chapters	4
Chapter 2. Manuscript 1.....	9
Cognitive Engagement in Self-regulated Learning: An Integrative Model.....	9
Abstract	10
Introduction.....	11
The Nature of Cognitive Engagement	13
Self-regulated Learning and Cognitive Engagement.....	18
An Integrative Model of SRL Engagement	31
Conclusion	37
Reference	39
Bridging Text.....	46
Chapter 3. Manuscript 2.....	47
Measuring Cognitive Engagement: An Overview of Measurement Instruments and Techniques	47
Abstract	48
Introduction.....	49
Methods Used in the Review	52
Current Practice in Measuring Cognitive Engagement	54
Guidelines for Future Research and Applications of Cognitive Engagement Measures.....	69
References.....	73
Bridging Text.....	81
Chapter 4. Manuscript 3.....	82

The Relationship between Cognitive Engagement and Students' Performance in a Simulation-based Training Environment: An Information-Processing Perspective.....	82
Introduction.....	84
Theoretical Background.....	85
Methods.....	89
Results.....	95
Discussion.....	100
Conclusion	103
References.....	105
Appendices.....	111
Bridging Text.....	114
Chapter 5. Manuscript 4.....	115
Automated Detection of Cognitive Engagement to Inform the Art of Staying Engaged in Problem-solving.....	115
Abstract	116
Introduction.....	117
Theoretical Background.....	118
Current Study	124
Method	125
Results.....	136
Discussion	142
Conclusion	147
References.....	149
Appendices.....	156
Chapter 6. Final Discussion	157
Contributions.....	159
Limitations and Future Directions	162
Concluding Remarks.....	166
Bibliography	171

Abstract

Cognitive engagement is a crucial topic in educational psychology that is continuing to attract attention from researchers across disciplines. However, the research on cognitive engagement suffers from a few conceptual, theoretical, and methodological challenges. For instance, there is little agreement on “what cognitive engagement is” and “how students manage their cognitive engagement in the context of self-regulated learning (SRL)”. The purpose of this dissertation is to address these fundamental yet unanswered questions about the nature, definition, and measurement of cognitive engagement and its roles and functions in SRL. In the first manuscript, we synthesized current perspectives and findings concerning the nature of cognitive engagement. We clarified some ambiguities on the relationships between cognitive engagement and SRL that remained in the literature. Furthermore, we proposed an integrative model of SRL engagement to clarify the functioning of cognitive engagement in different SRL phases and subprocesses. The second manuscript presented a critical review of the instruments and techniques used to measure cognitive engagement, which provided additional insights into this construct from a practical perspective. The third and fourth manuscripts presented two empirical studies to validate the theoretical claims made in the integrative model of SRL engagement. We situated these two studies in clinical reasoning, where the participants were required to diagnose virtual patients in an intelligent tutoring system. Findings from these two empirical studies provided strong evidence that students strategically regulated their cognitive engagement in SRL. Notably, in the fourth manuscript, we proposed a novel approach to measure students’ cognitive engagement from their facial behavioral cues, taking advantage of computer vision and machine learning techniques. This dissertation closes with a discussion of its contributions to the literature, limitations, and research directions for future studies.

Résumé

L'engagement cognitif est un sujet crucial en psychologie de l'éducation qui continue à attirer l'attention des chercheurs de toutes les disciplines. Cependant, la recherche sur l'engagement cognitif souffre de quelques défis conceptuels, théoriques et méthodologiques. Par exemple, il y a peu d'accord sur "ce qu'est l'engagement cognitif" et "comment les étudiants gèrent leur engagement cognitif dans le contexte de l'apprentissage auto-régulé (SRL)". L'objectif de cette thèse est de répondre à ces questions fondamentales mais sans réponse sur la nature, la définition et la mesure de l'engagement cognitif et de ses rôles et fonctions dans l'apprentissage autorégulé. Dans le premier manuscrit, nous avons synthétisé les perspectives et les résultats actuels concernant la nature de l'engagement cognitif. Nous avons clarifié certaines ambiguïtés sur les relations entre l'engagement cognitif et la SRL qui subsistent dans la littérature. En outre, nous avons proposé un modèle intégratif de l'engagement dans la recherche scientifique afin de clarifier le fonctionnement de l'engagement cognitif dans les différentes phases et sous-processus de la recherche scientifique. Le deuxième manuscrit présente un examen critique des instruments et des techniques utilisés pour mesurer l'engagement cognitif, ce qui permet de mieux comprendre ce concept d'un point de vue pratique. Les troisième et quatrième manuscrits présentent deux études empiriques visant à valider les affirmations théoriques du modèle intégratif de l'engagement dans la recherche scientifique. Nous avons situé ces deux études dans le raisonnement clinique, où les participants devaient diagnostiquer des patients virtuels dans un système de tutorat intelligent. Les résultats de ces deux études empiriques ont fourni des preuves solides que les étudiants régulent stratégiquement leur engagement cognitif dans la SRL. Notamment, dans le quatrième manuscrit, nous avons proposé une nouvelle approche pour mesurer l'engagement cognitif des étudiants à partir de leurs signaux

comportementaux faciaux, en tirant parti de la vision par ordinateur et des techniques d'apprentissage automatique. Cette thèse se termine par une discussion sur ses contributions à la littérature, ses limites et les directions de recherche pour les études futures.

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Dedication

I would like to dedicate this dissertation to my mother, Aiping Li, whose selflessness and resilience give me the determination to keep moving forward.

Preface and Contributions of Authors

I am the primary author of all the papers included in this dissertation and I am responsible for their content. I wrote each chapter independently. My doctoral supervisor Dr. Susanne Lajoie reviewed the final draft of the dissertation and provided feedback. Earlier versions of Chapters 2 and 3 were written independently as partial fulfillment of my comprehensive exam, and as such they benefited from the feedback from my comprehensive exam evaluation committee, which included Drs. Susanne Lajoie, Adam Dubé, and Eric Poitras. I received feedback from co-authors on the empirical manuscripts (Chapters 4 and 5). Their specific contributions are summarized below using the structured Contributor Role Taxonomy (CRediT)¹.

Chapter 2

Citation

Li, S., & Lajoie, S. P. (2021). Cognitive engagement in self-regulated learning: An integrative model. *European Journal of Psychology of Education*. 1-20.
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Contributions

An earlier version of this paper was prepared in partial fulfillment of my comprehensive exam. I conducted the literature review and wrote the manuscript in its entirety. Dr. Lajoie provided feedback on the full draft.

Chapter 3

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¹ Brand, A., Allen, L., Altman, M., Hlava, M., & Scott, J. (2015). Beyond authorship: attribution, contribution, collaboration, and credit. *Learned Publishing*, 28 (2), 151-155.

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Contributions

I conducted the literature review and wrote this paper in its entirety. An earlier version of this paper was prepared in partial fulfilment of my comprehensive exam, for which Drs. Susanne Lajoie, Adam Dubé, and Eric Poitras provided feedback.

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Shan Li: Conceptualization, Methodology, Investigation, Data Curation, Formal analysis, Writing – Original Draft.

Juan Zheng: Investigation, Resources, Writing- Reviewing and Editing.

Susanne P. Lajoie: Writing- Reviewing and Editing, Software, Supervision, Funding acquisition.

Chapter 5

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Contributions

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Juan Zheng: Investigation, Resources, Writing- Reviewing and Editing.

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List of Tables

<i>Table 1. A Comparison of the Six Dominant SRL Models</i>	<i>21</i>
<i>Table 2. Perspectives on the Relationships between SRL and Cognitive Engagement.....</i>	<i>23</i>
<i>Table 3. The Differences between SRL and Cognitive Engagement</i>	<i>25</i>
<i>Table 4. Some Definitions of Cognitive Engagement</i>	<i>50</i>
<i>Table 5. Prominent Cognitive Engagement Scales.....</i>	<i>58</i>
<i>Table 6. Descriptive Analysis of Diagnostic Behaviors and Information Processing Classes</i>	<i>96</i>
<i>Table 7. Fit Indices for Different Models with the Number of Clusters Ranging from 2 to 6</i>	<i>97</i>
<i>Table 8. The Three Clusters of Cognitive Engagement Profiles</i>	<i>98</i>
<i>Table 9. Pairwise Comparisons of Diagnostic Confidence and Efficacy</i>	<i>100</i>
<i>Table 10. The Surface and Deep Strategic Behaviors in Clinical Reasoning</i>	<i>131</i>
<i>Table 11. The Extracted Features from the OpenFacce System.....</i>	<i>134</i>
<i>Table 12. The Centroids of Engaged and Less Engaged States Identified by K-means Algorithm</i>	<i>137</i>
<i>Table 13. The Features Selected Using Recursive Feature Elimination.....</i>	<i>138</i>
<i>Table 14. 10-fold Cross Validation of Different Models in Predicting Cognitive Engagement</i>	<i>139</i>
<i>Table 15. Differences in Cognitive Engagement Levels Between High and Low Performers ..</i>	<i>142</i>

List of Figures

<i>Figure 1. The Integrative Model of SRL Engagement</i>	<i>31</i>
<i>Figure 2. The Process of Identifying Relevant Studies</i>	<i>53</i>
<i>Figure 3. The Interface of the BioWorld System</i>	<i>91</i>
<i>Figure 4. The Intelligent Tutoring System of BioWorld.....</i>	<i>127</i>
<i>Figure 5. Resampling RMSE Estimates for Random Forests Across Different Subset Sizes ...</i>	<i>138</i>
<i>Figure 6. ROC Curve to Comparing the Performance of Classification Models</i>	<i>140</i>

List of Appendices

<i>Appendix A. The Information Acquisition and Transformation Behaviors in Clinical Reasoning</i>	
.....	111
<i>Appendix B. The Mplus Code for the Unconditional Latent Profile Analysis.....</i>	112
<i>Appendix C. The Mplus Code for the Latent Profile Analysis with a Distal Outcome</i>	113
<i>Appendix D. An Illustration of the Data Collection Settings</i>	156

Chapter 1. Introduction

Students should be cognitively engaged in learning so that thoughtful, efficient, and effective learning can occur. However, there is a continuing debate in the literature on “how can we tell that a learner is cognitively engaged?” In other words, what is cognitive engagement? Some researchers define cognitive engagement based on the levels of information processing (e.g., use of shallow or deep strategies) (Corno & Mandinach, 1983; Craik & Lockhart, 1972; Greene, 2015), whereas others refer it as to motivational beliefs, such as students’ interest, willingness to learn, and control of schoolwork (Chi & Wylie, 2014; Finlay, 2006). Still others define cognitive engagement more broadly as students’ investment in learning (Boekaerts, 2016; D’Mello et al., 2017; Fredricks et al., 2004). Regarding the level of investment, it has been studied as the use of cognitive, metacognitive, and volitional strategies (Greene, 2015; Wang & Eccles, 2012), students’ motivations (e.g., perceived importance of schooling, and willingness to exert necessary effort for completing a task), and their mental involvement with learning (e.g., control, concentration, focus, absorption, and dedication) (Skinner & Pitzer, 2012). In sum, the concept of cognitive engagement, as pointed out by Fredricks et al. (2004), overlaps with many other constructs that have been studied previously. Although researchers, school administrators, educators, parents, and students all acknowledge the importance of cognitive engagement in learning, the meaning of cognitive engagement can vary greatly. The lack of consensus on this core question (i.e., the nature and definition of cognitive engagement) has hampered the field.

The other question that has received considerable attention from researchers and educational practitioners is “how to increase and maintain students’ cognitive engagement in learning?” While this question is crucial for improving students’ learning performance, answering this question has raised a few new questions that remain to be addressed. Representative questions include: Should students always keep their cognitive engagement at a

high level in learning and problem-solving? Can students proactively and efficiently manage their cognitive engagement to maximize cost-benefit? What is the appropriate level of cognitive engagement required to complete a task successfully? Are there significant differences in the characteristics of cognitive engagement between high and low performers? How do students strategically regulate their cognitive engagement to succeed? Leaving these questions unanswered makes it challenging to design quality educational interventions for enhancing cognitive engagement. Meanwhile, these questions exposed gaps in knowledge about the roles and functions of cognitive engagement in learning.

The purpose of this dissertation is to address the above questions by investigating students' cognitive engagement in the context of self-regulated learning (SRL). Given that we live in an age where lifelong learning is becoming increasingly important, learning both inside and outside of classrooms requires self-regulatory skills to a greater extent (Steffens, 2006). SRL theories describe how learners engage in self-regulatory learning by managing their cognitive and metacognitive efforts towards the fulfillment of personal goals (Panadero, 2017; Pintrich, 2004; Schunk & Greene, 2017; Winne & Hadwin, 1998; Zimmerman, 2000). Therefore, it seems plausible that SRL theory can guide research on cognitive engagement and some researchers have already begun to study cognitive engagement from an SRL perspective (Cleary & Zimmerman, 2012; Wolters & Taylor, 2012). This dissertation aims to address several fundamental questions regarding cognitive engagement and attempts to push the literature forward by establishing new paradigms of studying cognitive engagement with SRL theories.

The chapters contained in this dissertation address the following complementary research questions: (1) What is the nature of cognitive engagement? How should it be conceptualized? And how can cognitive engagement be studied within a SRL framework? (Chapter 2: Literature

Review); (2) What instruments and techniques are available to measure cognitive engagement? (Chapter 3: Literature Review); (3) Do students use different forms of cognitive engagement in SRL? Does the use of different forms of cognitive engagement lead to students' performance differences? (Chapter 4: Empirical study); (4) Are students' facial behaviors valid indicators of their cognitive engagement? How do students strategically manage their cognitive engagement in SRL? (Chapter 5: Empirical study). In addressing these questions, this dissertation contributes significantly to the literature on cognitive engagement regarding the nature, definition, and measurement of cognitive engagement and its roles and functions in SRL.

Overview of the Chapters

Chapter 2 presents a literature review of cognitive engagement in self-regulated learning. This chapter makes theoretical contributions to the literature. First, this chapter elaborated on the nature of cognitive engagement by synthesizing different perspectives of cognitive engagement and contemporary findings. Moreover, this chapter clarified the similarities and differences between cognitive engagement and SRL from a theoretical point of view. Finally, we proposed an integrative model of SRL engagement in this chapter, which is one of the first to clarify the functioning of cognitive engagement in different SRL phases and subprocesses. This chapter ends with a discussion of important implications drawn from the integrative model of SRL engagement, as well as some of the key issues to address in future research.

Chapter 3 provides a critical and comprehensive review of the instruments and techniques that have been used to measure cognitive engagement. Specifically, this study adopts an analytical perspective that focuses on the strength and weaknesses of each measurement method of cognitive engagement. Those measures include self-report scales, observations, interviews, teacher ratings, experience sampling method, eye-tracking, physiological sensors, trace analysis,

and content analysis. In this regard, this chapter represents a potentially valuable resource whereby researchers and practitioners can develop an understanding of the traditional and cutting-edge methods for measuring cognitive engagement. This chapter also provides recommendations for capturing cognitive engagement in future empirical studies.

Chapter 4 presents an empirical study that examined the forms of cognitive engagement students displayed in SRL and whether different forms of cognitive engagement influenced students' task performance. We situated this empirical study in the context of BioWorld (Lajoie, 2009), an intelligent tutoring system designed to help medical students practice clinical reasoning skills. The most important take-away message from this chapter is that students choose the 'appropriate' form of cognitive engagement in problem-solving based on the changing internal and external conditions, and these forms are not necessarily the most sophisticated form of cognitive engagement. The use of different forms of cognitive engagement might lead to performance differences in addressing clinical reasoning tasks.

Chapter 5 presents another empirical study that examined how students strategically regulated their cognitive engagement in SRL. This study uses a novel approach to measure students' cognitive engagement by analyzing student's facial expressions, taking advantage of computer vision and machine learning techniques. In doing so, we were able to examine how students' cognitive engagement unfolds in SRL at a fine-grain size. We found that there was no significant difference in the overall level of cognitive engagement between high and low performers in clinical reasoning, whereas high performers were more cognitively engaged than low performers when conducting deep learning behaviors.

Chapter 6 concludes with a summary of the contributions and limitations of this dissertation. Future research directions are also described to further advance this field of study.

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Chapter 2. Manuscript 1

Cognitive Engagement in Self-regulated Learning: An Integrative Model

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Abstract

Integrating the two dominant theories of self-regulated learning (SRL) and cognitive engagement could advance our understanding of what makes students more efficient, effective learners. An integration of these theories has yet to be explored, and this paper addresses this gap by proposing a novel integrative model of SRL engagement. Specifically, we identified the nature of cognitive engagement (i.e., changing consecutively, context-dependent, comprising of quantitative and qualitative dimensions, occurring consciously or unconsciously), based on which we compared the conceptual differences and similarities between cognitive engagement and SRL. We reviewed three models that have investigated cognitive engagement within the frameworks of SRL, analyzed their features and weaknesses, and proposed an extension of previous models linking SRL and cognitive engagement. The proposed model is one of the first to clarify the mechanisms of how SRL phases and subprocesses relate to the functioning of cognitive engagement. In addition to adding to the theoretical discussions of the relations between cognitive engagement and SRL, the model informs the design of adaptive scaffolding and the practice of learning analytics. Several recommendations are presented for future research in this area to test this new model empirically.

Keywords: Self-regulated Learning, Cognitive Engagement, Similarity and Difference, SRL Engagement, Integrative Model

Introduction

Research in the areas of self-regulated learning (SRL) and student engagement are distinct areas of research but both aim to understand students' functioning and performance within academic settings. Self-regulated learning (SRL) is a widely adopted theoretical framework in the education field for researchers to study how students consciously coordinate their behavioral, cognitive, affective, and motivational aspects of learning to obtain academic success (Pintrich, 2000; Winne & Hadwin, 1998; Zimmerman, 2000). Student engagement is often referred to as a learner's active participation and involvement in achievement-related activities (Boekaerts, 2016; Sinatra et al., 2015). Just as SRL has been referred to as a multidimensional construct, most researchers view student engagement similarly, in that it involves both overt, external factors (e.g., behavioral) as well as covert, internal factors (e.g., cognitive and emotional) (Eccles, 2016; Finn & Zimmer, 2012; Fredricks et al., 2004; Wolters & Taylor, 2012). Moreover, both SRL and student engagement have been found to play a mediating role between students' personal and contextual characteristics and their academic performance (Wolters & Taylor, 2012; Zusho, 2017).

Considering the substantial overlaps between the two frameworks (i.e., SRL and student engagement), Wolters and Taylor (2012) argue that "the research on self-regulated learning and student engagement can, and should, be integrated to a greater extent" (p. 647). A more integrated model of SRL and student engagement would benefit each area of research and enhance a holistic understanding of students' learning (Cleary & Zimmerman, 2012; Wolters & Taylor, 2012; Zusho, 2017). Therefore, the purpose of this paper is to advance the theoretical specifications of relations between SRL and student engagement. While we acknowledge that both the two frameworks involve multidimensional learning processes such as cognition and

emotion, our discussion will be focused primarily on the cognitive aspect of learning. One crucial consideration is that the integration between the two broad umbrella concepts of SRL and student engagement is beyond the scope of one study, considering that both SRL and student engagement are complex multi-componential, multitemporal constructs. Moreover, most SRL theories that rely on a cyclical feedback loop to describe how students' learning unfolds over time, are cognitive in nature (Cleary & Zimmerman, 2012).

To link the theories of SRL and cognitive engagement, this article builds from previous work that examined cognitive engagement in specific learning contexts (e.g., Jarvela, Jarvenoja, Malmberg, Isohatala, & Marta, 2016; Pardo, Han, & Ellis, 2017; Sinatra et al., 2015) and work that embedded cognitive engagement within models of SRL (Cleary & Zimmerman, 2012; Wolters & Taylor, 2012; Zusho, 2017). Specifically, we define cognitive engagement as “the extent to which individuals think strategically along a continuum across the learning or problem-solving process in a specific task.” This definition is adapted from Cleary and Zimmerman's (2012) but more plainly refers to the changing nature of cognitive engagement. In particular, the ideas in our definition of cognitive engagement are four-fold: First, this definition suggests that cognitive engagement is essentially a consecutive process, which fluctuates over time as students immerse themselves in learning; Second, cognitive engagement is meant to associate with specific topics or learning activities; Third, it indicates that cognitive engagement consists of both qualitative and quantitative dimensions, i.e., students can allocate varying amounts of cognitive resources for different strategies in learning, which is in consonance with the research of Miller (2015); And last, this definition highlights the cognitive aspect of learning, which could either occur unconsciously or be metacognitively governed. Conceptualizing cognitive engagement in this way represents a conceptual change among researchers from considering

cognitive engagement as a static aptitude or ability (Appleton et al. 2006; Jarvela et al., 2016; Rotgans & Schmidt, 2011) to a dynamic ever-changing series of events that exist along the learning process (Cleary & Zimmerman, 2012; Sinatra et al., 2015).

In the present paper, we first elaborate on the nature of cognitive engagement to pave the way for comparison with SRL in terms of theoretical similarities and differences. As pointed out by Azevedo (2015), a key issue that plagues the research of cognitive engagement is the lack of agreement among researchers about the nature of this construct. For example, a critical contention is whether researchers should view cognitive engagement as a stable, trait-like attribute or a dynamic, state-like process. This choice is crucial because different epistemologies lead to different study designs and measurements concerning cognitive engagement. Although our definition provides insights about what cognitive engagement is, it is necessary to draw a full picture of its features by synthesizing different perspectives and contemporary findings. We then examine similarities and differences between cognitive engagement and SRL. This discussion is followed by an introduction of recent attempts to investigating cognitive engagement within models of SRL. Finally, we end with a proposed integrative model of SRL engagement. We discuss a few important implications drawn from the integrative model of SRL engagement, as well as some of the key issues to address in future research.

The Nature of Cognitive Engagement

Cognitive Engagement as a Consecutive Process

Cognitive engagement is extensively studied as a dichotomous process, such as deep or meaningful versus shallow cognitive engagement, deep versus surface processing, cognitive engagement versus disengagement, and so on (Azevedo, 2015; Dinsmore & Alexander, 2012; Greene, 2015). As an example, Greene (2015) defined two types of cognitive engagement: deep

and shallow engagement, based on Craik and Lockhart's (1972) depth of processing model. Specifically, Greene (2015) viewed deep engagement as involving the active use of prior knowledge and deep strategies (e.g., monitoring and self-reflection) in learning, whereby more complex knowledge structures are generated. Shallow engagement involves the use of intentional but mechanical strategies that need limited thoughtful cognitive actions, such as verbatim memorization and rehearsal. However, as pointed out by Azevedo (2015), using dichotomies to investigate engagement-related processes is problematic, since the dichotomies underestimate the complex nature of cognitive engagement and do not help clarify this construct. Furthermore, since there is no robust theoretical basis for separating deep from shallow engagement, it is difficult to align behavioral and cognitive indicators to deep or shallow categories across studies (Bernacki et al., 2012). For instance, Dinsmore and Alexander (2012) examined 221 engagement-related studies and had difficulty making comparisons across these studies since there were varying clarifications of deep and surface processing and situational factors. Although cognitive engagement is often examined at a deep or surface level, researchers are reaching a consensus that cognitive engagement is not a dichotomous construct but rather a dynamic phenomenon that can change over time as learning occurs. Cognitive engagement, as basic processing operations to initiate or sustain students' interaction with specific tasks, activities, and learning environments, is inherent to all learning processes (Boekaerts, 2016).

Context Dependent

Researchers generally agree that cognitive engagement is context-specific, which means it varies across academic domains and learning situations (Boekaerts, 2016; Cleary & Zimmerman, 2012; Fredricks et al., 2004; Jarvela et al., 2016; Miller, 2015). Cognitive engagement occurs as students interact with specific learning tasks and environments. According

to Helme and Clarke (2001), there exist three interacting factors that impact cognitive engagement, i.e., the individual, the learning environment, and the tasks per se. First of all, the characteristics that the individual brings to the learning context (e.g., skills, disposition, and motivational beliefs) influence his/her cognitive engagement, which has already been corroborated by a wide range of empirical studies (Helme & Clarke, 2001). Furthermore, learning environments also play a role in cognitive engagement since they can either promote or constrain one's use of particular learning strategies and types of interactions with other stakeholders. Finally, the characteristics of tasks, be they well-structured versus ill-structured, have an impact on cognitive engagement, although the relations are not clear. For example, ill-structured tasks stimulate more deep strategies and effort when compared with well-structured tasks, but they might also hamper the cognitive engagement of a learner if he/she perceives the task as too difficult (Jarvela et al., 2016). In sum, cognitive engagement is dependent on the context, and it depends on the complex interplay of personal and contextual influences (Cleary & Zimmerman, 2012; Helme & Clarke, 2001; Greene, 2015).

Changes Quantitatively and Qualitatively in Learning

In a recent special issue on student engagement and learning in *Learning and Instruction*, Boekaerts (2016) found that all contributors found engagement to be malleable rather than stable across learning situations. Greene (2015) further argued that cognitive engagement is “not a stable characteristic of either a learner or a learning environment but rather a fluid set of processes that can be influenced by learners themselves and by the environment” (p. 27). These ideas support the context-sensitive nature of cognitive engagement. It appears that a consensus has been reached that cognitive engagement is malleable during learning. However, it is still worth highlighting the changing nature of cognitive engagement based on the following

considerations. First, researchers who defined cognitive engagement as involving students' willingness to learn still viewed this construct as a more or less stable trait of learners, disregarding the pressing need to distinguish cognitive engagement from motivational constructs as recognized by modern perspectives of cognitive engagement (Rotgans & Schmidt, 2011); Second, there are discrepancies between how researchers define cognitive engagement and how they measure this construct. That is, researchers are found to be using instruments designed to measure generally stable, trait-like cognitive engagement, such as retrospective self-report questionnaires and interviews, although they acknowledge that cognitive engagement is a dynamic process (D'Mello et al., 2017; Rotgans & Schmidt, 2011; Wolters & Taylor, 2012). In fact, few shreds of evidence can be obtained from previous studies about how cognitive engagement dynamically shifts or changes in students' learning processes (Cleary & Zimmerman, 2012).

Miller (2015) contributed to this area of research by providing a description of how changes in cognitive engagement in learning might be examined. According to Miller (2015), students' cognitive engagement changes quantitatively and qualitatively when solving a task. Students may distribute varying amounts and forms of cognitive resources between and within academic tasks. Specifically, high levels of cognitive engagement typically involve the allocation of large amounts of cognitive resources, as well as the use of deep processing and metacognitive strategies. On the contrary, students who have a low level of cognitive engagement would use a relatively small amount of cognitive resources to perform shallow processing and heuristic strategies. This depiction is partially in line with Linnenbrink's (2005) proposition that cognitive engagement included both the quality and quantity of self-regulation. Specifically, the quality of self-regulation refers to students' use of self-regulatory strategies, while the quantity of self-

regulation means their persistence in learning when facing obstacles. Furthermore, Miller's (2015) depiction is also consistent with Cleary and Zimmerman's (2012) definition of cognitive engagement, as well as with the definition proposed by this paper, since both definitions emphasize the importance of taking the quantitative (i.e., to what extent students think strategically) and qualitative (i.e., what types of thinking strategies students use) aspects of cognitive engagement into consideration. It is worth mentioning that the terms 'the extent to which students think strategically' and *persistence* can both describe the process of quantitative effort in learning whereby students engage actively and constructively toward personal goals. However, they are distinct constructs. The term 'the extent to which students think strategically' is concerned with simply the amount of effort students invest in learning, whereas persistence refers to students' tendency to maintain effort when obstacles are encountered. Persistence as such requires a continuing investment in learning and substantial effort.

To conclude, cognitive engagement changes quantitatively in that students continuously change the frequency, duration, and intensity of effort over the learning or problem-solving process. From a SRL perspective, students are active participants who can purposefully manage the allocation of effort based on their internal conditions and task environments. At the same time, cognitive engagement changes qualitatively in that students adaptively choose different learning strategies to fulfill personal goals (Boekaerts, 2006; Miller, 2015).

Can be either Conscious or Unconscious

According to Boekaerts (2006), students who are already cognitively engaged in a task may consciously or unconsciously – increase or decrease their levels of cognitive engagement by manipulating the amount of attention, energy, or time in the process of problem-solving. The idea of adjusting one's cognitive engagement, consciously or unconsciously, is in accordance

with Dole and Sinatra's (1998) research, in which they report a continuum of cognitive engagement from “low cognitive engagement” (which they defined as minimal cognitive effort and use of surface-level strategies) to “high metacognitive engagement” (which they defined as more cognitive effort and use of deep and metacognitive strategies). Along this continuum, the “low cognitive engagement” is considered automatic, without personal consciousness, while the other end is considered “high metacognitive engagement”, which is deliberate and metacognitively governed (Miller, 2015). In short, sustaining cognitive engagement in learning can be either conscious or unconscious, depending on whether or not metacognitive activities are involved.

Self-regulated Learning and Cognitive Engagement

Self-regulated Learning

Panadero (2017) conducted a review of SRL models and found that six models were prevalent in the literature, including those developed by Pintrich (2000), Zimmerman (2000), Winne and Hadwin (1998), Boekaerts and Niemivirta (2000), Efklides (2011), and Hadwin, Järvelä, and Miller (2011). We provided a comparison of the six dominant SRL models in Table 1. In particular, the SRL model proposed by Pintrich (2000) puts emphasis on how motivational constructs, especially goal orientation, are related to SRL processes. Zimmerman's (2000) cyclical phases model of SRL is very similar to that of Pintrich (2000) in terms of background theory, definition, components, and empirical research (Puustinen & Pulkkinen, 2001). The four-stage model of SRL proposed by Winne and Hadwin (1998) argued that metacognitive monitoring produces internal feedback in each phase of SRL, which distinguishes this model from all the others (Puustinen & Pulkkinen, 2001). In addition, Winne and Hadwin's (1998) SRL model differed from others in that the model described each SRL phase with the COPES (i.e.,

Conditions, Operations, Products, Evaluations, and Standards) cognitive structure. In the extended model of adaptable learning (Boekaerts & Niemivirta, 2000), there are two goal pathways (i.e., the mastery/growth pathway and the well-being pathway) that drive students' regulation of behaviors, cognitions, and emotions. Regarding the metacognitive and affective model of SRL (MASRL) (Efklides, 2011), it is unique in that the model distinguishes two levels of functioning in SRL, namely, the Person level and the Task x Person level. The most salient feature of the model developed by Hadwin, Järvelä, and Miller (2011) is probably the distinction between the three modes of regulation in collaborative settings: self-regulation, co-regulation, and shared regulation. In this study, we do not intend to duplicate Panadero's (2017) review of the six SRL models, since he provided a detailed description of the history, development, features, and measurement instruments for each model. Instead, we discuss some basic assumptions underlying most SRL models and the state of the art of SRL research so that a shared understanding can be reached when comparing SRL with other constructs.

Researchers generally agree that SRL models form an integrative and coherent framework (Panadero, 2017). Across most SRL models, self-regulated learning is reviewed as an active, iterative process through which learners purposefully control and monitor their behavioral, cognitive, emotional, and motivational aspects of learning to fulfill learning goals (Boekaerts, Maes, & Karoly, 2005; Pintrich, 2004; Wolters & Taylor, 2012). Moreover, all the SRL models share four basic assumptions about learning (Pintrich, 2000). One assumption is that learners are active, constructive participants who can construct their own meanings from the information available in the internal and external environments. Second, all the models assume that learners can potentially monitor, control, and regulate certain aspects of learning process and environments. A third assumption is that self-regulation of learning and performance is goal-

driven, suggesting that learners continuously compare their learning processes with certain criteria or standards. Lastly, there are complicated interplays between personal/contextual characteristics and actual performance, which are mediated by learners' self-regulatory activities. In addition to these four basic assumptions, researchers have reached a consensus that SRL is a contextualized, cyclical process consisting of feedback loops (Schunk & Greene, 2017).

While the six SRL models are all theoretically sound and are supported by ample empirical evidence, they are not without shortcomings. As shown in Table 1, one weakness of the six models lies in the fact that they comprise a limited number of components, typically ranging from three to five cyclical phases or elements (Zeidner, 2019). Considering that the complexity of the learning process has been simplified in the six dominant SRL models, they explain only a fraction of learning phenomena. As pointed out by Zeidner (2019), 'future models may need to be less simplistic and more complex than current models, incorporating dynamic concepts and additional structural components in the model' (p. 266). This study takes the initiative to enrich the repertoire of SRL models by exploring the role of cognitive engagement in SRL.

Table 1*A Comparison of the Six Dominant SRL Models*

SRL Model	Background theory	Phases and processes	Main distinguishing features
Pintrich (2000): A general framework for SRL	Social cognitive theory	Four phases: Forethought, monitoring, control, and reflection	The model emphasizes the role of motivation, especially goal orientation, in SRL
Zimmerman (2000): Cyclical phases model of SRL	Social cognitive theory	Three phases: forethought, performance, and self-reflection	The model suggests that SRL is both motivation and strategy oriented
Winne and Hadwin (1998): Four-stage model of SRL	Information-processing theory	Four phases: task definition, goal setting and planning, studying tactics, and adaptations to metacognition	Each phase shares the same COPES (Conditions – Operations – Products – Evaluations – Standards) structure
Boekaerts and Niemivirta (2000): An extended model of adaptable learning	Action control theory and transactional stress theory	Five key processes: an identification process, two interpretation processes (task-focused and self-focused), and primary and secondary appraisal processes	The model describes two parallel processing modes: a mastery or learning mode, and a coping or well-being mode
Efklides (2011): Metacognitive and affective model of SRL (MASRL)	Social cognitive theory and extant SRL models	Three phases in the task processing: task representation, cognitive processing, and performance	The model distinguishes two levels of functioning in SRL, namely, the Person level and the Task x Person level
Hadwin, Järvelä, and Miller (2011): A model of regulation in collaboration	Heavily influenced by Winne and Hadwin's (1998) SRL model	Four phases: task understanding, goal setting and planning, task enactment, and large- and small-scale adaptation	The model describes self-regulation, co-regulation, and shared regulation in collaborative learning environments

Similarities and Differences between SRL and Cognitive Engagement

Regarding the relationships between SRL and cognitive engagement, there mainly exist three perspectives, as shown in Table 2. Wolters and Taylor (2012) examined the relations between the cognitive aspects of SRL and cognitive engagement and concluded that there are considerable overlaps between these two constructs. For instance, students viewed as self-regulated learners should be cognitively engaged in learning or problem-solving, while cognitive engagement is explicitly defined by some researchers as involving the use of SRL strategies (Furlong & Christenson, 2008; Horner & Shwery, 2002). The increased use of cognitive/metacognitive strategies is considered essential in both the SRL framework and cognitive engagement. There is also little practical difference between the cognitive aspect of SRL and cognitive engagement in some research (Wolters & Taylor, 2012). As an example, Pizzimenti and Axelson (2015) drew upon the SRL framework, specifically the Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich & de Groot, 1990), to infer students' level of cognitive engagement.

Table 2*Perspectives on the Relationships between SRL and Cognitive Engagement*

Relationship	Argumentation
SRL contains cognitive engagement	Self-regulated learners should be cognitively engaged. Cognitive engagement is defined as involving the use of SRL strategies (Furlong & Christenson, 2008; Horner & Shwery, 2002). There is little difference between cognitive engagement and the cognitive aspect of SRL with respect to their measurements (Wolters & Taylor, 2012).
SRL is one form of cognitive engagement	There are four forms of cognitive engagement, i.e., SRL, task focus, resource management, and recipience. SRL is the highest form of cognitive engagement (Corno & Mandinach, 1983).
SRL associates with cognitive engagement	Cognitive engagement has a role in each of the SRL components, i.e., cognitive strategies, management and control of effort, and metacognitive strategies (Pintrich & de Groot, 1990). Cognitive engagement unfolds across and within SRL phases (Goh & Zeng, 2014; Jarvela et al., 2016).

Considering the substantial conceptual consistency, some researchers considered SRL as a special form of cognitive engagement. For example, Mandinach and Corno (1985) conceptualized four forms of cognitive engagement: self-regulated learning, resource management, recipient learning, and "task-focused" learning. Specifically, self-regulated learning is the highest form of cognitive engagement during which students are cognitively engaged in planning, monitoring, and adjusting their own problem-solving processes (Corno & Mandinach, 1983). Resource management refers to the situation where students reduce their self-regulatory learning activities to some extent and rely on external resources to accomplish a task, while recipient learning requires a minimal investment of cognitive effort as students receive information passively. Task-focused learning refers to investing considerable effort but failing to

consider information beyond the task itself, i.e., cues and feedback. SRL is considered the most sophisticated form of cognitive engagement, while the other three forms of cognitive engagement emphasize different aspects of SRL. Students may use a form of cognitive engagement qualitatively different from SRL by emphasizing some SRL processes and deemphasizing others (Corno & Mandinach, 1983). The application of appropriate forms of cognitive engagement according to task demands and instructional features is essential to learning (Mandinach & Corno, 1985).

Despite conceptual overlaps between the SRL and cognitive engagement constructs, there are points on which they diverge (see Table 3). For one, learning is not necessarily an SRL process, whereas cognitive engagement is inherent in all learning processes (Boekaerts, 2016). For example, when students are forced to accomplish a task with rigid but clear procedures, they may appear cognitively engaged but would likely not be self-regulated (Wolters & Taylor, 2012); Secondly, SRL is metacognitively governed (Boekaerts, 2006), which means self-regulated learners metacognitively monitor qualities of their problem-solving processes and exercise control to make adjustments (Winne, 2010). In contrast, changing or sustaining one's level of cognitive engagement can be either conscious or unconscious (Dole & Sinatra, 1998); Thirdly, SRL has clear stages that complete the process of learning or problem-solving, while cognitive engagement has been considered as a continuous variable along a continuum. For example, Winne and Hadwin (1998) argued that SRL consists of four interdependent and recursive phases: task definition, goal setting and planning, enactment, and adaptation. Zimmerman (2000) contended that SRL involves three cyclical phases: forethought, performance, and self-reflection. With respect to cognitive engagement, it exists along a continuum from the level of low to high across the learning process (Dole & Sinatra, 1998;

Gonzalez, Rodriguez, Failde, & Carrera, 2016); Lastly, the cognitive aspect of SRL is more than cognitive engagement. It also involves other components, such as the management of environmental or internal constraints during learning (Cleary & Zimmerman, 2012).

Table 3

The Differences between SRL and Cognitive Engagement

SRL	Cognitive Engagement
Learning is not necessarily an SRL process	Cognitive engagement is inherent in all learning processes
SRL is metacognitively governed	Cognitive engagement may occur unconsciously or consciously
SRL is a cyclical process that consists of clear phases or subprocesses	Cognitive engagement has been considered as a continuous variable changing along a continuum
SRL involves a variety of cognitive processes, such as the management of mental effort, environmental influences, and internal constraints	Cognitive engagement is mainly concerned with the investment and allocation of mental effort on learning strategies

Thus, taking SRL as the highest form of cognitive engagement could be problematic, given that SRL is an evolving process in nature, whereby students exert an *appropriate* amount of cognitive resources to solve a task. It does not necessarily mean sustaining the highest level of cognitive engagement across the whole SRL process (Greene, 2015). Furthermore, it is problematic to explore cognitive engagement by only utilizing parts of SRL questionnaires, such as the MSLQ, since (1) it mixes the boundary between SRL and cognitive engagement, and (2) it often captures the qualitative aspect of cognitive engagement, i.e., the use of SRL strategies, while the quantitative aspect of cognitive engagement (i.e., to what extent students apply SRL strategies) is overlooked. However, research on SRL and cognitive engagement has advanced mutual theoretical frameworks and helped researchers develop a more holistic understanding of

students' learning. For example, Greene (2015) mentioned that Pintrich and de Groot's (1990) conceptualization of self-regulated learning (SRL) contributed to cognitive engagement studies by introducing two types of learning strategies: cognitive strategy (which can be further classified into shallow strategies and deep strategies) and self-regulation. Thus, Greene (2015) developed a scale that consisted of three components (i.e., self-regulation, deep strategy use, and shallow strategy use) to measure the extent to which students engaged cognitively in the problem-solving process. Meanwhile, research on SRL also benefited from the literature on cognitive engagement. Inspired by research on deep versus surface learning, Blom and Severiens (2008) identified two types of learning patterns, self-regulated deep learning and self-regulated surface learning. In self-regulated deep learning, students apply deep learning strategies, like elaboration and critical thinking, to accomplish tasks, while students mainly use surface strategies (e.g., rehearsal) in self-regulated surface learning.

In summary, SRL and cognitive engagement are two distinct constructs, but they share many similarities. Researchers who adopted this perspective tended to focus on the mechanisms of how SRL phases are related to the functioning of cognitive engagement instead of considering one construct contains the other. For instance, Pintrich and de Groot (1990) argued that there were three crucial components of SRL, i.e., cognitive strategies, students' management and control of their effort, and metacognitive strategies. Cognitive engagement has a role in each of these SRL components. For instance, different cognitive strategies such as rehearsal and elaboration foster an individual's cognitive engagement; students' management and control of effort necessitates learners' cognitive engagement; and metacognitive strategies serve to adjust the levels of cognitive engagement in response to internal and external feedback. There are also emerging empirical studies examining how cognitive engagement unfolds across and within SRL

phases. For example, Jarvela et al. (2016) collected 84 hours of video recordings of 44 students' interaction in collaboration during a math course and coded these video recordings in terms of types of engagement (i.e., cognitive and socioemotional) and SRL phases (i.e., forethought, performance, and reflection). Goh and Zeng (2014) reported a longitudinal study involving four students engaged with SRL activities in English listening tests. They tracked the learners' engagement during four phases of SRL, namely task definition, goal setting and planning, strategy enactment, and metacognitive adaptation. Both studies found that cognitive engagement occurred differently across the SRL phases, regardless of different SRL models.

Models Linking SRL and Cognitive Engagement

To further advance our understanding of the role cognitive engagement play in SRL, one necessary step is to establish more comprehensive theoretical specifications as to how cognitive engagement and SRL are related. Some progress has been made in this direction, as is shown by the work of Butler and Winne (1995), Cleary and Zimmerman (2012), and Zusho (2017).

The Elaborated Model of SRL

Butler and Winne (1995) proposed an elaborated model of SRL for analyzing students' cognitive processes, which spotlights "the cognitive operation of monitoring as the hub of self-regulated cognitive engagement" (p. 245). According to Butler and Winne (1995), self-regulated cognitive engagement describes a process during which students are aware of the qualities of their cognitive engagement, and the discrepancy between the current level of cognitive engagement and a predetermined goal. Students can monitor and self-regulate the extent to which they cognitively engage in learning. There are two main arguments in Butler and Winne's (1995) description of self-regulated cognitive engagement: first, the goals students adopt in SRL drive their cognitive engagement. When encountering obstacles in pursuing a goal, students may

modify their cognitive engagement by adjusting existing ones or even set new goals. Second, internal monitoring and feedback play a crucial role in self-regulated engagement. Specifically, internal monitoring of one's cognitive engagement in SRL generates feedback, which in turn influences the individual's regulation of subsequent cognitive engagement. However, Butler and Winne (1995) did not provide a clear definition of self-regulated cognitive engagement. Unfortunately, they used SRL, self-regulated engagement, and self-regulated cognitive engagement interchangeably, causing some confusion on how such terms differ. Moreover, they did not draw a distinction between cognitive engagement and cognitive processing in their research. They define cognitive engagement as a broad term referring to as an unfolding cognitive process that involves students' beliefs, knowledge, and learning strategies. Although Butler and Winne (1995) expanded the research examining the relations between cognitive engagement and SRL, questions remain as to how cognitive engagement should be conceptualized in SRL contexts, and how it unfolds dynamically in SRL.

The Theoretical Framework of Self-regulatory Engagement

Cleary and Zimmerman (2012) linked the constructs of SRL and cognitive engagement and delineated a theoretical framework of self-regulatory engagement. In this framework, Cleary and Zimmerman (2012) were primarily concerned with the extent to which students became cognitively engaged in the three sequential phases of self-regulatory learning, i.e., forethought, performance, and self-reflection. Students who proactively engage in the forethought phase seek to identify the requirements of a learning task (task analysis), set goals, and develop plans to achieve one's goals. During the performance phase, highly SRL-engaged students utilize various self-control processes (e.g., self-instruction, attention focusing, use of cognitive and metacognitive strategies) to optimize their problem-solving trajectories. In terms of the self-

reflection phase, SRL-engaged learners evaluate whether their levels of cognitive engagement yield expected performance, attribute success and failure to the strategies they applied during learning and make adjustments to their learning strategies correspondingly. Although students can attribute their performance to other contextual and personal factors, a key point in the self-reflection phase of SRL-engaged learning is that students display consistent thinking in the sphere of strategies (Cleary & Zimmerman, 2012). Having been rooted in the three-phase SRL theory proposed by Zimmerman (2000), the framework of self-regulatory engagement delineates a clearly defined “process” account of how students self-regulate their levels of cognitive engagement over time. However, this framework does not address the question of how students initially become cognitively engaged in learning. The question related to the functioning of cognitive engagement in SRL phases is also unclear. Moreover, this framework emphasizes the use of strategies but overlooks the extent to which students allocate mental effort on strategy use.

The Integrative Model of Student Learning

A recent study by Zusho (2017) also contributed to the development of an integrated model of SRL and cognitive engagement. Specifically, Zusho (2017) proposed an integrative model of student learning by first providing a critical analysis of three distinct yet overlapping streams of research (i.e., SRL, patterns of learning, and student engagement) and by taking into consideration the strengths of each of these approaches. At the heart of this model is the interaction between cognition (i.e., use of cognitive and self-regulatory strategies) and motivation, which is influenced by both personal and contextual factors at varying levels. Zusho (2017) argued that the interacting effect of cognitive and motivational processes accounted for students' learning outcomes, including understanding, academic risk-taking, engagement, and achievement. Engagement was considered an outcome and was indicated by effort, choice, and

persistence. A marked feature of Zusho's (2017) model is its ambitious attempt to integrate the three influential models of students' learning; however, this integrated model was not without criticism. First, some central theoretical claims pertaining to each stream of research (e.g., SRL and student engagement) were overlooked in the integrated model. Although Zusho (2017) claimed that this model was heavily influenced by SRL research, she provided no illustration with regards to how students self-regulate their learning in a cyclical feedback loop. Instead of delineating the functioning of various types of engagement (e.g., cognitive and behavioral) and their roles in SRL, Zusho (2017) used the term student engagement broadly. Furthermore, some researchers question whether engagement can be categorized as a learning outcome since many researchers considered engagement as an inherent aspect of the learning process (Boekaerts, 2016; D'Mello et al., 2017; Eccles, 2016).

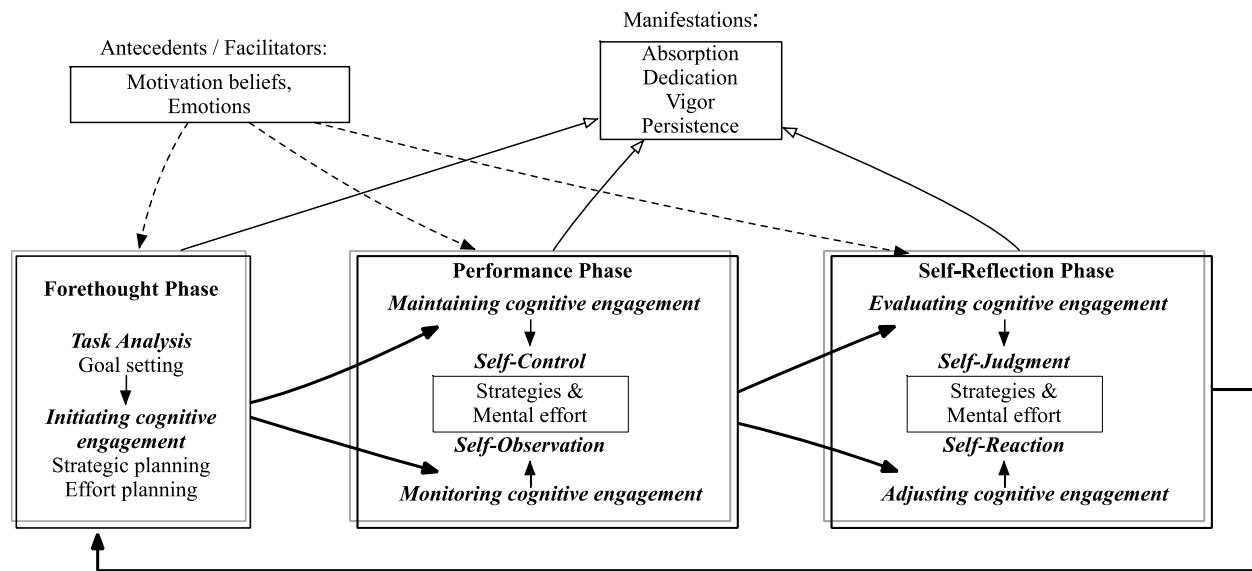
In a word, more work is needed to advance the integration of theories of SRL and cognitive engagement, since each of the aforementioned models has its own shortcomings. Researchers generally agree that the integration of SRL and cognitive engagement is still in its infancy (Wolters & Taylor, 2012; Cleary & Zimmerman, 2012; Zusho, 2017). Nevertheless, it is noteworthy that previous research can inform future studies: First, an integrative model should situate the construct of cognitive engagement in the context of SRL rather than SRL being considered part of cognitive engagement; Second, cognitive engagement should be clearly defined to avoid conceptual confluences with existing constructs, and the integrative model should be integrally consistent with that definition of cognitive engagement; And lastly, the integrative model should not only describe SRL-engaged learning but also illustrate the mechanisms of how students shift or change their cognitive engagement within and across SRL phases.

An Integrative Model of SRL Engagement

We propose an extension of previous models linking SRL and cognitive engagement and label it as an integrative model of SRL engagement. The proposed integrative model of SRL engagement is shown in Figure 1. Rooted in Zimmerman's (2000) three-phase SRL model, the integrative model of SRL engagement also consists of three sequential phases: forethought, performance, and self-reflection.

Figure 1

The Integrative Model of SRL Engagement



In the forethought phase, students analyze the task and set goals. They also plan the strategies used to solve the task and corresponding effort needed on these strategies to reach their goals. Our model is different from Zimmerman's (2000) model, which only involves strategic planning in the forethought phase. Our model consists of two subprocesses of planning: strategic planning and effort planning. This emphasis is in line with Dweck and Leggett's (1988) research, which claimed that students with learning goals could plan not only their learning processes (e.g., planning hypothesis-testing strategies), but also their levels of mental effort exerted in

these processes. The two subprocesses are driven by the goals set before, whereby learners initially become cognitively engaged in learning or problem-solving. Consistent with Butler and Winne's (1995) argument that the goals students adopt in SRL drive their cognitive engagement, this model also considers a predetermined goal to be the primary source that influences the self-regulation of cognitive engagement in the three cyclical SRL phases.

In terms of the performance phase, students maintain their initial level of cognitive engagement to reduce performance discrepancy against a goal state. In this phase, students generally self-control: (1) what cognitive strategies they choose, and (2) the level of intensity (e.g., the amount of mental effort) in which they engage in the utilization of a strategy. Although the use of deep level strategies implies that students are more cognitively intensely involved in learning compared with the use of relatively simple or surface-level strategies (e.g., rehearsal), there are differences among students on the allocation of mental efforts towards even the same deep strategy, reflecting by their choices of the frequency, duration or intensity of that strategy (Pintrich & Schauben, 1992). This argument provides important insights into the SRL studies regarding the optimization of the problem-solving process. Students adaptively assemble appropriate strategies and amounts of mental effort to solve problems rather than exert themselves on tasks. In this sense, the proposed model describes how self-regulated learners strategically manage their engagement to be cognitively efficient in learning or problem-solving. Cognitive efficiency is a core feature of SRL engagement. As a subprocess of the performance phase, self-observation serves an information function in that students become aware of the state and qualities of their cognitive engagement. From an engagement perspective, this regulatory process involves monitoring one's use of strategies and the mental effort invested in these strategies.

During the self-reflection phase, students first make judgments on their self-monitored cognitive engagement to see whether the current level of cognitive engagement is sufficient for reaching expected performance. This process is crucial because it determines how students adjust their cognitive engagement to meet their predetermined goals. Although the two subprocesses (i.e., self-judgment and self-reaction) are the same as Cleary and Zimmerman's (2012) SRL engagement model, there are two main differences: First, the focus of self-judgment in the proposed model is one's cognitive engagement, i.e., the effectiveness of learning strategies and the appropriateness of amounts of mental effort. However, the focus of self-judgment in Cleary and Zimmerman's (2012) model is one's level of success or performance, based on which students make adjustments to their learning strategies; Second, self-reflection in Cleary and Zimmerman's (2012) model is considered as a multicomponent cognitive process involving subprocesses of self-evaluation, causal attributions, adaptive inferences, self-satisfaction and so on (Cleary & Zimmerman, 2012). To keep theoretical and conceptual consistencies in illustrating the mechanisms of cognitive engagement in SRL, the self-reflection phase in the proposed model mainly focuses on students reflecting the extent to which (i.e., mental effort) they think strategically (i.e., learning strategies) in performance.

It is notable that our model highlights the changing nature of cognitive engagement, suggesting that individuals are always in the process of making adjustments on the fly in terms of the quantitative and qualitative aspects of cognitive engagement. The flexible adjustments of the two aspects of cognitive engagement occur in an ongoing manner throughout the learning process, although students do not necessarily change the two aspects simultaneously. Considering that cognitive engagement is inherent in all learning processes (Boekaerts, 2016), the quantitative component of cognitive engagement (i.e., level of mental effort) does not vanish

in learning but changes along a continuum ranging from effortlessness to maximum effort.

Regarding the qualitative component of cognitive engagement, students continuously activate or deactivate certain learning strategies depending on their judgments or reflection of the effectiveness of such strategies. We contend that the two components of cognitive engagement do not compensate or constrain each other in general, although varying initial levels of mental effort are needed for different learning strategies to be activated. For example, a student may sustain a high level of mental effort on a shallow strategy (e.g., rehearsal) for a long time. It might also be the case that students spend relatively little time on deep strategies. Moreover, this model gives particular emphasis to the issue of how cognitive engagement unfolds across and within SRL phases. In particular, students' personal goals initiate the quantitative and qualitative aspects of cognitive engagement, performance discrepancy sustains the two aspects of cognitive engagement, and student self-reflection drives the adjustments of cognitive engagement.

While admitting that motivation beliefs and emotions are integral to the SRL process, this model views these components as antecedents or facilitators of cognitive engagement in the three SRL phases. This is in line with previous research, which claims that motivation constructs predict or facilitate one's level of cognitive engagement (Corno & Mandinach, 1983; Greene, 2015; Greene et al., 2004). In addition, our model steps further to differentiate cognitive engagement from its manifestations such as absorption, dedication, vigor, and persistence (Wouters et al., 2017). Contrary to Zusho's (2017) model in which engagement is characterized as outcomes, we consider the manifestations of cognitive engagement rather than cognitive engagement per se to be learning products.

Taken together, the elaborated integrative model of SRL engagement contributes significantly to the body of research on the integration of SRL and cognitive engagement. A

unique feature of this model is that it takes the nature of cognitive engagement into account, allowing new educational research leads to emerge to reveal the essence of students' learning. Moreover, the development of the proposed model is based on a thorough analysis of the similarities and differences between cognitive engagement and SRL, as well as an analytical review of the three prominent integrated frameworks. Furthermore, the proposed SRL engagement model is one of the first to clarify the mechanisms of how SRL phases and subprocesses are related to the functioning of cognitive engagement. In addition to adding to the theoretical discussions of the relations between cognitive engagement and SRL, our model informs the design of adaptive scaffoldings and the practice of learning analytics. In particular, this model suggests that high performers can strategically regulate their cognitive engagement in different SRL phases, which means that shallow engagement is not always dysfunctional and detrimental to students' performance. On a practical level, instructors should allow the presence of shallow engagement, since keeping students deeply engaged throughout the learning process can be cognitively demanding or even impractical in certain circumstances. The focus of instructional scaffoldings or interventions should be placed on the key subprocesses of learning, where a high level of cognitive engagement contributes most to students' performance. Moreover, this model highlights the importance of tracking, modeling, and visualizing the dynamics of cognitive engagement over the course of SRL, which informs the practice of learning analytics. For instance, it is suggested to model not only what strategies high-performing students use in different SRL phases but also the extent to which they use such strategies, in order to reveal significant and effective problem-solving patterns.

Based on the integrative model of SRL engagement, many fruitful lines of research can be generated. First, the proposed model calls for more empirical studies designed to validate its

theoretical specifications, such as whether or not students plan not only learning strategies but also the amount of mental effort needed in the forethought phase. Of particular interest for future research is to examine how cognitive engagement shifts or sustains within and across SRL phases, considering it is an underexplored research area (Cleary, 2011; Cleary & Zimmerman, 2012). It is also valuable to recognize the common truth regarding how cognitive engagement changes in cyclical SRL phases from studies conducted in various contexts and with different populations. A second line of future research that scholars may find important is the joint effects of SRL and cognitive engagement on learning performance (Pardo et al., 2017). Considering the absence of studies documenting students' effort on various learning strategies in different SRL phases, as a consequence, there is no surprise that much work is needed to be done when taking an extra factor of students' performance into consideration (Wolters & Taylor, 2012). In addition, researchers studying student engagement are highly interested in promoting students' cognitive engagement, leaving the efficiency of cognition and engagement largely unexplored. Therefore, it would be promising to investigate the efficiency of SRL engagement and its associations with students' SRL skills, task features, and performance. A final recommendation for future research is to study the influences of motivation and emotion on cognitive engagement in different SRL phases. For example, self-efficacy has been shown to be a crucial motivational source of students' cognitive engagement (Cleary & Zimmerman, 2012), while a predetermined goal has been claimed to drive one's cognitive engagement (Butler & Winne, 1995). It is unclear whether a predetermined goal plays a more significant role in sustaining one's cognitive engagement than self-efficacy or vice versa. The future research directions described here are not inclusive but have shown promise for providing new knowledge on the research of SRL and cognitive engagement.

While the proposed model opens up new research directions, a crucial question that needs to be addressed first is how can we measure cognitive engagement in a way that captures its nature? In an attempt to answer this question, we proposed several suggestions which could inform future researchers of the measurement of cognitive engagement underlying the proposed model. The core idea of cognitive engagement, as illustrated in this paper, is about how students allocate their mental effort on different learning strategies. Therefore, it is a necessity to collect multichannel data using multiple methods so that the level of mental effort (i.e., the quantitative aspect of cognitive engagement) and corresponding learning strategies (i.e., the qualitative aspect of cognitive engagement) can be assessed simultaneously. In fact, researchers are increasingly calling for the use of multiple methods to measuring cognitive engagement rather than relying merely on a single instrument (Greene, 2015; Sinatra et al., 2015; Betts, 2012). Moreover, the measurement should be able to capture the dynamics of cognitive engagement, especially the changing levels of mental effort, at a fine-grained temporal resolution. Experience sampling method (ESM) provides a feasible solution since it allows students to report on their changing effort levels during different stages of learning or problem-solving. Alternatively, researchers can use advanced techniques, such as eye-tracking, psychological measures (e.g., EEG), and text mining, to capture the changes of mental effort in fine grain sizes. The use of learning strategies can be measured via observations, think-aloud, and log files. Take one of our previous studies as an example (Li et al., 2021), we inferred the learning strategies students used in solving a clinical problem from system log files, and we detected the level of mental effort that was allocated on each learning strategy based on students' facial behavioral cues.

Conclusion

The research on SRL and student engagement is at a crossroads. They both attempt to

understand students' learning processes and the underlying factors that account for students' academic success and task performance. Nevertheless, studies on SRL and student engagement have been conducted by separate research groups to date (Zusho, 2017), which prevents researchers from obtaining a holistic understanding of how learning occurs and how to improve learning. In this paper, we focused on the integration of SRL and cognitive engagement, which could potentially help the field move forward. Specifically, we identified the nature of cognitive engagement (i.e., changing consecutively, context-dependent, comprising quantitative and qualitative dimensions, occurring consciously or unconsciously), based on which we compared the differences and similarities between cognitive engagement and SRL. Afterward, we reviewed three models that have investigated cognitive engagement within the frameworks of SRL, analyzed their features and weaknesses, and proposed an integrative model of SRL engagement. The proposed model explicitly illustrates the functioning of cognitive engagement in SRL phases, for example, when cognitive engagement begins and how it relates to different learning subprocesses.

We recognize that the proposed model is not without limitations. Although the model is theoretically solid, there is currently few empirical evidence to verify its effectiveness. More research is needed in the future to address concerns regarding the model's validity. Moreover, we consider students' motivational beliefs and emotions as antecedents or facilitators of cognitive engagement in the three SRL phases. However, the underlying mechanisms of how motivational beliefs or emotions affect the dynamic changes of cognitive engagement in SRL are still unclear, which instills some obscurity into our model. Despite the limitations, our model provides a framework for asking important research questions and guiding future research.

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Bridging Text

In Chapter 2, I presented a literature review of cognitive engagement in self-regulated learning which addressed several fundamental yet unanswered questions about cognitive engagement and its functions in SRL, specifically: (a) what is an appropriate definition of cognitive engagement? (b) what is the nature of cognitive engagement? (c) what are the similarities and differences between cognitive engagement and SRL? (d) what efforts have been made to theoretically link cognitive engagement to SRL? and (e) if a theoretical model is needed, that integrates cognitive engagement and SRL, what should it be? Moreover, I discussed some of the future research directions that could contribute to our understanding of how students manage their cognitive engagement in SRL. However, a crucial aspect that has been neglected in this chapter is the measurement of cognitive engagement.

In Chapter 3, I present a critical review of the instruments and techniques used to measure cognitive engagement, which could provide additional insights into this construct from a practical perspective. Most remarkably, I provide an analysis of the strength and weaknesses of each measurement method of cognitive engagement. I analyze the theoretical foundations and rationales behind the design of cognitive engagement measurements whenever possible. Recommendations for measuring cognitive engagement in future empirical studies are also discussed. This chapter has methodological importance that could help move this field forward. Specifically, this review is useful to practitioners in exploiting the affordances and minimizing the constraints of different cognitive engagement measures. I propose that a multimethod approach to capturing cognitive engagement is a necessity for future empirical work.

Chapter 3. Manuscript 2

Measuring Cognitive Engagement: An Overview of Measurement Instruments and Techniques

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Abstract

This paper adopted an analytical perspective to review cognitive engagement measures. This paper provided a comprehensive understanding of the instruments/techniques used to measure cognitive engagement, which could assist researchers or practitioners in improving their measurement methodologies. In particular, we conducted a systematic literature search, based on which the current practice in measuring cognitive engagement was synthesized. We organized and aggregated the information of cognitive engagement measures by their types, including self-report scales, observations, interviews, teacher ratings, experience sampling, eye-tracking, physiological sensors, trace analysis, and content analysis. We provided a critical analysis of the strength and weaknesses of each measurement method. Recommendations for measuring cognitive engagement were also provided to guide future empirical work in a meaningful direction.

Keywords: Cognitive engagement; Measurement instruments and techniques; Systematic literature search; Research synthesis; Multiple methods

Introduction

The literature on student engagement is diverse, reflected in a plethora of engagement-related terminologies (e.g., student engagement, school engagement, academic engagement, and task engagement) and a vague understanding of engagement components. For instance, Fredricks, Blumenfeld, and Paris (2004) differentiated between three dimensions of engagement: behavioural, emotional, and cognitive. Whereas Finn and Zimmer (2012) state that researchers use four dimensions of engagement repeatedly in the literature, namely, academic, social, cognitive, and affective engagement. While many issues are yet to be answered in engagement studies, an essential issue is how to measure engagement. If the measurement instruments cannot precisely capture the construct, the data collected for interpretation would be problematic, and no meaningful conclusions can be guaranteed.

This review pays particular attention to the cognitive component of engagement, focusing on its measurement instruments and techniques. One reason is that educational psychologists and instructors traditionally emphasized cognition and metacognition in predicting students' performance. Another consideration is that this review aims to facilitate a concise but detailed discussion on a specific engagement phenomenon (i.e., cognitive engagement) since a general review of student engagement may raise more questions than it answers. Moreover, recent years have witnessed a surge in the use of advanced techniques, for example, eye tracker, EEG (Electroencephalograph) sensor, and text mining techniques, to capture students' in-time cognitive engagement. However, studies vary radically in how they operationalize cognitive engagement, depending on the researchers' conceptualizations of this construct, the grain size of measurement (e.g., institution, class, or task level), and the types of data that are available for collection in a given circumstance. As an illustration, Table 4 shows some definitions of

cognitive engagement widely used in the literature. Nevertheless, these definitions differ from each other regarding granularity and focus.

Table 4

Some Definitions of Cognitive Engagement

Study	Definition	Level of Granularity	Foci
Furlong and Christenson (2008)	The extent to which students perceive the relevance of school to future aspirations. It is expressed as interest in learning, goal setting, and the self-regulation of performance	School and Task levels	Motivation - Interest; Being strategic or self-regulating
Rotgans and Schmidt (2011)	The extent to which students are willing and able to take on the learning task at hand	Task level	Motivation – Level of autonomy
Appleton et al. (2006)	It includes less observable, more internal indicators, such as self-regulation, the relevance of schoolwork to future endeavours, the value of learning, and personal goals and autonomy	School and Task levels	Motivation – Level of autonomy, goal, value; Being strategic or self-regulating
Richardson and Newby (2006)	The integration and utilization of students' motivation and strategies in the course of their learning	School and Task levels	Motivation; Being strategic or self-regulating
D'Mello, Dieterle, and Duckworth (2017)	Learners' investment in the learning task, such as how they allocate effort toward learning, and their understanding and mastery of the material	Task level	Psychological investment
Fredricks, Blumenfeld, and Paris (2004)	Students' level of investment in learning. It incorporates thoughtfulness and willingness to exert the effort necessary to comprehend complex ideas and	School and Task levels	Psychological investment

master difficult skills.

Helme and Clarke (2001)	The deliberate task-specific thinking that a student undertakes while participating in a classroom activity	Task level	Being strategic or self-regulating
Cleary and Zimmerman (2012)	The extent to which individuals think strategically before, during, and after performance on some learning activity	Task level	Being strategic or self-regulating
Li et al. (2021)	The extent to which individuals think strategically across the learning or problem-solving process in a specific task	Task level	Being strategic or self-regulating

Therefore, a review that summarizes the studies that have measured the construct of cognitive engagement is crucial. On the one hand, it will help researchers better understand this divergent research base. On the other hand, a critical review of cognitive engagement measures will provide more insights into the nature of this construct. This study represents a potentially valuable resource for researchers and practitioners about traditional and cutting-edge methods for capturing cognitive engagement.

In short, this paper aims to provide a synthesis of how students' cognitive engagement is measured across various contexts. In particular, this paper adopts an analytical perspective to provide a comprehensive understanding of the instruments/techniques used to measure cognitive engagement and assist researchers or practitioners in improving their cognitive engagement methodologies. As such, this paper distinguishes itself from a systematic review or a meta-analysis by summarizing all available cognitive engagement instruments/techniques that existed in contemporary literature and, at times, using selected literature to serve as examples of the state-of-the-art measures. This paper also provides a critical analysis of the strength and

weaknesses of each measurement method.

Methods Used in the Review

This review is based on a broad conception of cognitive engagement regardless of its definition since the overarching goal of this paper is to provide an overview of the current practice in measuring cognitive engagement. We purposefully selected studies in the literature that best described the use of the instruments/techniques of cognitive engagement. Therefore, the studies reviewed in this paper were by no means exhaustive. As aforementioned, this paper was neither a systematic review nor a meta-analysis. Instead, we used an approach that was similar to qualitative synthesis to accomplish our research goals. To this end, this review included the following three phases: (1) creation of selection criteria and identification of relevant research, (2) critical appraisal and extraction of instruments/techniques concerning the measurement of cognitive engagement, and (3) synthesis of the findings and evaluation of different measurements.

Selection Criteria

- Peer-reviewed pieces, ideally full journal papers. Conference proceedings were limitedly used to stay true to the criteria of using peer-reviewed studies. Conference presentations were not included.
- Empirical studies that had sufficient details about the measurement of cognitive engagement. Theoretical discussions and review papers concerning cognitive engagement instruments/techniques were also included as background material.
- Research studies that had explicitly measured the construct of cognitive engagement.
- Studies conducted in student learning or problem-solving settings.
- Studies that had been published in English.

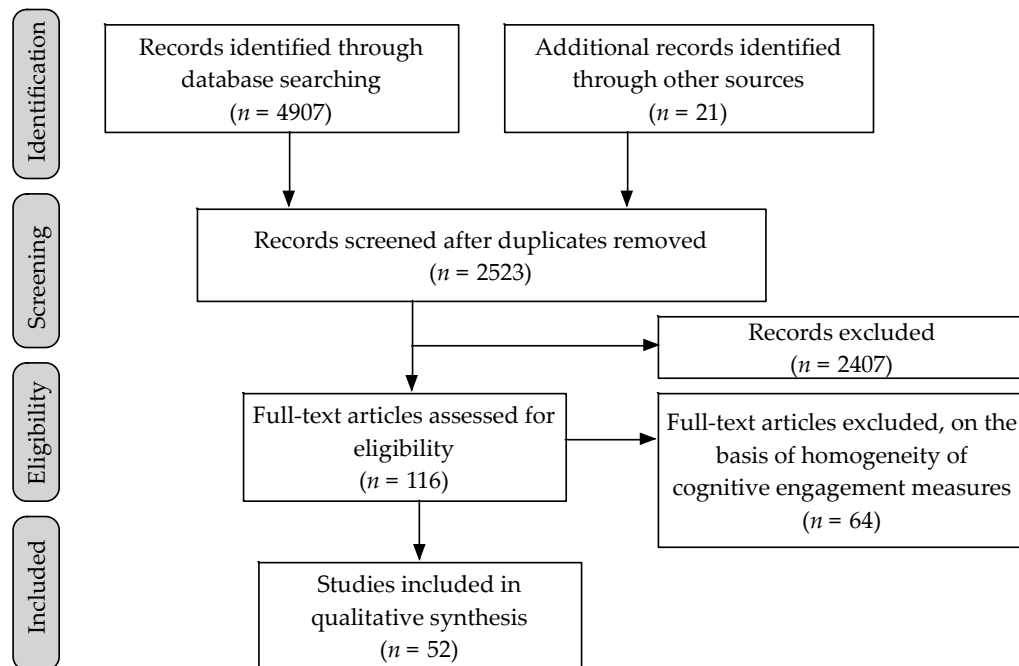
- There were no limitations on the date of publication.

Identification of Studies

A systematic literature search was conducted on prominent online databases, including ERIC (ProQuest), Web of Science, Google Scholar, and PsycINFO. The syntax used for the literature search was shown below: (cognitive engagement) AND (measure* OR scale* OR instrument* OR technique* OR tool* OR questionnaire* OR method*) AND (student* OR learn*). The processes of searching for the literature and screening for inclusion were displayed in Figure 2. The search identified 4907 publications in total. By removing duplications and applying the above selection criteria, we narrowed down the publications to 116 full-text articles. Finally, we identified 52 articles that were relevant for this study through full-text reading.

Figure 2

The Process of Identifying Relevant Studies



Data Extraction and Synthesis

We read the full text of each of the 52 articles with a central question in mind: How did

the author(s) capture the construct of cognitive engagement? In particular, we extracted applicable information from each study regarding the instrument or technique used to measure cognitive engagement, as well as its definition, characteristics, assumptions, subcomponents, sample items, strength, and weakness. The extracted information served as the basis for literature synthesis. We then organized and aggregated cognitive engagement measures by their types, such as self-reports, observations, or teacher ratings.

Current Practice in Measuring Cognitive Engagement

We found that many instruments and methods that intend to measure cognitive engagement exist in the extant literature, including self-report scales, observations, interviews, teacher ratings, experience sampling, eye-tracking, physiological sensors, trace analysis, and content analysis. In general, self-report scales are the most common approach to assessing cognitive engagement (Greene, 2015; Fredricks & Mccolskey, 2012).

Self-report Scales

Concerning the operationalization of cognitive engagement, three streams of self-report measures existed in literature, including those scales that emphasized (1) school-related motivations (e.g., students' beliefs about the value of schooling or control of schoolwork), (2) learning strategy use (i.e., cognitive strategies, self-regulatory or metacognitive strategies), and (3) students' mental involvement or psychological investment, such as effort, persistence, and dedication (Fredricks & Mccolskey, 2012). Specifically, the self-report scales that derived from a larger student engagement scale (e.g., cognitive engagement subscale of Student Engagement Instrument) usually contained items that measure school-related motivations and, by their nature, were not context-specific (Fredricks & Mccolskey, 2012; Fredricks et al., 2004). For example, Fredricks et al. (2011) identified 14 self-report scales measuring student engagement, in which

only three scales explicitly had subscales labelled *cognitive engagement*: School Engagement Measure (SEM) – MacArthur (Fredricks, Blumenfeld, Friedel, & Paris, 2005), Student School Engagement Survey (SSES) (Finlay, 2006), and Student Engagement Instrument (SEI) (Appleton et al., 2006). Nevertheless, the three instruments asked students about their perceived importance of schooling, control of schoolwork, or future aspirations to represent cognitive engagement in general. None of these instruments measured cognitive engagement in specific learning contexts. The failure of linking cognitive engagement to a target task created confusion among researchers and muddled interpretation of research findings (Greene, 2015). Thus, there is now a growing body of studies reducing the specificity of measuring cognitive engagement to a class or even a specific task.

In terms of the instruments for measuring cognitive engagement in a class- or task-specific environment, much effort has been made to delineate the relevant aspects of this construct and to identify attributes that constitute it. For instance, Greene and her colleagues (2004) viewed cognitive engagement as the same as meaningful cognitive strategies (i.e., deep levels of information processing to connect or integrate new material with one's prior knowledge). Thus their measure of cognitive engagement in the Approaches to Learning Instrument focused on meaningful strategies. Similar to the instruments by Greene et al. (2004), Patrick, Ryan, and Kaplan (2007) also found that a single dimension of self-regulation strategies could constitute the construct of cognitive engagement. Therefore, they measured students' cognitive engagement by assessing the extent to which students plan, monitor, and regulate their cognition. Wolters (2004) also used strategy to represent students' cognitive engagement; however, both cognitive and metacognitive strategies were measured as two dimensions of cognitive engagement in his instrument. Specifically, the measure of cognitive strategies

included eight items asking students' use of rehearsal and elaboration strategies. Metacognitive strategies consisted of nine items reflecting students' use of planning, monitoring, and regulatory strategies.

In line with the measure used in Wolters's (2004) research, Meece, Blumenfeld, and Hoyle (1988) assessed students' cognitive engagement in the Science Activity Questionnaire (SAQ) with 15 items on students' use of cognitive strategies and self-regulated learning, such as planning, monitoring, and help-seeking. However, Meece et al. (1988) also included effort-avoidant strategies as indicators of cognitive engagement in the questionnaire, and a sample item was '*I guessed a lot so that I could finish quickly.*' While the SAQ emphasized students' use of effort-avoidant strategies, the Student Engagement in the Mathematics Classroom Scale (SEMCS) that developed by Kong, Wong, and Lam (2003) included reliance along with the other two subscales (i.e., surface strategy and deep strategy) to measure cognitive engagement. According to Kong et al. (2003), reliance refers to students' perceived beliefs about the optimal learning approach and their learning preferences. A sample item was "*I would solve problems in the same way as the teacher does.*"

Several conclusions can be drawn from the aforementioned self-report measures of cognitive engagement. First, strategies are generally considered an indicator of cognitive engagement, although researchers frame students' use of strategies differently (e.g., cognitive, metacognitive, deep, shallow or surface strategies). Second, the measures tended to stay close to information processing and self-regulation theories as to the foundational framework. Thus, it is no wonder that some studies applied the Motivated Strategies for Learning Questionnaire (MSLQ) as a measure of cognitive engagement since it was initially designed to measure strategy use and self-regulation (Pintrich & de Groot, 1990; Fredricks & Mccolskey, 2012).

Greene (2015) developed the Motivation and Strategy Use Survey to measure cognitive engagement, which contained similar subscales with the MSLQ, namely, self-regulation, deep strategy use, shallow strategy use, and persistence. Third, little consensus has been reached among researchers about the indicators of cognitive engagement, which are reflected from the variations in dimensions and subcomponents of the measures.

Instead of focusing on strategy use, some researchers measured cognitive engagement the other way around, such as assessing ‘how often’ students perform self-regulatory behaviours when solving a task. Linnenbrink (2005) proposed that cognitive engagement included both quality and quantity of self-regulation, so she developed two scales (i.e., the Quality of Self-regulation Scale and the Quantity of Self-regulation Scale) for students to report their cognitive engagement. Specifically, the Quality of Self-regulation Scale asks students how often they plan, monitor, and evaluate their problem-solving processes. The Quantity of Self-regulation Scale assesses students' persistence behaviours but emphasizes how often they do so. According to Rotgans and Schmidt (2011), cognitive engagement consisted of three elements: (1) engagement with the task at hand, (2) effort and persistence, and (3) experience of flow or having been completely absorbed by the activity. Based on this understanding, they developed the 4-item Situational Cognitive Engagement Measurements (SCEM) to assess students' levels of cognitive engagement. Similar to the SCEM, the Utrecht Work Engagement Scale for Students (UWES-S) also had nothing to do with students' use of strategies (Schaufeli et al., 2002). In the UWES-S, cognitive engagement was characterized by three components of vigour, dedication, and absorption. In sum, the three scales (i.e., the Quality and Quantity of Self-regulation Scale, SCEM, and UWES-S) contributed to the effective measurement of cognitive engagement by bringing in more variables as indicators of this construct and by trying to capture cognitive

engagement without any further inferences.

Table 5 lists the student self-report measures of cognitive engagement discussed earlier and their underlying theoretical foundations, components, and sample items. Along with the challenges for measuring cognitive engagement, such as theoretical contentions on its dimensions and components, the items across different scales are different even though they are designed to describe the same indicator of cognitive engagement. As pointed out by D'Mello et al. (2017), methodological advances have unfortunately lagged behind theoretical developments in this area of research.

Table 5

Prominent Cognitive Engagement Scales

Questionnaire	Foundations	Components (items) and Sample Items
Motivation and Strategy Use Survey (Greene, 2015)	Depth of Processing and Self-regulation Theories	Self-Regulation (9): <i>"I organize my study time well for this class."</i> Deep Strategy Use (7): <i>"I classify problems into categories before I begin to work them."</i> Shallow Processing Strategy (4): <i>"I try to memorize the steps for solving problems presented in the text or in class."</i> Persistence (8): <i>"If I have trouble understanding a problem, I go over it again until I understand it."</i>
Approaches to Learning Instrument (Greene et al., 2004)	Depth of Processing	Meaningful cognitive strategies (12): <i>"I have a clear idea of what I am trying to accomplish in this class."</i>
The Quantity and Quality of Self-regulation Scale (Linnenbrink, 2005)	Self-regulation Theories	The Quantity of Self-regulation (4): <i>"Even when I do not want to work on math, I force myself to do the work."</i> The Quality of Self-regulation (5): <i>"When I do math, I ask myself questions to help me understand what to do."</i>

Situational Cognitive Engagement Measurements (SCEM) (Rotgans & Schmidt, 2011)	Contextual Dependence of Cognitive Engagement	Engagement at hand (1): <i>"I was engaged with the topic at hand."</i> Effort & Persistence (2): <i>"I put in a lot of effort."</i> Experience of flow (1): <i>"I was so involved that I forgot everything around me."</i>
Utrecht Work Engagement Scale for Students (UWES-S) (Schaufeli et al., 2002)	A Positive Psychology View of Engagement	Vigor (5): <i>"When I study, I feel like I am bursting with energy."</i> Dedication (5): <i>"My studies inspire me."</i> Absorption (4): <i>"When I am studying, I forget everything else around me."</i>
Science Activity Questionnaire (SAQ) (Meece et al., 1988)	Depth of Processing and Self-regulation Theories	Active engagement (8): <i>"I tried to figure out how today's work fit with what I had learned before in science."</i> Superficial engagement (7): <i>"I guessed a lot so that I could finish quickly."</i>
Not applicable (Patrick et al., 2007)	Self-regulation Theories	Self-regulation strategies (6): <i>"When I finish my math work, I check it to make sure it was done correctly."</i>
Motivated Strategies for Learning Questionnaire (MSLQ) (Pintrich & de Groot, 1990)	Self-regulation Theories	Cognitive and metacognitive strategies (31): <i>"I try to relate ideas in this subject to those in other courses whenever possible."</i> Resource management strategies (19): <i>"I make good use of my study time for this course."</i>
Strategy Use Questionnaire (Wolters, 2004)	Self-regulation Theories	Cognitive strategies (8): <i>"When I study for math, I try to connect what I am learning with my own experiences."</i> Metacognitive strategies (9): <i>"If what I am working on for math is difficult to understand, I change the way I learn the material."</i>
The Student Engagement in the	Depth of Processing and Approaches to	Surface strategy (7): <i>"I find memorizing formulas is the best way to learn mathematics."</i> Deep strategy (7): <i>"When I learn mathematics, I</i>

Mathematics Classroom Scale (SEMCS) (Kong et al., 2003)	Learning	<i>would wonder how much the things I have learned can be applied to real life. ”</i> Reliance (7): <i>“I would learn what the teacher teaches.”</i>
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Note: The UWES-S and the scale used by Patrick et al. (2007) were not explicitly mentioned to measure cognitive engagement, but the items used in these instruments were to measure the cognitive aspect of engagement; Some studies used MSLQ to measure cognitive engagement, but they varied in subscales and items of MSLQ for capturing cognitive engagement.

Observations

Cognitive engagement has also been measured by observational methods at both the individual and classroom levels (Fredricks & Mccolskey, 2012). The underlying assumption is that cognitive engagement can be reliably recognized by specific behavioural and linguistic indicators, verified by some research (Helme & Clarke, 2001; Greene, 2015; Lee & Anderson, 1993). For instance, Helme and Clarke (2001) assessed students' cognitive engagement in a math class using classroom videotape data as a primary source, whereby linguistic indicators of strategy use (e.g., explanations and verbalization of thinking) and non-verbal correlates of cognitive engagement (e.g., gestures and body orientation) had been taken into consideration for measuring this construct. Lee and Anderson (1993) observed science classrooms for indicators of cognitive engagement such as initiating activities to understand science topics, requesting clarification, and applying scientific knowledge to solve real-world problems. Another example is Greene (2015) and her team's observations of students' interactions with teachers to infer students' levels of cognitive engagement in science classes, noting that the observational method was effective in detecting different engagement patterns.

The primary advantage of using observations to measure cognitive engagement is that this approach can provide detailed descriptions of both students' responses and contextual factors to help researchers understand the steady states of students' cognitive engagement (Fredricks &

Mccolskey, 2012). Despite this advantage, as pointed out by Helme and Clarke (2001), very few studies have used direct observations of students' behaviours to assess levels of cognitive engagement. Fredricks et al. (2004) also noticed that the observational method was less common as a choice for researchers to measure cognitive engagement. There are several reasons: First, the information obtained via observational methods is highly inferential, especially when assessing the quality of students' mental investments such as effort or thinking (Fredricks et al., 2004; Appleton et al., 2006). Some students observed to be off-task may be highly cognitively engaged in problem-solving. Thus, there are some concerns about the reliability of the observational method since this technique relies heavily on the observers' ability to make accurate observations and their judgments about what should be observed (Turner & Meyer, 2000). Second, observational methods sometimes blur the boundary between cognitive engagement and behavioural engagement measures, although the literature is robust to tell them apart. Finally, observational methods are labour-intensive and usually applicable to a relatively small amount of participants (Fredricks & Mccolskey, 2012).

Interviews

The interview is another method that has been used to measure students' cognitive engagement. Dent and Koenka (2016) pointed out that researchers who viewed cognitive engagement as the use of cognitive and metacognitive strategies often applied structured interviews to obtain information about students' strategy use by asking for further explanations of their prospective or retrospective behaviours. For example, a frequently used structured interview was the Self-Regulated Learning Interview Schedule (SRLIS) developed by Zimmerman and Martinez-Pons (1986), which asked students to describe how they would use self-regulated learning strategies in a hypothetical learning scenario. The study by Helme and

Clarke (2001) with students in mathematics classes was another example of using an interview technique to examine students' cognitive engagement levels. To be specific, twenty-four students were interviewed multiple times through the study, resulting in one hundred and nine interviews, which were then analyzed for evidence of cognitive engagement. Beyond the twenty behavioural indicators of cognitive engagement identified from class observations, four additional indicators were discovered from the interview records, such as 'claims to have been engaged during the lesson (e.g., I really put my minds to it)'. The SRL (Self-regulated Learning) microanalysis, which measures cognitive engagement in cyclical SRL processes, is designed to assess students' regulatory behaviours and thoughts in context-specific tasks (Cleary & Zimmerman, 2012). An essential feature of this approach is the use of a structured interview protocol whereby context-specific questions delineated the three-phase model of SRL (i.e., forethought, performance, and self-reflection) in a temporally appropriate sequence. Specifically, forethought phase questions are administered "before" a task, performance questions "during" the task, and self-reflection questions "after" performance on the task (Cleary & Zimmerman, 2012).

Interviews provide additional information to help researchers interpret the observed actions or self-report results. Besides, interviews allow for the construct of cognitive engagement to be redefined by the participants and for new understandings of theoretical claims to emerge (Turner & Meyer, 2000). However, the interviewing method is not without disadvantages. First of all, the validity of the interview method depends on the degree to which the participants are willing and able to share their ideas. Second, the interviewers' knowledge and skills could affect the type, quality, and depth of participants' responses. A third disadvantage is the problem of social desirability. Students may answer questions in order to 'look good' or please the interviewers (Fredricks & McColskey, 2012; Turner & Meyer, 2000).

Teacher ratings

A few studies have used teacher ratings to assess students' cognitive engagement. As an example, Wigfield et al. (2008) developed the Reading Engagement Index (REI) for teachers to rate each student's engagement in a reading task. Specifically, teachers rated students' cognitive engagement on the following three items: (1) works hard in reading (effort), (2) uses comprehension strategies well (strategies), and (3) thinks deeply about the content of texts (conceptual orientation). The rating was based on teachers' perceptions, with 1 = *not true* to 4 = *very true*. Thus, students received a score of 3 to 12 in terms of their levels of cognitive engagement. To avoid overburdening teachers in a study with 340 participants, the Teacher Rating Scale developed by Lee and Reeve (2012) asked teachers to assess each student's cognitive engagement with only one comprehensive item of "this student uses sophisticated learning strategies, is a planful and strategic learner, and monitors, checks, and evaluates work". Teachers made their ratings using a 7-point response scale, with 1 = *strongly disagree* to 7 = *strongly agree*. Fredricks and Mccolskey (2012) pointed out that teacher ratings can be beneficial for studies with younger children since they may have limited comprehension and literacy skills to complete self-report surveys. However, it is vital to notice that teacher ratings have their challenges. A recurring problem is that teachers are aware of students' task performance and their past class-specific abilities. Thus, teachers tend to use both performance-based and ability-based information to inform their inferences of students' cognitive engagement, which could inflate teachers' confidence in ratings (Lee & Reeve, 2012).

Experience Sampling

Another technique for assessing student cognitive engagement is the experience sampling method (ESM), which usually involves the use of electronic or digital devices to interrupt

students to probe their thoughts and feelings at that moment (Xie et al., 2018). The essential characteristic of ESM is that students' feelings, thoughts, and/or actions are measured regularly as they are experiencing in an authentic context (Zirkel et al., 2015). In general, researchers who conceptualized engagement from the perspective of flow (i.e., considering engagement as highly dynamic, fluctuating, and interactive) often used this technique to capture students' subjective experiences (Shernoff et al., 2016; Fredricks & McColskey, 2012). One example of ESM-based data collection is Salmela-Aro and her team's (2016) study to measure situational engagement with smartphone applications that triggered short questionnaires several times in the science classes. Specifically, students received smartphones with an application that prompted questionnaires and emitted short acoustic signals at fixed time intervals in science lessons. The students were asked to report on the 4-point Likert scale immediately on the application after hearing the signal. Instead of relying merely on fixed sampling, Xie et al. (2018) designed two sampling methods, i.e., fixed and event-based ESM. Students were required to answer mini-surveys for event-based ESM, which contained cognitive engagement items, as they triggered certain study events in a mobile-learning environment.

The ESM is a promising technique to explore an individual's intra-psychological states, such as cognitive engagement, so that the individual is being asked to respond when required in repeated manners (Järvelä et al., 2008). Moreover, ESM is considered a more sensitive method of measuring cognitive engagement than traditional self-report measures since it collects data in the moment of learning or problem-solving. The experience sampling technique, although it provides researchers with an innovative approach to assess cognitive engagement as it occurs in a context, suffers from several limitations. The idea of ESM is to interrupt students regularly at unexpected times, which may disturb their thinking processes or even irritate participants due to

its intrusiveness nature. Studies with ESM can also be time-consuming; thus, such research requires a high level of commitment from participants (Zirkel et al., 2015). Moreover, considering participant fatigue, the survey is usually kept short, which may not be suitable for research consisting of a wide range of variables.

Eye-tracking

Researchers have also embraced eye-tracking, a non-intrusive but informative technique, to collect the eyes' positions and movements of students to infer their cognitive engagement (Antonietti, Colombo, & Nuzzo, 2015; D'Mello et al., 2017; Miller, 2015). Using eye-tracking to measure engagement is based on three foundational assumptions: (1) The baseline of engagement is the simple act of paying attention, while eye-tracking can identify this act by measuring if students' eyes have rested on an object for a minimum amount of time. This assumption is based on that students cannot be even minimally cognitively engaged in a task if they are not paying attention to the stimulus. (2) Secondly, the eye-mind-engagement assumption asserts that fixation duration (i.e., the length of time an eye is still for extracting information from a particular stimulus) reflects the quantity and quality of one's cognitive effort; and (3) Increase in pupil size associates with an individual's increased cognitive effort once the external factors (e.g., the brightness of objects) are controlled (Miller, 2015).

Benefits of using the eye-tracking technique to assess cognitive engagement include real-time analysis of eye movement data, a precise indication of visual attention distribution, and availability of a rich quantified dataset for establishing user models (Kruger, Hefer, & Matthew, 2014; van Gog & Jarodzka, 2013). However, as pointed out by Miller (2015), more research is still needed to develop mature procedures for collecting eye movements and pioneer methodological techniques for extracting reliable engagement-related information. For one,

multiple eye movement indices were recommended to advance a more precise measurement of engagement, but meanwhile, it also made interpretation more difficult (Miller, 2015).

Physiological Measures

Most of the physiological methods aim to measure electrical signals produced in the skin (Electrodermal activity, EDA), brain (Electroencephalograph, EEG), or muscles (electromyogram, EMG), and to provide researchers physiological data to make inferences about participants' emotional and cognitive states (D'Mello et al., 2017; Stevens, Galloway, & Berka, 2007). Since the physiological methods provide rich data sources in fine-grained size, there has been a surge in using these techniques to measure engagement. To step further, EDA and EMG are usually used to measure emotional engagement, and EEG is used to measure cognitive engagement (Charland et al., 2015; Schuurink, Houtkamp, & Toet, 2008).

EEG is an electrophysiological monitoring technique that measures electrical activities of the brain, with the electrodes attached to different locations on the scalp (Berka et al., 2007). Researchers commonly analyze the power spectral density (PSD) of specific frequency spectrums of electrical signals to quantify cognitive engagement during a task (Charland et al., 2015). The analysis of PSD can be done with various EEG systems. For example, Kruger, Hefer, and Matthew (2014) used an EmotivTM Neuro-headset EEG to record 68 students' brain activities while watching a recorded lecture. Precisely, the EEG was placed on students' heads as they were seated comfortably on a stable chair. Once accurate recordings were confirmed and the baselines for analyzing various EEG channels were identified, students were instructed to watch a video recording of a Psychology lecture, during which the information of their brain activities was collected. Based on the raw EEG data, engagement as one of the five categorized EEG channels was generated by the EmotivTM software. In Stevens et al.'s (2007) study, a wireless

EEG sensor headset was used to record 12 participants' electrical signals generated from their brains during scientific problem-solving. Data sampling speed was at 256 samples per second, based on which the engagement index, ranging from 0.1 to 1.0, was calculated for each 1-second epoch for each student via the B-Alert software.

The advantages of using EEG to measure engagement include the ability to monitor levels of engagement continuously, unobtrusiveness, and being a fine-grained measure. However, several challenges remain in this area of measurement. For a practical one, EEG-based research can be labor-intensive and expensive for both researchers and participants. Another important consideration is that EEG devices and software operation can usually be very complicated, requiring researchers to accumulate sufficient skills and experiences. Besides, the engagement-related indices generated from EEG systems are not always accurate, especially considering individual differences and contextual factors (Stevens et al., 2007).

Log Files

Researchers who conceptualized cognitive engagement from the depth of processing and self-regulation theories are increasingly using log files to assess cognitive engagement, since log files provide a wealth of information about the timing, occurrence, frequency, and pattern of learning activities as students engage in computer-based learning environments (CBLEs) for learning and problem-solving (Greene, 2015; Bernacki et al., 2012). Log files can be comprehensive if researchers pinpoint the types of learning events meaningfully associated with students' cognitive engagement. Moreover, log files provide new opportunities for understanding the dynamic nature of cognitive engagement since students' digital footprints during the interaction with CBLEs are recorded automatically and unremittingly. In general, cognitive engagement is assessed by extracting students' cognitive and metacognitive strategies from logs

of learners' behaviours (Bernacki et al., 2012; Chen & Pedersen, 2012). Meanwhile, log files have also been used in other ways to infer levels of cognitive engagement. For example, many studies have operationalized the construct of cognitive engagement in terms of time-on-task (Helme & Clarke, 2001; Järvelä et al., 2008). In a recent study, Li, Zheng, Poitras, and Lajoie (2018) analyzed log file data to identify patterns in the allocation of cognitive resources of 62 medical students in solving patient cases. Findings from their research demonstrated that students' cognitive engagement, which was assessed by students' on-task time, varied across and within problem-solving phases (i.e., forethought, performance, and reflection).

Language and Content Analyses

Cognitive engagement is inherently unobservable and hard to measure. Thus researchers have explored another method, language and content analysis, to detect this construct from students' use of verbal languages or written materials, since language is the most reliable way for individuals to translate their internal thoughts into a form that others can understand (Tausczik & Pennebaker, 2010; Ireland & Henderson, 2014). At its simplest, word count reflects how engaged students are in a conversation or activity (Tausczik & Pennebaker, 2010). Researchers have also made a few attempts to extract language features from verbal or written materials to infer levels of cognitive engagement using a variety of text mining techniques. For example, a computerized text analysis program of Linguistic Inquiry and Word Count (LIWC) has been used in a wide range of experimental settings to study various forms of engagement by comparing students' written samples with its psychologically meaningful categories (Pennebaker, Boyd, Jordan, & Blackburn, 2015; Tausczik & Pennebaker, 2010).

Rather than using systematic, strict textual analysis, researchers have also used content analysis in a more qualitative, interpretive way to make inferences about students' cognitive

engagement. For example, Zhu (2006) developed the Analytical Framework for Cognitive Engagement in Discussion to code students' levels of cognitive engagement based on collected discussion messages as students participated in asynchronous online discussions. While this qualitative approach of content analysis can address some of the issues that existed in textual analysis, the biggest challenge is that considerable effort should be made to reach objectivity in rating levels of cognitive engagement and solve discrepancies among raters.

All in all, there are various promising instruments and methods to measure cognitive engagement, and each type of measure has strengths and weaknesses. Based on the literature reviewed previously, we have identified some guidelines for future research and practice to measure cognitive engagement.

Guidelines for Future Research and Applications of Cognitive Engagement Measures

To improve the measurement of cognitive engagement, one of the first steps for researchers is to describe the construct of cognitive engagement more clearly, given the variations in its definitions (Fredricks et al., 2011; Miller, 2015; Samuelsen, 2012). On the one hand, the many conceptualizations of cognitive engagement make it into a broad umbrella term covering a wide range of concepts and ideas. Researchers need to be aware of their preferences of a particular definition of cognitive engagement and the theories underlying that definition, otherwise constructs other than cognitive engagement would be included to mess up the measurement (Greene, 2015). For example, Sinatra et al. (2015) pointed out that the operational definition of cognitive engagement sometimes has much in common with existing motivation constructs. On the other hand, cognitive engagement has been conceptualized at different levels, such as an individual's cognitive engagement in tasks and a group of students' cognitive engagement in school. Thus, it is recommended that the nature of the research context (e.g.,

school, classroom or a specific task) and one's research goals (e.g., basic research or school policy) should be kept in mind (Azevedo, 2015), since they determine the grain-size of measurement of cognitive engagement and corresponding instruments.

Moreover, it has been reminded by some researchers that large-scale engagement surveys should be used cautiously, since they are usually developed for non-academic purposes. The large-scale surveys present little evidence of their validity (Veiga et al., 2014). For example, the High School Survey of Student Engagement (HSSSE) is administered every year to collect information about students' views of school learning environment, schoolwork, and interactions with the school community, with an attempt to assist schools in recognizing areas for improvement (Fredricks & McColskey, 2012). The National Survey of Students Engagement (NSSE), another large-scale instrument initiated every two years, has elicited considerable criticism from the engagement research community for lacking validity (Veiga et al., 2014; Fredricks et al., 2011). Consequently, researchers who use subscales or sets of items adapted from a larger instrument need to pay particular attention to the instruments' reliability and validity. Otherwise, the construct of cognitive engagement would be measured differently from what it is supposed to measure (Fredricks et al., 2011).

Another necessity in advancing the measurement of cognitive engagement is to distinguish indicators of cognitive engagement from its antecedents and facilitators (e.g., willingness, interest, self-efficacy) and its direct or indirect outcomes, such as procrastination, grade, and task performance (Veiga et al., 2014). Take the Student School Engagement Survey (SSES) as an example. Items like 'Most of my teachers know the subject matter well' and 'I get good grades in school' were included to capture students' cognitive engagement. However, the prior item relates to teachers' competency in teaching, and the latter one associates with students'

academic performance, which are the antecedent and outcome of cognitive engagement, respectively.

In addition, more advanced statistical techniques are needed to differentiate the salient indicators of cognitive engagement from the trivial ones and to exclude the repetitive elements since a variety of indicators for measuring cognitive engagement have been proposed. For instance, to what extent do students' experiences of flow (i.e., an indicator of cognitive engagement in the SCEM) relate to the indicator of absorption as measured in UWES-S? The same question can be posed with other instrument items. Betts (2012) suggested that statistical modelling techniques, especially confirmatory factor analysis and item response theory, should be considered in constructing and evaluating cognitive engagement measures. Samuelsen (2012) also argued that statistical methods, such as differential item functioning, could address some of the measurement issues. Lastly, researchers are increasingly calling for the use of multiple methods to measure cognitive engagement rather than relying merely on a single method (Greene, 2015; Sinatra et al., 2015; Betts, 2012). Researchers may overcome some of the limitations of using only one approach by adopting multiple methods (Azevedo, 2015). For example, using self-reports along with the experience sampling method (ESM), researchers may gain a more nuanced understanding of students' cognitive engagement since students would be more sensitive to survey questions as they are still in the proximity of time and space in the context of problem-solving (Xie et al., 2018; Zirkel et al., 2015). Moreover, multiple methods might reveal more components or manifestations of cognitive engagement than a single method. For instance, Helme and Clarke (2001) used both observation and interview techniques to examine students' cognitive engagement levels, whereby twenty indicators of cognitive engagement were identified from observations, and four additional indicators were discovered

from the interview records. Furthermore, the combination of different approaches to measuring cognitive engagement allows researchers to triangulate and therefore establish the validity of the data, which is a robust way to study how cognitive engagement changes over time (Greene, 2015). While keeping the strengths of multiple methods for measuring cognitive engagement in mind, it is vital to notice that construct definition drives the choice of measures rather than the opposite, considering that different methodologies often imply different theoretical orientations of cognitive engagement (Sinatra et al., 2015). Thus, a clear definition of cognitive engagement should be provided before the selection of measurements.

Taken together, this paper adopts an analytical perspective to review contemporary measurement methods of cognitive engagement used in broader academic settings. In doing so, no prospective method is omitted, and many possibilities are offered to researchers when exploring how cognitive engagement unfolds within and across learning phases. In addition, this review is particularly useful to practitioners in exploiting the affordances and minimizing the constraints of different cognitive engagement measures. Moving forward, we propose that a multimethod approach to capturing cognitive engagement is a necessity for future empirical work. Analyzing multimodal data about cognitive engagement may open new scientific leads to come closer to the essence of this construct, and this review paved the way for fulfilling this goal.

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Bridging Text

Chapters 2 and 3 present some of the conceptual, theoretical, and methodological gaps in the research of cognitive engagement. In Chapter 2 we address several fundamental questions about cognitive engagement and its roles and functions in SRL and presents a critical review of the instruments and techniques used to measure cognitive engagement in Chapter 3. However, empirical studies are needed to validate the theoretical claims proposed in Chapter 2, following the recommendations of how to measure cognitive engagement made in Chapter 3.

In Chapter 4, I present an empirical study to explore the forms of cognitive engagement students use in the context of self-regulated learning in the context of clinical reasoning. Medical students' cognitive engagement and SRL were examined while they were diagnosing virtual patients independently in an intelligent tutoring system designed to help medical students practice clinical reasoning skills. We also examine the relationships between different forms of cognitive engagement and students' task performance. The main purpose of this chapter is to test the assumption that students accomplish a task at an appropriate level of cognitive engagement, instead of always using the most sophisticated form of cognitive engagement.

Chapter 4. Manuscript 3

The Relationship between Cognitive Engagement and Students' Performance in a Simulation-based Training Environment: An Information-Processing Perspective

Li, S., Zheng, J., & Lajoie, S. P. (2020). The relationship between cognitive engagement and students' performance in a simulation-based training environment: An information-processing perspective. *Interactive Learning Environments*. 1-14.
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Abstract

In this paper, we adopted an information-processing perspective to examine the relationship between cognitive engagement and students' performance in a simulation-based training environment. In particular, we examined what forms of cognitive engagement students used while diagnosing virtual patients and whether engagement forms predicted students' diagnostic confidence and efficacy. A total of 88 medical students from a large North American university voluntarily participated in this study. We used latent profile analysis (LPA), a person-centered statistical method, to identify groups of students with similar information processing patterns. Findings from this study revealed that students displayed various forms of cognitive engagement, i.e., recipience, resource management, and task-focused. Moreover, we found that group difference in diagnostic confidence was moderated by task complexity. In terms of diagnostic efficacy, students who were task-focused or resource managers did better than the recipience students. The findings advance our understanding of theories of cognitive engagement as well as inform the design of effective interventions in developing simulation-based learning environments.

Keywords: Simulation-based Training Environment, Cognitive Engagement, Information Processing, Student Performance, Latent Profile Analysis

Introduction

Decades of research on student engagement have shown that a higher level of engagement associates with better learning achievements across various disciplines (Fredricks, Blumenfeld, & Paris, 2004; Perry & Steck, 2015; Richardson & Newby, 2006). However, should students always keep their engagement at a high level to succeed in learning or problem-solving? There is no clear answer to this question since high engagement requires a substantive investment of effort and commitment, which is cognitively demanding and sometimes impractical in certain circumstances (Bangert-Drowns & Pyke, 2001; Carroll et al., 2019). Research on self-regulated learning (SRL) suggests that students need to both plan the strategies they will use prior to learning or problem-solving and estimate the amount of effort needed to achieve their goals (Greene, 2015). Consequently, it is reasonable that students choose the ‘right’ form of engagement instead of one that requires effort significantly above and beyond the required minimum. For instance, Bangert-Drowns and Pyke (2001) used a seven-level taxonomy of engagement to classify students by engagement types as they interacted with educational software in science and technology classes. They found that no students revealed behaviors at the highest level of engagement. Moreover, some students preferred a particular engagement strategy (e.g., task-focused) if he/she has developed such a cognitive schema in previous learning experiences. Other research has demonstrated that some students consistently address problems by gathering available information using an exhaustive approach, while others terminated their solution once their analytic strategies determined a solution (Corno & Mandinach, 2004).

In this study, we examined forms of engagement in the context of clinical reasoning. In particular, we were interested in what forms of cognitive engagement medical students use while diagnosing patients and whether engagement differences lead to differences in clinical reasoning

performance. Clinical reasoning is a thinking and decision-making process in which medical practitioners integrate their knowledge with initial patient information to form a case representation of the problem. Medical practitioners then use the problem representation to guide the acquisition of additional information (e.g., ordering lab tests), based on which they revise the problem representation. They repeat the information acquisition-transformation cycle until they reach a threshold of confidence in that representation to support a final diagnosis (Gruppen, 2017). Clinical reasoning components, including but not limited to hypothesis generation, problem representation, data acquisition, data interpretation, and diagnostic verification, rest heavily on medical practitioners' cognitive processes (Young et al., 2018). Therefore, cognitive engagement is integral to the clinical reasoning process. However, the relationship between different forms of cognitive engagement and clinical reasoning performance remains unclear. Only when we answer the question about how different forms of cognitive engagement affect performance in clinical reasoning can we inform medical practitioners about effective instructional designs and interventions.

Theoretical Background

Engagement refers to “the basic processing operations that describe how students react to and interact with the learning materials and environments” (Boekaerts, 2016, p. 81). Fredricks et al. (2004) conceptualized engagement as a multidimensional construct, which includes behavioral, emotional, and cognitive dimensions. According to Fredricks et al. (2004), behavioral engagement includes involvement in school-related activities such as homework completion and class attendance, while emotional engagement is about positive or negative reactions towards school, teachers, classmates, and academics. Cognitive engagement is described as thoughtfulness and willingness to exert effort in learning or problem-solving. It was

not until recently that the concept of engagement was considered in terms of individual student engagement (Jarvela, Jarvenoja, Malmberg, Isohatala, & Marta, 2016). For our study, we paid particular attention to cognitive engagement since (1) the other two dimensions of engagement (i.e., behavioral and emotional engagement) were generally examined at the school level, and (2) clinical reasoning composes of a variety and range of decision-making activities, which is regarded as the cognitive process. In line with Walker, Greene, and Mansell's (2006) definition of cognitive engagement, we referred to cognitive engagement as the amount and types of learning strategies students used in learning or problem-solving.

The dichotomous view of cognitive engagement is prevalent in the literature, such as deep versus shallow engagement, meaningful versus surface engagement, deep versus surface processing, etc. (Azevedo, 2015; Dinsmore & Alexander, 2012). For instance, Greene (2015) distinguished two types of cognitive engagement using a depth of processing paradigm: deep engagement and shallow engagement. Specifically, Greene (2015) defined deep engagement in terms of deep types of learning strategies (e.g., elaboration) while she viewed shallow engagement as involving cognitive actions that are more mechanical than thoughtful. Another example is the research of Walker, Greene, and Mansell (2006), who examined how the constructs of identification with academics, motivation, and self-efficacy predicted two types of engagement: meaningful and shallow cognitive engagement. However, Azevedo (2015) warned that such dichotomies minimize the complex nature of engagement and do not help explain students' performance. Some students may comply with minimal requirements for completing assignments (i.e., procedurally engaged students), while others known as disengaged students are off-task (Bangert-Drowns & Pyke, 2001). Another reason that researchers should rethink the dichotomy of cognitive engagement, as pointed out by Dinsmore and Alexander (2012), lies in

the fact that the prevailing assumption that deep processing yields better learning outcomes while surface processing leads to poorer learning outcomes has been called into question. Dinsmore and Alexander (2012) reviewed 221 studies and found inconsistent and ambiguous results concerning the relations between levels of processing and performance existed in literature.

For this study, we concur with the view of different levels of processing, but we suggest that there are stylistic differences in how students process information and how they engage cognitively in problem-solving as argued by Corno and Mandinach (2004). In fact, some researchers have proposed a more detailed differentiation of cognitive engagement, which could represent a variety of groups of students regarding the approach they took to solving problems. For instance, Salmela-Aro, Moeller, Schneider, Spicer, and Lavonen (2016) identified four distinct groups of students using latent profile analyses: engaged, engaged-exhausted, moderately burned out (risk for burnout), and burned out. Additionally, Butler, Cartier, Schnellert, Gagnon, and Giammarino (2011) recognized four engagement profiles of students as they engaged in curriculum-based learning through reading activities: actively engaged, actively inefficient, disengaged, and inactively efficient (not deliberately strategic). Furthermore, Bangert-Drowns and Pyke (2001) developed a framework to understand seven forms of engagement as students worked with computer software in class, which were literate thinking, critical engagement, self-regulated interest, structure-dependent engagement (trying all available operational options regardless of learning goals or interest), frustrated engagement (possessing clear goals but failing to achieve these goals due to operational incompetence), unsystematic engagement (moving from one incomplete activity to another without apparent reason), and disengagement. As noticed, the classifications of cognitive engagement vary in how researchers define this construct (e.g., being strategic or motivated) and are highly dependent on the contexts. To date, there is little research

that explores forms of cognitive engagement in the context of clinical reasoning, especially from an information processing perspective (Padgett, Cristancho, Lingard, Cherry, & Haji, 2018).

Anderson and Bower (2014) defined two types of information processing, acquisition and transformation. Information acquisition processing refers to taking in information primarily from the environment. Information transformation processing refers to learners integrating new information with their existing knowledge structures to develop their understanding and to advance the accomplishment of the task. Corno and Mandinach (2004) argued that students vary in their choice of processing and may use either the acquisition or transformation processes for a given task. For example, some students may deliberately rely on information acquisition but avoid carrying out transformation activities for problem-solving. Corno and Mandinach (1983) described this approach as a 'resource management' form of cognitive engagement. Another form of engagement is termed 'recipience', which involves little mental investment in both information acquisition and transformation. Recipience refers to passivity or learner short cuts. Other students may be 'task-focused'. Students who display such a form of cognitive engagement spend more time on transformative processes and less on the acquisition processes. The highest form of cognitive engagement is known as 'self-regulated learning', where students make efforts to be engaged deeply in both the acquisition and transformation processes (Corno & Mandinach, 2004). For the interest of this study, we adopt these four forms of cognitive engagement (resource management, recipience, task focus, SRL) derived from the information processing perspective. Beyond the fact that few studies have shed light on the variations of cognitive engagement in clinical reasoning, one crucial reason is that the nature of clinical reasoning is about how students gather information concerning patients and diseases and apply that information for diagnosis.

Research has revealed that students who demonstrate SRL (the highest form of cognitive engagement) are more effective than the task focus, resource management, or recipient group in learning or problem-solving; however, it does not mean that one particular form of cognitive engagement is superior to another. According to Richardson and Newby (2006), Students' prior learning and environmental factors (e.g., task features, internal or external support) jointly determine the types of cognitive engagement students exhibit. For instance, it would be cognitively efficient for students to be a resource manager rather than to be a self-regulated learner if the task requires mostly information gathering and little analytic response. Thus, we cannot recommend students to be substantially engaged to gain high performance without considerations of students' characteristics and problem-solving contexts. The discussion of students' cognitive engagement in an authentic environment, i.e., medical students diagnose patients, is still scarce. No studies have examined the operationalization of cognitive engagement in clinical reasoning using the conceptual framework of information processing, let alone the relations between cognitive engagement and diagnostic performance. This study addresses these gaps by examining cognitive engagement in medical students as they diagnose virtual patients. Specifically, this study aims to answer the following research questions: (1) Do various forms of cognitive engagement exist in clinical reasoning? (2) How are different forms of cognitive engagement connected to diagnostic performance, i.e., diagnostic confidence and efficacy?

Methods

Participants

A total of 88 medical students from a large North American university voluntarily participated in this study. Excluding 5 participants who did not report their demographic information, the students comprised of 50 females (60.24%) and 33 males (39.76%), with an

average age of 23.99 ($SD = 3.10$). The students had completed a prerequisite course on endocrinology, metabolism, and nutrition. Therefore, the students shared a similar level of knowledge on the problem-solving scenarios that were designed specifically for this study. Moreover, we had obtained the research ethics approval from the university. Students were required to sign the consent form prior to the study so that they were aware of the research purposes, procedures, and consequences. In addition, the students all claimed that they felt comfortable diagnosing virtual patients in a simulation environment. They could also withdraw from the experiment at any time.

Task and Learning Context

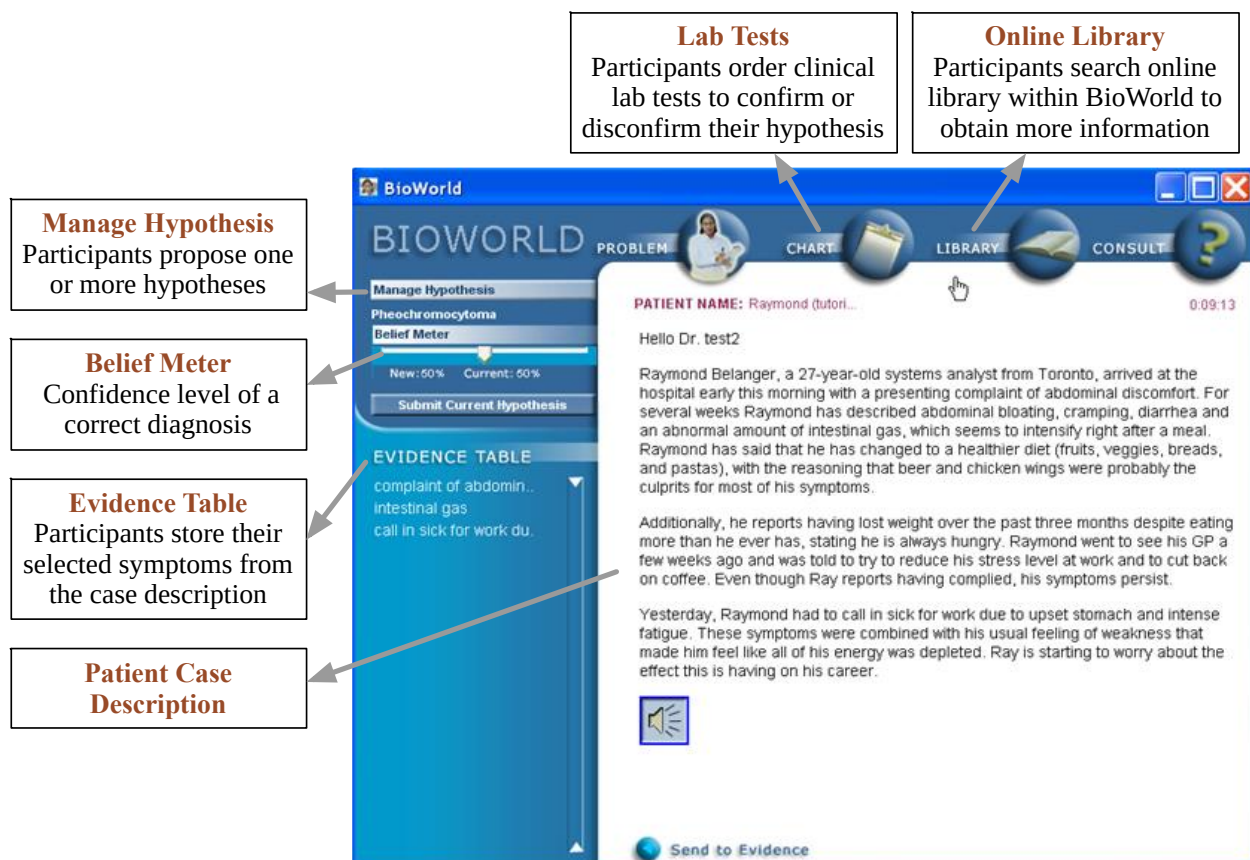
Students were tasked with diagnosing two virtual patient cases, i.e., an easy case of Amy and a difficult case of Cynthia, which were referred to by the patient names. Specifically, the two cases were developed by a content expert and were validated by two other experts. The correct diagnoses for the Amy and Cynthia cases were diabetes mellitus (Type 1) and pheochromocytoma, respectively.

The students performed the diagnoses in a simulation environment of BioWorld (Lajoie, 2009), a computer-based platform designed to help medical students practice clinical reasoning skills. As shown in Figure 3, students begin the diagnosis by first reading the description of the patient case, based on which they extract useful information (e.g., the patient's life experience and key symptoms) for the development of diagnostic hypotheses. They can propose one or more hypotheses regarding the disease. Students also need to report their confidence levels for each of the hypotheses in the clinical reasoning process. To confirm or disconfirm their hypotheses, students can obtain laboratory test results by ordering lab tests (e.g., biochemistry – urinalysis/glucose, hematology – coagulation bleeding time) within the BioWorld system.

Participants can also search an online library within the system to get more information about unfamiliar medical terms and diagnostic procedures. Afterward, students link collected evidence/test results to respective hypotheses. Meanwhile, they label these evidence/test results as either useful, useless, or neutral. After submitting a final diagnosis, students justify their solutions by making a summary of their clinical reasoning processes.

Figure 3

The Interface of the BioWorld System



Procedure

A training session about the BioWorld system was provided to students prior to the experiment. In particular, a researcher-guided introduction of the BioWorld system, along with the diagnosis of a sample patient case, were provided to help students familiarize themselves

with the system. During the 1.5 hours-long experiment, students were required to diagnose the two patient cases (i.e., Amy and Cynthia cases) independently. However, they could ask research assistants for help if they encountered technical issues. When diagnosing the cases, each participant's problem-solving behaviors were automatically recorded in BioWorld log files. Specifically, the log files of BioWorld contained a record of all actions conducted by an individual and their corresponding timestamps and results. All the participants solved the Amy case, but six students did not finish the Cynthia case.

Diagnostic Behaviors and Performance

Seven types of diagnostic behaviors were extracted from the BioWorld log files based on the coding scheme developed by Li, Zheng, Poitras, and Lajoie (2018). These behaviors were then classified into two classes of information processing: the acquisition process and the transformation process (see Appendix A). Specifically, the information acquisition process included three behaviors of *collect evidence from case descriptions*, *search library*, and *order lab tests*, while the information transformation process consisted of *propose hypotheses*, *link evidence to hypothesis*, *categorize and prioritize evidence items*, and *write a case summary*. The number of each class of information processing activities was calculated for all participants.

Two performance indices, namely, diagnostic confidence and efficacy, were extracted from the BioWorld log files as well. To be specific, diagnostic confidence referred to the extent of a participant's perceived belief that his/her diagnosis was accurate. In the clinical reasoning process, students used the Belief Meter function to indicate their level of confidence in diagnostic accuracy (see Figure 3). The values of diagnostic confidence range from 0 to 100. With respect to diagnostic efficacy, it was defined as the percentage of evidence matches between the participant's and the expert's diagnoses.

Data Analysis

We used latent profile analysis (LPA), a statistical modeling technique that identifies classes of individuals based on their common characteristics, to find latent groups from the observed dataset, i.e., students' information processing behaviors in diagnosing patients. In LPA, models are estimated for a successively increasing number of classes to find which model is the best fit to the data; therefore, it is more flexible than cluster analysis. Specifically, we conducted LPA in *Mplus* 7.4 using a maximum likelihood (ML) estimation via the expectation maximization (EM) algorithm. See Appendix B for the *Mplus* codes. The maximum likelihood-EM approach uses multiple sets of random starting values in LPA, which enables the convergence of class memberships to be reached at a global solution rather than a local solution (Hipp & Bauer, 2006; Muthén & Muthén, 2012). In particular, the logarithmic value of the likelihood (the log-likelihood or LL) is used in the ML estimation since it is mathematically tractable (Pastor, Barron, Miller, & Davis, 2007). The LL of the final parameter estimates provides a quantitative criterion to evaluate model fit, with higher values indicating better fit than lower values (Pastor et al., 2007).

The input variables for latent profile analysis were the two classes of information processing activities. We counted the total number of diagnostic behaviors that were coded as either an information acquisition or an information transformation process to represent the attribute of each class. We used the information processing activities instead of the seven diagnostic behaviors because the aggregation of similar behaviors into less granular classes can be helpful when it matters less what specific diagnostic behavior learners enact than whether they are enacting a type of cognitive engagement (Greene et al., 2019). The aggregated classes, which were in conformity with the conceptual framework of information processing (Corno &

Mandinach, 2004), were better indicators of students' problem-solving patterns than the finer-grained activity data (Greene & Azevedo, 2009).

In this study, we used the descriptive goodness-of-fit indices of the Akaike's information criteria (AIC), Bayesian information criteria (BIC), and sample size-adjusted Bayesian information criteria (Adjusted BIC), to determine the optimal number of classes. The three model fit indices are based on the LL estimates of model parameters for selecting the most accurate and parsimonious model (Tein, Coxe, & Cham, 2013). The algorithms for the three model fit indices are:

$$AIC = -2LL + 2p \quad (1)$$

$$BIC = -2LL + p * \ln(N) \quad (2)$$

$$Adjusted\ BIC = -2LL + p * \ln(N * (N + 2)/24) \quad (3)$$

where p is the number of estimated parameters, and N is the sample size. Considering the intent of ML estimation is to find the highest LL value and the three indices take the -2 times of the LL value into the calculation; thus lower values of AIC, BIC, and the adjusted BIC are indicative of better model fit (Pastor et al., 2007; Tein et al., 2013).

Moreover, we examined the significance levels of the Bootstrapped Likelihood Ratio Test (BLR) and the Lo-Mendell- Rubin Adjusted Likelihood Ratio Test (LMR). In particular, the p values generated for BLR and LMR indicate whether a k class solution fits better than a $k-1$ solution. In addition, we examined the entropy value for each cluster solution, with its value larger than .80 indicating acceptable classification accuracy (Clark, 2010). Lastly, we checked whether or not the latent classes were theoretically meaningful, and the classes represented distinct information processing patterns.

To address our second research question, we predicted the distal outcomes (i.e., diagnostic confidence and efficacy) from latent class membership. The traditional approach is to assign individuals to latent classes based on their maximum posterior probability and then to examine differences in distal outcomes between class memberships (Asparouhov & Muthén, 2014; Lanza, Tan, & Bray, 2013). Considering that there is uncertainty in each individual's true class membership, this approach may yield biased results when it comes to subsequent outcome analysis (Lanza et al., 2013). In this study, we adopted the approach developed by Bolck, Croon, and Hagenaars (2004), which is well-known as the BCH approach, to control classification errors in the process of estimating class differences in distal outcomes (see Appendix C for the codes). In particular, the BCH approach performs a weighted analysis of variance (ANOVA), and the weights are inversely related to the classification error probabilities (Bakk, Tekle, & Vermunt, 2013; Bakk & Vermunt, 2016). Furthermore, the BCH method is robust even when the variance of a distal outcome differs substantially across latent classes (Asparouhov & Muthén, 2014).

Results

Unconditional Latent Profile Analysis

The descriptive statistics of students' information processing activities (i.e., information acquisition and information transformation) and corresponding diagnostic behaviors were shown in Table 6. As aforementioned, we took the two classes of information processing activities as the input variables for latent profile analysis. Results in Table 7 demonstrated that a 3-cluster solution was better than a 2-cluster solution for the Amy case since the p values of both BLR and LMR for the 3-cluster solution were significant. Furthermore, the descriptive goodness-of-fit indices of AIC, BIC, and adjusted BIC all decreased, indicating a good model fit as well. Although the information criteria of AIC and adjusted BIC decreased in a 4-cluster solution

compared to the 3-cluster solution, the BIC value increased. As pointed out by Nylund, Asparouhov, and Muthén (2007), the BIC performed the best of the three descriptive informative criteria, suggesting that a 4-cluster solution is not superior to a 3-cluster solution. Moreover, the LMR test also revealed that the 4-cluster solution did not fit better than the 3-cluster solution ($p = .080$). The LMR and BLR were not significant for both the 5-cluster and 6-cluster solution. Therefore, the 3-cluster solution was optimal.

Table 6*Descriptive Analysis of Diagnostic Behaviors and Information Processing Classes*

Case	Class / Behavior	Mean	SD	Min	Max
Amy	Acquisition	28.08	11.32	6	56
	CO	13.92	3.41	5	27
	SE	3.75	5.39	0	22
	OR	10.41	7.69	0	40
	Transformation	70.90	39.41	8	187
	PR	13.68	8.28	4	42
	LI	12.63	16.17	0	100
	CA	43.60	31.62	0	161
	WR	.99	.11	0	1
Cynthia	Acquisition	40.12	19.20	12	111
	CO	14.96	3.86	8	34
	SE	7.87	13.29	0	79
	OR	17.29	10.39	0	48
	Transformation	75.56	40.41	0	207
	PR	16.79	9.86	0	53
	LI	14.27	14.54	0	69
	CA	43.52	32.16	0	170
	WR	.98	.16	0	1

Note: CO = Collecting evidence items, SE = Searching library, OR = Ordering lab tests, PR = Proposing hypotheses, LI = Linking evidence to hypothesis, CA = Categorizing and prioritizing evidence, WR = Writing a case summary; SD = Standard deviation, Max = Maximum value, Min = Minimum value.

Table 7*Fit Indices for Different Models with the Number of Clusters Ranging from 2 to 6*

Case	Model	AIC	BIC	Adjusted BIC	<i>p</i> <i>BLR</i>	<i>p</i> <i>LMR</i>	Entropy	Smallest cluster freq.
Amy	2 clusters	1555	1572	1550	.000	.038	.780	28(.318)
	3 clusters	1530	1555	1524	.000	.009	.879	14(.159)
	4 clusters	1527	1559	1518	.040	.080	.855	8(.091)
	5 clusters	1531	1570	1520	1.00	.710	.815	5(.057)
	6 clusters	1533	1580	1521	.667	.225	.526	6(.068)
Cynthia	2 clusters	1535	1552	1530	.000	.001	.966	6(.073)
	3 clusters	1516	1540	1508	.000	.002	.959	6(.073)
	4 clusters	1514	1545	1504	.200	.558	.902	5(.061)
	5 clusters	1518	1557	1506	1.00	.338	.869	1(.012)
	6 clusters	1511	1557	1497	1.00	.398	.877	2(.024)

Note: AIC = Akaike's information criteria, BIC = Bayesian information criteria, *p* BLR = *p* values for the Bootstrapped Likelihood Ratio test, *p* LMR = *p* values for the Lo-Mendell-Rubin adjusted likelihood ratio test.

As shown in Table 8, the three clusters represented distinct forms of cognitive engagement when solving the Amy case. The first group consisted of 60 participants who conducted relatively less acquisition and transformation information processing activities, which was labeled as *recipience* according to Corno and Mandinach's (1983) conceptualization. The second group comprised of 14 students who performed relatively more acquisition behaviors compared with the other two groups. This group was labeled as *resource management*. The third group also comprised 14 participants who activated moderate acquisition behaviors but comparatively more transformation behaviors, which was categorized as *task-focused*. Moreover, the 3-cluster solution was theoretically meaningful. Although Corno and Mandinach (1983) proposed four forms of cognitive engagement (i.e., recipience, resource management, task-focused, and self-regulated learning), they acknowledged that the first three forms were

engagement variations on self-regulated learning. Students may not display self-regulated learning (SRL) if they lack SRL skills or simply because the problem-solving process does not require such an advanced form of engagement.

Table 8

The Three Clusters of Cognitive Engagement Profiles

Case	Group	No.	Acquisition		Transformation	
			<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
Amy	Recipience	60	22.35	6.51	52.45	23.54
	Resource Management	14	48.07	5.65	81.57	20.95
	Task-focused	14	32.64	5.33	139.29	26.65
Cynthia	Recipience	70	35.90	11.98	66.40	27.68
	Resource Management	6	92.83	13.32	76.33	30.21
	Task-focused	6	36.67	14.71	181.67	16.90

In the same vein, the results of the latent profile analysis displayed in Table 7 showed that the 3-cluster solution was also optimal for the Cynthia case. A thorough examination of the means of the acquisition and transformation activities in Table 8 demonstrated that participants also displayed the three forms of cognitive engagement, *recipience*, *resource management*, and *task-focused*. Specifically, there were 70, 6, and 6 students in these three groups, respectively. As pointed out by Stanley, Kellermanns, and Zellweger (2017), no profile should contain less than 5% of the respondents to ensure the usefulness of the profiles. Although the profile sizes of the latter two groups were relatively small, the two groups both contained more than 5% of the participants. In addition, the pattern of the results for each profile was theoretically meaningful, as it aligned well with the conceptual framework of information processing proposed by Corno and Mandinach (2004). Students with a recipience profile conducted the fewest behaviors of either information acquisition or transformation among the three clusters. Students in the

resource management group used information acquisition behaviors extensively, whereas those in the task-focused group highly relied on information transformation behaviors.

Latent Profile Analysis with Distal Outcomes

The BCH approach was used in latent profile modeling with distal outcomes to examine whether the three latent classes varied significantly in diagnostic confidence and efficacy. As shown in Table 9, the *task-focused* group reported a significantly higher diagnostic confidence than the *recipience* group ($\chi^2 = 7.59, p = .006$) when solving the easy patient case of Amy. However, there were no significant differences in diagnostic confidence among the three groups as students solved the difficult case of Cynthia. In terms of diagnostic efficacy, both the *task-focused* group and *resource management* group were significantly higher than the *recipience* group in the Amy case, with $\chi^2 = 30.39, p < .001$, and $\chi^2 = 5.20, p = .023$, respectively. With regards to the Cynthia case, the *task-focused* group was significantly higher than the *resource management* group ($\chi^2 = 14.94, p < .001$) and *recipience* group ($\chi^2 = 15.88, p < .001$) on diagnostic efficacy, but there was no significant difference between the *resource management* and *recipience* groups.

Table 9*Pairwise Comparisons of Diagnostic Confidence and Efficacy*

Case	Index	Group	Mean	SE	Chi-Square (<i>p</i> value)		
					1	2	3
Amy	Confidence	1	.80	.03	--		
		2	.80	.07	.00 (.991)	--	
		3	.90	.03	7.59 (.006)	1.83 (.176)	--
	Efficacy	1	33.59	2.73	--		
		2	49.58	6.37	5.20 (.023)	--	
		3	62.09	4.24	30.39 (.000)	2.43 (.119)	--
Cynthia	Confidence	1	.76	.02	--		
		2	.78	.04	.13 (.719)	--	
		3	.83	.06	1.48 (.224)	.65 (.419)	--
	Efficacy	1	48.86	2.47	--		
		2	47.65	3.58	.08 (.784)	--	
		3	72.79	5.43	15.88 (.000)	14.94 (.000)	--

Note: The automatic BCH approach was used to estimate the distal outcomes (i.e., diagnostic confidence and efficacy) across latent class. The numbers of 1, 2, and 3 refer to the Recipience, Resource Management, and Task-focused groups, respectively. SE = Standard Error.

Discussion

This study identified three distinct groups of students with different forms of cognitive engagement when diagnosing virtual patients in a simulation environment, regardless of the difficulty of the tasks. These results indicated that students had different dispositions in clinical reasoning in terms of information processing. Some students emphasized the acquisition of external resources and hints, while others preferred the use of deep learning strategies such as inferencing and summarizing. It is noteworthy that the majority of the medical students (i.e., the recipience group) approached the tasks ‘passively’. Two contrary explanations contended in the literature account for this fact (Corno & Mandinach, 1983; Shernoff et al., 2016). One argument

is that those students are actually experienced learners who use mental shortcuts (e.g., educated guesses or intuitive judgments) for diagnosing patients. Therefore, they perform relatively less information acquisition and transformation behaviors. The other explanation is that this group of students are less able learners, who do not know ‘what information to collect’ and ‘how to relate, extend, or transfer information’ in clinical reasoning. Considering the performance differences between the three groups, this study suggested that the latter explanation is more likely. As it is apparent that students in the recipience group still need to ‘learn how to learn’.

Students did not display behavioral patterns at the highest form of cognitive engagement (SRL), which was conceptualized by Corno and Mandinach (1983) as high levels of acquisition and transformation processes, in solving both the Amy and the Cynthia case. Research from Shernoff et al. (2016) revealed that cognitive engagement varies from one task to another, partly as a function of variation in environmental complexity. It is possible that students did not perceive task complexity as challenging enough to trigger the highest form of cognitive engagement. While we acknowledge that cognitive engagement is highly influenced by learning environments and task features, students also choose what they believe appropriate forms of engagement rather than the form requiring the most allocation of mental resources. We propose further that cognitive engagement is the joint product of learning or problem-solving environments and students' self-judgment systems. However, more research is needed to answer questions such as: What factors influence a student's self-judgment about whether to be a resource manager or a task-focused learner? To what extent does environmental complexity affect students' decisions about the degree to which they cognitively engage with tasks?

In addition, this study found that students in the resource management group performed significantly better than those in the recipience group in terms of diagnostic efficacy when

solving the easy patient case of Amy but not the difficult case of Cynthia. These results corroborated the claims made by Corno and Mandinach (2004) that exceptional use of information acquisition during some tasks permits students to succeed but is not appropriate for all types of tasks. Furthermore, we also found that students in the task-focused group demonstrated significantly better performance than the *recipience* group in the Amy case. Regarding the Cynthia case, the task-focused group had better performance than both the resource management and the *recipience* groups, suggesting that information transformation behaviors became crucial as the task complexity increased.

Interestingly, this study suggested that the *task-focused* group was more confident than the *recipience* group when solving the easy patient case of Amy. However, there were no significant differences in diagnostic confidence among the three groups as students solved the difficult case of Cynthia. A simple explanation for these findings was that students all decreased their confidence as the task complexity increased, making the group differences not large enough to yield statistically significant results. It is also possible that students' level of confidence was relatively insensitive to case difficulty (Meyer, Payne, Meeks, Rao, & Singh, 2013). As pointed out by Meyer et al. (2013), students were overconfident in the diagnostic process in general, and the level of overconfidence in accuracy increased as the case difficulty increased. Another explanation lies in the *Dunning-Kruger effect*, which refers to a cognitive bias whereby the incompetent are often unable to recognize their own incompetence (Pennycook, Ross, Koehler, & Fugelsang, 2017). The mismatch between students' subjective confidence and accuracy may be the reason why students with different forms of cognitive engagement showed no differences in diagnostic confidence when solving the difficult case.

Findings from this research could advance the theoretical development of the conception of cognitive engagement as well as inform the design of effective interventions in developing clinical reasoning skills for medical students. For one, this study added evidence to the body of literature demonstrating that students do not always use the most sophisticated form of cognitive engagement, but plan the strategies and efforts needed based on the context (Corno & Mandinach, 1983; Winters, Greene, & Costich, 2008). Examining cognitive engagement from an information processing perspective allows researchers to identify what types of behaviors students engage in to reach their goals. We situated such examination in the context of clinical reasoning, but the operationalization of the forms of cognitive engagement informs other domains across various contexts. Furthermore, it is important to note that the concept of self-regulated learning (SRL) has been growing in dominance in educational theory and practice (Coertjens, 2018; Kaplan, 2008). However, some researchers defined SRL quite differently instead of viewing this construct as the highest form of cognitive engagement. For instance, Pintrich (2000) defined SRL as an iterative process whereby students plan, monitor, and regulate certain aspects of learning (i.e., behavioral, cognitive, metacognitive, motivational, and affective aspects) to achieve their pre-set learning goals. It would be fruitful to examine how students regulate their cognitive engagement from an SRL perspective, which may answer questions of students' choices of being resource managers or task-focused learners. Another potential contribution to the literature is the finding of a weak association between the forms of cognitive engagement and diagnostic confidence. This study also has practical implications. Given that students had different information processing dispositions, adaptive instructional interventions should be designed and delivered to different groups of students.

Conclusion

This study contributed to the body of engagement research by adopting a person-oriented approach to reveal groups with different forms of cognitive engagement based on students' information processing activities. These groups were then examined to see if differences in cognitive engagement led to differences in confidence and efficacy in clinical reasoning. This study has several strengths. To our knowledge, this is the first study to directly examine the relationships between the forms of cognitive engagement, diagnostic efficacy, and confidence within the context of clinical reasoning. We asked students to rate their confidence in diagnostic accuracy unobtrusively, i.e., the measurement of students' confidence was integrated as a means to monitor their clinical reasoning processes. Moreover, we assessed students' diagnostic efficacy (i.e., evidence match between the participant's and the expert's diagnoses) rather than a dichotomous result of accurate or inaccurate diagnosis. Nevertheless, this study is not without limitations. The participants were from a single university located in North America, which may not be representative of medical students as a whole. Although the numbers of students with different forms of cognitive engagement were statistically meaningful, a larger and different cohort of medical students is expected to yield more balanced profiles of students. Furthermore, we situated our study in a technology-rich simulation environment instead of an authentic problem-solving scenario, which may influence students' cognitive engagement and its relationship with performance (Rudolph, Simon, & Raemer, 2007). Another shortcoming that needs to be addressed in future research is the limited number of patient cases. Specifically, more cases of varying difficulty should be considered when examining the effects of case difficulty on diagnostic efficacy and confidence.

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Appendices

Appendix A

The Information Acquisition and Transformation Behaviors in Clinical Reasoning

Activity	Clinical Behaviors	Code	Description
Information Acquisition	Collecting evidence items	CO	Collecting evidence items from the patient description by recalling one's prior knowledge pertaining to the symptoms
	Ordering lab tests	AD	Conducting medical lab tests
	Searching library	SE	Searching for information in the library for additional explanations
Information Transformation	Proposing hypotheses	RA	Outlining a single or multiple diagnostic hypothesis based on the collected evidence
	Linking evidence/results	LI	Justifying the probability of a hypothesis being correct to the disease
	Categorizing evidence/results	CA	Checking the relevance of evidence items and lab test results towards specific hypothesis (i.e., whether the evidence/tests in support, against or neutral of one hypothesis)
	Prioritizing evidence/results	PR	Ranking evidence items and lab test results according to their importance to a hypothesis
	Summarization for final diagnosis	SU	Making the final diagnosis by writing a summarization

Note. This coding scheme is adapted from Li et al. (2018).

Appendix B*The Mplus Code for the Unconditional Latent Profile Analysis*

TITLE: latent profile analysis

DATA:

! enter the name of the data set

FILE = LPA.dat;

VARIABLE:

! y2 and y3 refer to information acquisition and transformation activities, respectively

NAMES = y1-y4;

USEVARIABLES = y2-y3;

CLASSES = c (3);

ANALYSIS:

TYPE = mixture;

! The tech1 option is used to request the arrays containing parameter specifications and starting

! values for all free parameters in the model

! The tech11 option provides the LMR-LRT (Lo-Mendell-Rubin Likelihood Ratio Test)

! The tech14 option provides the BLRT (Bootstrap Likelihood Ratio Test)

OUTPUT: tech1 tech11 tech14;

SAVEDATA:

FILE = class.txt;

! Save posterior probabilities and most likely class membership to file

SAVE = cprob;

FORMAT = free;

Appendix C*The Mplus Code for the Latent Profile Analysis with A Distal Outcome*

TITLE: 3-class latent profile analysis with a distal outcome

DATA:

! enter the name of the data set

FILE = LPA.dat;

VARIABLE:

! y2 and y3 refer to information acquisition and transformation activities, respectively

! y4 is a continuous distal outcome (either diagnostic confidence or diagnostic efficacy)

NAMES = y1-y4;

USEVARIABLES = y2-y4;

CLASSES = c (3);

! Using the BCH method to estimate a distal outcome model

AUXILIARY = y4(bch);

ANALYSIS:

TYPE = mixture;

Bridging Text

In Chapter 4, I present an empirical study that examines what forms of cognitive engagement students demonstrate in the context of SRL and whether different forms of cognitive engagement predict students' task performance. Findings from this study provide strong support that students use an appropriate form of cognitive engagement that is cognitively efficient for problem-solving. Students do not always use the most sophisticated form of cognitive engagement. However, these findings provided only indirect evidence in support of the integrative model of SRL engagement presented in Chapter 2. Moreover, Chapter 4 did not advance the measurement of cognitive engagement since it relied exclusively on system log files to infer students' cognitive engagement.

The goal of Chapter 5 is to extend the research in Chapter 4 by testing more directly whether students can strategically regulate their cognitive engagement in SRL. This study also builds from the recommendations in Chapter 4 to measure cognitive engagement at a fine-grained size with advanced techniques. Consistent with Chapter 4, this empirical study is situated in the same task environment where medical students are required to diagnose virtual patients independently in an intelligent tutoring system. Whereas the participants recruited for the study in Chapter 4 were all medical students in a North America university, Chapter 5 consists of a different cohort, students who study medicine in China, to test the robustness of the findings regarding students' self-regulation of cognitive engagement.

Chapter 5. Manuscript 4

Automated Detection of Cognitive Engagement to Inform the Art of Staying Engaged in Problem-solving

Li, S., Lajoie, S.P., Zheng, J., Wu, H., & Cheng, H. (2021). Automated detection of cognitive engagement to inform the art of staying engaged in problem-solving. *Computers and Education*. 163, 104114. <https://doi.org/10.1016/j.compedu.2020.104114>

Abstract

In the present paper, we used supervised machine learning algorithms to predict students' cognitive engagement states from their facial behaviors as 61 students solved a clinical reasoning problem in an intelligent tutoring system. We also examined how high and low performers differed in cognitive engagement levels when performing surface and deep learning behaviors. We found that students' facial behaviors were powerful predictors of their cognitive engagement states. In particular, we found that the SVM (Support Vector Machine) model demonstrated excellent capacity for distinguishing engaged and less engaged states when 17 informative facial features were added into the model. In addition, the results suggested that high performers did not differ significantly in the general level of cognitive engagement with low performers. There was also no difference in cognitive engagement levels between high and low performers when they performed shallow learning behaviors. However, high performers showed a significantly higher level of cognitive engagement than low performers when conducting deep learning behaviors. This study advances our understanding of how students regulate their engagement to succeed in problem-solving. This study also has significant methodological implications for the automated measurement of cognitive engagement.

Keywords: Cognitive engagement, Facial behaviors, Machine learning, Problem solving, Self-regulation of engagement

Introduction

Engagement is a multidimensional construct that consists of three key components: behavioral, cognitive, and emotional engagement (Azevedo, 2015; D'Mello et al., 2017; Finn & Zimmer, 2012; Fredricks et al., 2004; Greene, 2015; Wolters & Taylor, 2012; Xie et al., 2019). Research on engagement stems from the literature on school engagement with a focus on educational failure and reform (Finn & Zimmer, 2012). In recent years, we have witnessed a gradual emphasis on student engagement at the individual level, in specific learning or problem-solving contexts. The present study examines students' cognitive engagement in the context of solving authentic problems. Cognitive engagement denotes the level of mental investment in learning, which is indicated by being thoughtful, persistent, and experiencing flow (Boekaerts, 2016; Rotgans & Schmidt, 2011). There is some evidence suggesting a positive correlation between cognitive engagement and students' performance (Chi & Wylie, 2014; Greene, 2015; Miller, 2015). However, there is a crucial question that needs to be answered. As educators, should we encourage students to stay highly engaged in problem-solving to succeed or should we teach students to manage their cognitive engagement in a way that maximizes outcomes with least effort? Put differently, do achievers need to stay highly engaged in problem-solving or do they need to regulate their cognitive engagement to solve problems? There is currently a paucity of empirical research on how students manage their cognitive engagement in learning and the relationship between engagement and performance (Azevedo, 2015; Boekaerts, 2016; Eccles, 2016; Galikyan & Admiraal, 2019; Rotgans & Schmidt, 2011).

Additionally, measurement instruments play key roles in determining how an area of research evolves (Winne, 2019). When it comes to the research on engagement, Boekaerts (2016) argued that "the success of future research on engagement critically depends on the

availability of validated instruments (p.78)". To date, researchers have relied intensively on self-report survey data when measuring cognitive engagement (Henrie et al. 2015; Xie et al., 2019). These findings are somewhat surprising, given advances in technology-rich learning environments that provide affordances to study the temporal nature of student engagement. Stagnation in methodological advances has hampered theoretical developments of student engagement (Azevedo, 2015; Boekaerts, 2016; D'Mello et al., 2017; Rotgans & Schmidt, 2011). More recently, researchers have been exploring the possibility of using facial movements to infer students' engagement (Grafsgaard et al., 2013; Monkaresi et al., 2016; Thomas & Jayagopi, 2017; Whitehill et al., 2014). However, these studies viewed engagement as a general term rather than as a meta-construct that includes different components such as behavioral and cognitive engagement (Xie et al., 2019). To our knowledge, no studies have inferred students' cognitive engagement from their facial behavioral cues in the process of solving authentic problems. Therefore, the purpose of this study is two-fold: examining how students manage their cognitive engagement to solve authentic problems; and exploring whether or not cognitive engagement can be inferred from students' facial behavioral cues. This study provides researchers with both theoretical and methodological insights.

Theoretical Background

Self-regulation of Engagement

Self-regulated Learning (SRL) refers to a dynamic and cyclical process whereby students actively control, monitor, and adapt different aspects of learning (i.e., behavioral, cognitive, metacognitive, motivational, and emotional aspects) toward the fulfillment of personal goals (Pintrich, 2004; Schunk & Greene, 2018; Winne, 2018; Zimmerman, 2000). It is a widely adopted theoretical framework to understand the functioning of students' learning processes and

their relations to performance. Considering that self-regulated learners should be cognitively engaged in learning or in problem-solving, there is a substantial conceptual consistency and little practical difference between the cognitive aspect of self-regulation and cognitive engagement in the current literature (Wolters & Taylor, 2012). For instance, some researchers defined cognitive engagement as including the use of self-regulation strategies such as rehearsal and summarization (Greene, 2015; Miller, 2015). Consequently, there is a growing interest in integrating cognitive engagement into the self-regulation framework (Cleary & Zimmerman, 2012; Wolters & Taylor, 2012). As an example, Cleary and Zimmerman (2012) proposed a definition of SRL engagement, which referred to the extent to which learners think strategically across the three phases of SRL, i.e., forethought, performance, and self-reflection. This definition focused heavily on the notion of being cognitively and strategically engaged in learning. Hence, when we mentioned the term of self-regulation of engagement in the present study, we also meant self-regulating the cognitive aspect of engagement, i.e., cognitive engagement.

In a previous study we elaborated upon Cleary and Zimmerman's (2012) research to explain the process of self-regulating one's cognitive engagement. In particular, we defined cognitive engagement as the extent to which individuals think strategically across the learning or problem-solving process in a specific task. Our definition was adapted from Cleary and Zimmerman's (2012) definition of SRL engagement, which highlighted the ever-changing nature of cognitive engagement. In line with the research of Miller (2015), our definition also suggested that cognitive engagement consists of two dimensions: how much mental effort (quantitative dimension) a student allocates to different learning strategies (qualitative dimension). From a self-regulation perspective, students can purposely plan, control, and regulate their cognitive engagement across the learning or problem-solving process. Before solving a learning task,

students first analyze the task features, set personal goals, and make strategic plans. In particular, self-regulated learners can plan what learning strategies to use (i.e., strategic planning) and also establish expectations for the levels of mental effort needed for different learning strategies (i.e., effort planning) to reach their goals. The strategic and effort planning processes are driven by an individual's predetermined goal, which determines the initial level of their cognitive engagement. In the process of solving a task, students control and monitor the quantitative and qualitative dimensions of cognitive engagement (i.e., learning strategies and corresponding mental effort) to reduce performance discrepancy against a goal state. Moreover, they evaluate whether or not the assembling of learning strategies and mental effort is sufficient for reaching expected performance. For instance, two students may perform the same learning behavior, but they vary in how much mental effort is exerted on this behavior. If students find that the current levels of cognitive engagement for either a specific type of learning strategy or amount of invested mental effort are not sufficient, they reassemble the two dimensions of cognitive engagement for the next step of problem-solving. While SRL emphasized the processes of controlling and monitoring to achieve learning goals (Winne, 2019), the central idea of self-regulation of engagement is to optimize the goal-pursuing process by adaptively allocating an *appropriate* amount of mental effort on different learning strategies in SRL. Nevertheless, there are few empirical studies examining how students regulate their cognitive engagement in SRL over time due to lack of theoretical foundations and methodological stalemate (Azevedo, 2015; Boekaerts, 2016; Cleary & Zimmerman, 2012; D'Mello et al., 2017; Eccles, 2016).

Automated Measurements of Engagement

Engagement can be measured by a multitude of instruments and techniques. One challenge of measuring engagement is to determine the grain size of measurement, which refers

to “the level at which engagement is conceptualized, observed, and measured” (Sinatra et al., 2015, p. 2). According to Sinatra et al. (2015), the grain size of engagement measurement can range from a microlevel to a macrolevel. At a microlevel, researchers use a person-oriented approach to measure an individual’s engagement in a specific task or activity. Measurement at a microlevel could include trace data, response time, physiological or psychophysiological indicators such as eye tracking, facial expression, and body movements. At a macrolevel, which is context-oriented, researchers capture student engagement from a more holistic, contextualized, and social theoretical perspective, taking the characteristics of social culture, community, school, and classroom into account. Researchers may use discourse analysis, teacher ratings, interviews, classroom observations, as well as cultural and critical analyses (Sinatra et al., 2015). When it comes to automated measurements of engagement, a microlevel grain size of measurement is superior to macrolevel measures given that engagement data can be collected automatically at fine-grained temporal resolutions in a particular learning activity.

Traditional measures of engagement include self-report scales, observations, interviews, teacher ratings, experience sampling method, and discourse analysis (Azevedo, 2015; D’Mello et al., 2017; Fredricks & McColskey, 2012; Greene, 2015). While traditional measures of engagement are useful with rich implementation and analytical guidelines, they suffer from several limitations. For example, they cannot capture the dynamics of engagement at a microlevel. Moreover, they are usually labor-intensive and time-consuming. As noticed by D’Mello et al. (2017), the field needs radical improvements in measurement approaches that capture “fine-grained components of engagement in a fully automated fashion (p. 104)”. Only when engagement can be measured fully automated in fine-grained size can we address questions about how engagement changes over time and how to provide real-time interventions.

D'Mello et al. (2017) conceptualized this new and promising approach as the advanced, analytic, and automated (AAA) approach, with its methodological foundation being rooted in digital signal processing and machine learning.

According to Whitehill et al. (2014), there were three classes of automated, real-time measurements of engagement. The first class of automated engagement measurement is based on the log files generated in intelligent tutoring systems. Specifically, log files can provide detailed information about the timing, frequency, antecedents, and outcomes of learning activities, whereby researchers examine the depth of information processing in learning and consequently students' engagement levels. For instance, many studies have used the time spent on specific learning behaviors as indicators of students' cognitive engagement (Greene, 2015; Helme & Clarke, 2001; Li et al., 2018). Physiological and neurological sensors are another method of measuring engagement with respect to arousal. The sensors usually collect electrical signals produced in the skin (Electrodermal activity, EDA), brain (Electroencephalograph, EEG), or muscles (electromyogram, EMG) as students engage in learning or problem-solving activities. Researchers then analyze the levels of arousal in those electrical signals to make inferences about students' engagement states. The third kind of automatic engagement recognition is based on computer vision. This approach uses advanced computational techniques (e.g., deep learning models) to estimate an individual's engagement by analyzing facial behavioral cues, body posture, and hand gestures recorded in digital images (Grafsgaard et al., 2013; Monkaresi et al., 2016; Thomas & Jayagopi, 2017; Whitehill et al., 2014).

The research on the relationships between facial behaviors and engagement is still in its infancy. We conducted a comprehensive literature search to find that limited studies have shed light on the automated detection of engagement from facial behavioral cues. As an example,

Grafsgaard et al. (2013) traced students' facial movements (i.e., eyebrow raising, brow lowering, eyelid tightening, and mouth dimpling) to predict their engagement and affective states during tutoring, using the Computer Expression Recognition Toolbox (CERT). In particular, they defined engagement as the overall success of the interaction with the tutoring system and users' willingness to recommend the system to others in the future. They found that upper face movements were predictors of students' engagement. Monkaresi et al. (2016) also used students' facial features to build engagement-detection models based on the ground-truth measurements of concurrent and retrospective self-reported engagement. Specifically, Monkaresi et al. (2016) asked students to verbally report their engagement (i.e., engaged or not) as they completed a structured writing activity. The focus of Whitehill's et al. (2014) study was to examine whether or not automatic engagement detection from facial expressions can reach a similar level of accuracy to that of human observers. They classified engagement in four levels, i.e., not engaged at all, nominally engaged, engaged in task, and very engaged. Nevertheless, Whitehill et al. (2014) acknowledged that the guidelines for labelling the four levels of engagement included not only elements of behavioral engagement but also cognitive and emotional engagement. In sum, studies on the automated detection of engagement from facial behaviors vary radically in how researchers operationalized engagement. No research has explicitly defined cognitive engagement and inferred this construct from facial behaviors using computer vision techniques. In addition, vision-based methods for engagement recognition are context-dependent (Whitehill et al., 2014). To the best of our knowledge, no studies have explored the automated measurement of cognitive engagement in the context of clinical reasoning.

Current Study

The present study has two research goals. The first goal examines whether or not facial behavioral cues reveal reliable information about students' cognitive engagement as students solve clinical reasoning problems. Meeting this objective could advance the state-of-the-art of automated measurement of cognitive engagement by providing researchers a unique tool to capture real-time cognitive engagement in an automated fashion. Our second goal is to examine how students manage their cognitive engagement levels in general, and specifically when performing different learning strategies in clinical reasoning. We focused on clinical reasoning since cognitive engagement is essential for students to solve clinical problems and to develop diagnostic competence (Linsen et al., 2018). Clinical reasoning requires declarative knowledge as well as the acquisition of procedural knowledge for establishing a diagnosis. The outcome of clinical reasoning includes not only the development of critical thinking and reasoning skills but also a sound, reliable clinical judgement to an authentic patient problem. Due to the uncertainty of diagnosing the patient accurately, clinical reasoning requires students to be effectively and cognitively engaged throughout the reasoning process otherwise adverse events may occur. As noticed by Jessee (2018), "most current clinical education is implemented in a traditional group model" (p. 8), and the grain size of measurement and analysis of students' engagement is too large to capture its variations in a particular task. Our objective is to deepen our understandings of how individual students allocate their cognitive engagement in clinical reasoning and ultimately, to inform research on effective interventions. Findings from this study also inform the theoretical framing of self-regulation of engagement.

Our specific research questions are: (RQ1): Can we predict students' cognitive engagement by their facial behavioral cues? (RQ2): How do high and low performing groups

allocate their cognitive engagement during the problem-solving process? For the first research question, we hypothesized that students' facial behavioral cues are effective indicators of their cognitive engagement in the context of clinical reasoning, since some progress has made in measuring engagement from facial behavioral cues in other contexts (Grafsgaard et al., 2013; Monkaresi et al., 2016; Whitehill et al., 2014). For our second research question, we cannot propose specific hypotheses since research on self-regulation of engagement is still in an early stage (Wolters & Taylor, 2012). Consequently, we explore the possibility of two contentions in the context of clinical reasoning. One is that students should sustain a high level of cognitive engagement throughout the problem-solving process to succeed. The other contention is that students can and should effectively manage their cognitive engagement levels to maximize problem-solving outcomes. Based on the SRL literature, however, we can make some assumptions. Specifically, we anticipate that students can self-regulate their cognitive engagement to be more efficient problem solvers in clinical reasoning. Specifically, we expect that there would be no difference in cognitive engagement levels between high and low performers in general. Nevertheless, high performers would be more cognitively engaged in deep learning behaviors than low performers.

Method

Participant

Prior to the study, ethics approval was obtained from the Research Ethics Board Offices of a large North American university and a top Chinese university. The participants consisted of 61 medical students (52.5% males) who came from the university located in Beijing, China. All the participants were in their third year of medical studies, with an average age of 21. Moreover, they all could speak English. In addition, they were taking a mandatory course of

Pathophysiology, which is the study of the disordered physiological processes and their associations with diseases. Therefore, the students shared the same level of knowledge on the problem-solving scenarios, i.e., diagnosing virtual patients.

Learning Environment and Task

The participants in this study were required to diagnose a virtual patient (VP) in a simulation-based environment of BioWorld (Lajoie, 2009). See Figure 4. BioWorld is an intelligent tutoring system designed to help medical students practice clinical reasoning skills. In BioWorld, students begin the diagnosis by reading a patient case description, during which they need to collect relevant information that informs their diagnosis. Patient symptoms and history (e.g., extreme thirst, weight loss) are collected as evidence items to inform their decisions. The collected evidence items are stored in the evidence palette, which serves as a metacognitive tool for students to monitor what and how much information they have gathered for the diagnosis. Students can order medical lab tests (e.g., blood sugar levels, urinalysis) in the system to obtain more information about the patient. Moreover, students can search a library within the system if they are not familiar with a particular disease or test. Students can propose one or more diagnostic hypotheses and they confirm or disconfirm those hypotheses in the process of acquiring information (i.e., collecting evidence items, ordering lab tests, and searching library). Afterward, students need to check the relevance of evidence items and lab tests towards their diagnostic hypotheses. Meanwhile, they link relevant evidence items and lab tests with corresponding diagnoses. After submitting a final diagnostic hypothesis, students rank evidence items and lab tests based on their importance to the diagnosis. Finally, students write a case summary of how they diagnosed the patient case.

The VP case used in this study was created jointly by a panel of medical experts and learning scientists, and the correct diagnosis was Diabetes Mellitus Type 1. Prior to the study, the teaching office in the School of Basic Medical Sciences and another three medical professors from the Department of Physiology and Pathophysiology at the university where the study was conducted reviewed the patient case to ensure it was a suitable practice for the participants.

Figure 4

The Intelligent Tutoring System of BioWorld

Collecting Evidence Items

Ordering Lab Test

Managing Hypotheses

Searching Library

Procedure

A training session was provided to help students familiarize themselves with the BioWorld system a week before the study. Students had the opportunity to go over the diagnostic procedures repeatedly with a sample case. In the study, students were asked to log into the

system and diagnose the VP independently. Students' facial behaviors during the problem-solving process were video-recorded using a webcam and the OBS (Open Broadcaster Software) Studio. Specifically, students were asked to start the video recording manually when they confirmed their faces were in the webcam, and they were ready to solve the patient case. They ended the recording after they finished the diagnosis. The OBS Studio is an open-source, cross-platform software suite for live streaming and recording. The resolution for the recorded videos was set as 1152 x 720p. There were no students wearing religious face coverings, but we reminded students not to cover their faces with any parts of their body during the problem-solving process. Students were informed that they could ask for help if they encountered technical issues; however, other questions were not allowed during problem-solving. The recorded videos were stored in the computer hard drives and were uploaded by students to a free cloud storage space that was only accessible with authorization.

Moreover, we used the event-based experience sampling method (ESM) to measure students' cognitive engagement during the problem-solving process, wherein the situational cognitive engagement instrument was triggered three times. As pointed out by Järvelä et al. (2008), ESM is a promising technique to explore a student's intra-psychological states as the individual's feelings, thoughts, or actions are measured repeatedly while the event is actually happening in real-time. Therefore, ESM can be used to collect data on engagement in the moment rather than retrospectively, which helps reduce the problems with recall failure (Fredricks & McCloskey, 2012; Sinatra et al., 2015). In this regard, ESM is more accurate than traditional self-report measures as participants are still in the proximity of time and space when giving responses (Sinatra et al., 2015; Xie et al., 2019). Moreover, ESM allows for a more fine-grained exploration of engagement in learning activities, given that an ESM device usually emits

stimulus signals multiple times in a study (Xie et al., 2019). The event-based ESM alerts participants to fill out a self-report questionnaire when a particular event of interest occurs. In particular, students were required to provide responses to the instrument when they finished any of the following activities: collection of evidence items, confirmation of final diagnosis, and submission of a diagnosis summary. In addition, all operational behaviors and corresponding timestamps for each student were automatically recorded in the log files of the BioWorld as they proceeded to diagnose the patient. See Appendix D for an illustration of the data collection settings. On average, students spent 40 minutes accomplishing the task during school hours.

Measurement

Cognitive Engagement

The situational cognitive engagement instrument was devised and validated by Rotgans and Schmidt (2011), who argued that it could capture students' cognitive engagement in situ. The instrument is a short questionnaire consisting of four items that measure three facets of engagement, i.e., (1) engagement with the task at hand ("I was engaged with the task at hand"), (2) effort and persistence ("I put in a lot of effort", "I kept thinking deeply about the task"), and (3) experience of flow ("I was so involved that I forgot everything around me") (Rotgans & Schmidt, 2011). The four items of the instrument were presented using a 5-point Likert scale with 1 for 'strongly disagree', 3 for 'neutral', and 5 for 'strongly agree'. The measure of Cronbach's alpha was used to assess the reliability or the internal consistency of the instrument, which yielded a value of .821 for this study. Therefore, the combination of the instrument and the ESM technique was considered adequate, considering that ESM studies usually involved a small number of items (Fredricks & Mccolskey, 2012).

Performance

Students' performance was assessed by whether or not they reported a correct diagnosis. Four students did not submit a final diagnosis, leaving the sample size of 57 when it came to the analyses related to students' performance. In particular, there were 21 and 36 students who provided a correct and incorrect diagnosis, respectively. We considered the students who correctly diagnosed the VP as high performers and the rest as low performers.

Data Preprocessing

During the problem-solving process, there were 59 students who reported their cognitive engagement for a total of 167 times. We aligned the period between self-reports with corresponding video segment that captured students' facial behaviors. For example, we aligned the video segment starting from the end of a student's first self-reports to the time point where they started to fill in the second questionnaire. Since students reported their cognitive engagement for 167 times, the recorded videos were labelled into 167 segments accordingly. For each video segment, we removed the video frames during which students were reporting on their thoughts and feelings about engagement. In addition, we also removed the obscure images and the images where students' faces were covered from the videos, which accounted for a percentage of 3.9% of the facial expression videos on average.

For students' problem-solving behaviors, we coded two categories of strategic behaviors (i.e., surface and deep learning behaviors) from raw trace data following the practice of Greene et al. (2019). As aforementioned, students performed eight types of diagnostic behaviors to solve the patient case (see Table 10). The eight types of behaviors were then aggregated into two categories of behaviors. Specifically, the behaviors of *collecting evidence items*, *ordering lab tests*, and *searching library* were identified as information acquisition, a process whereby students took in information from the environment. We labelled these three behaviors as surface

learning behaviors. We considered the behaviors of *proposing hypotheses*, *categorizing*, *linking*, and *prioritizing evidence items and results*, and *writing case summary*, as deep learning behaviors. When conducting deep learning behaviors, students engaged in a different level of information processing, whereby they used various strategies such as speculation, argumentation, and self-reflection to accomplish the task. The categories of surface and deep learning behaviors aggregated similar activities into less granular classes, which were better predictors of students' performance than specific problem-solving behaviors (Greene & Azevedo, 2009).

Table 10

The Surface and Deep Strategic Behaviors in Clinical Reasoning

Category	Clinical Behaviors	Code	Description
Surface	Collecting evidence items	CO	Collecting evidence items from the patient description by recalling one's prior knowledge pertaining to the symptoms
	Ordering lab tests	AD	Conducting medical lab tests
	Searching library	SE	Searching for particular information in the library for additional explanations
Deep	Proposing hypotheses	RA	Outlining a single or multiple diagnostic hypothesis based on the collected evidence
	Categorizing evidence/results	CA	Checking the relevance of evidence items and lab test results towards specific hypothesis (i.e., whether the evidence/tests in support, against or neutral of one hypothesis)
	Linking evidence/results	LI	Justifying the probability of a hypothesis being correct to the disease
	Prioritizing evidence/results	PR	Ranking evidence items and lab test results according to their importance to a hypothesis
	Summarization for final diagnosis	SU	Making the final diagnosis by writing a summarization

Note: the coding scheme was developed by Li et al. (2018).

Data Analysis

To address our first research question, we followed four main steps to detect students' cognitive engagement states from their facial behavioral cues. For the first step, we applied the K-means clustering algorithm to classify students' problem-solving processes into engaged and less engaged states. We used students' cognitive engagement states rather than the levels of cognitive engagement because this practice could significantly improve the accuracy of our prediction model. We then analyzed the recorded videos of students' facial behaviors to extract facial features using the OpenFace 2.0. Next, a feature selection technique was applied to the facial behavioral data to reduce the dimensionality of the feature space. Finally, we used supervised machine learning classification techniques on selected features to predict students' cognitive engagement states. We discussed below the classification of cognitive engagement states, feature extraction, feature selection, and model building in detail.

Cognitive Engagement States

K-means clustering is the most commonly used unsupervised machine learning algorithm for classifying a given dataset into k clusters. In particular, the K-means algorithm aims to choose centroids that minimise the total within-cluster variation. In this study, we used the standard algorithm, which defines the total within-cluster variation as the sum of squared Euclidean distances between items and the corresponding centroid. See the equation 1.

$$\sum_{k=1}^k W(C_k) = \sum_{k=1}^k \sum_{x_i \in C_k} (x_i - \mu_k)^2 \quad (1)$$

where k refers to the number of the clusters, x_i is a data point of the cluster C_k , and μ_k is the mean value of the points assigned to the cluster C_k

Feature Extraction

We used OpenFace 2.0 to extract students' facial features from the recorded videos of their facial behaviors. OpenFace 2.0 is a tool intended for automatic facial behavior analysis. It consists of computer vision algorithms for eye-gaze estimation, head pose estimation, and facial action unit recognition. In particular, facial action unit recognition is one of the main building blocks in automatic facial expression analysis, and it describes facial muscle activations (Baltrušaitis et al., 2015; Ekman, 1997). It is noteworthy that OpenFace 2.0 employed a person-specific normalisation approach in the training and modeling of facial behaviors in order to address the individual difference challenge (Baltrušaitis et al., 2015). Moreover, the tool is able to analyze an individual's facial behaviors from a simple webcam without any specialist hardware (Baltrušaitis et al., 2018).

In this study, the recorded videos were analyzed at 30 frames per second and the 31 features were extracted for each frame. The extracted features and corresponding explanations were shown in Table 11. Therefore, the output for each participant was a matrix consisting of 31 feature columns and approximately 72,000 rows, since students took 40 minutes to accomplish the task on average. In line with Thomas and Jayagopi's (2017) research, we calculated the mean and the standard deviation of gaze- and pose-related parameters and the mean of each facial action unit, which yielded a total of 45 predictors.

Table 11*The Extracted Features from the OpenFace System*

	Parameters	Notes
Gaze	Gaze_0_x, Gaze_0_y, Gaze_0_z, Gaze_1_x, Gaze_1_y, Gaze_1_z	Eye gaze direction vector in world coordinates for the leftmost eye (0) and the rightmost eye (1)
	Gaze_angle_x, Gaze_angle_y	Eye gaze direction in radians in world coordinates averaged for both eyes. An individual looking left-right and up-down will result in changes of Gaze_angle_x and Gaze_angle_y, respectively.
Pose	pose_Tx, pose_Ty, pose_Tz	The location of the head with respect to camera in millimeters
	pose_Rx, pose_Ry, pose_Rz	The rotation of the head in radians around X, Y, Z axes
Facial Action Units	AU01, AU02, AU04, AU05, AU06, AU07, AU09, AU10, AU12, AU14, AU15, AU17, AU20, AU23, AU25, AU26, AU45	The system can detect the intensity (from 0 to 5) of 17 facial action units. These action units refer to inner brow raiser, outer brow raiser, brow lowerer, upper lid raiser, cheek raiser, lid tightener, nose wrinkler, upper lip raiser, lip corner puller, dimpler, lip corner depressor, chin raiser, lip stretcher, lip tightener, lips part, jaw drop, lip suck, and blink, respectively.

(Baltrušaitis et al., 2018; Ekman, 1997)

Feature Selection

We used recursive feature elimination (RFE) to determine the optimal subset of the predictors, considering the inclusion of irrelevant variables can negatively impact the performance of predictive model. RFE is basically a backward selection of the predictors (Guyon et al., 2002). It begins by building a model on the entire set of predictors and computing an importance score for each predictor. It then eliminates the least relevant feature, rebuilds the model, and computes the importance score again. In this study, random forest (RF) is used with

REF because the combination of the two algorithms provides unbiased and stable results with improved accuracy (Granitto et al., 2006). In addition, RF has a well-known internal method for measuring feature importance and helps to avoid overfitting (Fawagreh et al., 2014).

Specifically, a RF algorithm with 10-fold cross validation is implemented on each iteration of the feature elimination process. The Root Mean Square Error of cross validation ($RMSE_{CV}$) is calculated to determine the goodness-of-fit of the RF model. In particular, $RMSE_{CV}$ is estimated by the equation 2 and 3.

$$RMSE_{CV} = \sqrt{\sum_{i=1}^{10} \frac{RMSE_i^2}{10}} \quad (2)$$

$$RMSE_i = \sqrt{\sum_{j=1}^{N_i} \frac{(\hat{y}_{ij} - y_{ij})^2}{N_i}} \quad (3)$$

where $\hat{y}_{ij}$ and y_{ij} refer to the predicted value and the observed value, respectively, and N_i is the number of observations of cross validation instance i . The RF model with a minimum $RMSE_{CV}$ is set as the optimal model. The subset that builds the optimal RF model are then selected to train the final predictive model.

Machine Learning Models

Five types of machine learning classification techniques, including Naïve Bayes, k-NN, decision tree, random forest, and Support Vector Machine, were used on selected features to predict students' cognitive engagement states. We compared the performance of these five machine learning algorithms by checking the AUC (Area Under the Curve) – ROC (Receiver Operating Characteristics) curve, one of the most important evaluation metrics for assessing classification model's performance (Fawcett, 2006). In general, a ROC is a probability curve showing the performance of a classification model at different thresholds, and an AUC represents the model's overall capacity for distinguishing between classes. An AUC falls

between 0.7 to 0.8, 0.8 to 0.9, and above 0.9 is considered acceptable, excellent, and outstanding, respectively (Mandrekar, 2010).

Once an optimal machine learning model is determined, we use that model to predict students' cognitive engagement when they perform shallow and deep strategic behaviors. As mentioned before, we identified the time slots when students were engaged in shallow and deep behaviors. We then applied the optimal machine learning model to predict each student's cognitive engagement state (i.e., engaged or less engaged) at each 10-s interval, using the 10-s momentary time sampling method (Muis et al., 2015; Ozdemir, 2011). The 10-s interval allows for a reliable detection of changes in engagement states. It is also an appropriate grain size for this study given that students spent 40 minutes accomplishing the task. We calculated an individual's cognitive engagement level as the proportion of engaged states to total states (i.e., the sum of engaged and less engaged states). In particular, students' cognitive engagement levels for shallow and deep behaviors were calculated separately. To address our second research question, we compared the differences in cognitive engagement levels of both shallow and deep behaviors between high and low performing students.

Results

(1) Can we predict students' cognitive engagement by their facial behavioral cues?

As mentioned before, the K-means clustering algorithm was used to label students' problem-solving segments into either engaged or less engaged states. In particular, the algorithm clustered on the four items measuring situational cognitive engagement, and the number of clusters was set as two. The results in Table 12 showed that 82 and 85 segments were identified as engaged and less engaged states, respectively.

Table 12*The Centroids of Engaged and Less Engaged States Identified by K-means Algorithm*

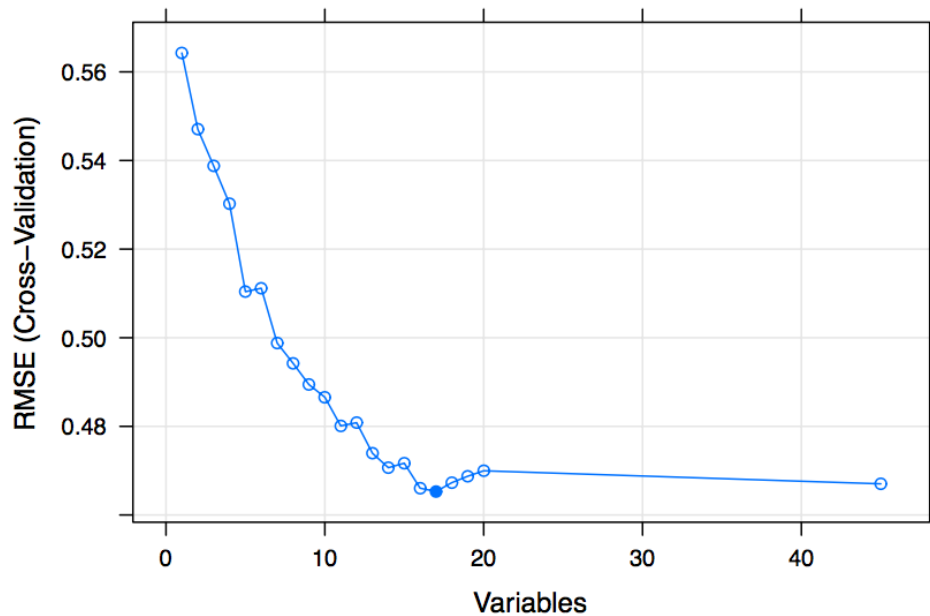
States	Item1	Item2	Item3	Item4	No.
Engaged	4.22	4.28	4.20	3.94	82
Less Engaged	3.15	3.20	3.22	2.70	85

Note: Item 1-4 represent the four items measuring situational cognitive engagement, No. = the number of engaged or less engaged states.

In order to remove irrelevant parameters concerning students' facial behavioral cues, we applied the recursive feature elimination-random forest (RFE-RF) on 45 facial features, which consist of three categories of facial behaviors: eye-gaze, head pose, and facial action unit (see Table 11). Figure 5 plotted the number of features along with their cross-validated RMSE (Root Mean Square Error) test scores. The figure showed that the curve had a minimum RMSE of cross validation when 17 informative features were added into the model, indicating the optimal number of features was 17. The selected features were shown in Table 13. Specifically, the 17 features included 4 gaze-related parameters, 5 head pose parameters, and 8 facial action units.

Figure 5

Resampling RMSE Estimates for Random Forests Across Different Subset Sizes



Note: RMSE = Root Mean Square Error. RMSE tells how concentrated the data is around the line of best fit. The figure shows that the best subset size was estimated to be 17 predictors, yielding the minimum RMSE of cross validation.

Table 13

The Features Selected Using Recursive Feature Elimination

	Parameters
Gaze	Gaze_0_x, Gaze_1_x, Gaze_1_z, Gaze_angle_x
Pose	pose_Tx, pose_Tz (M & SD), pose_Ry, pose_Rz
Facial Action Units	AU01, AU04, AU14, AU17, AU20, AU23, AU25, AU45

Note: The meaning of each parameter was explained in Table 11. pose_Tz (M & SD) refers to two parameters – the mean of pose_Tz and the standard deviation of pose_Tz. The rest parameters refer to their mathematical means.

We then trained the five types of supervised machine learning models (i.e., Naïve Bayes, k-NN, decision tree, random forest, and Support Vector Machine) on the selected 17 features of facial behavioral cues, taking students' self-reports of cognitive engagement states as the ground-

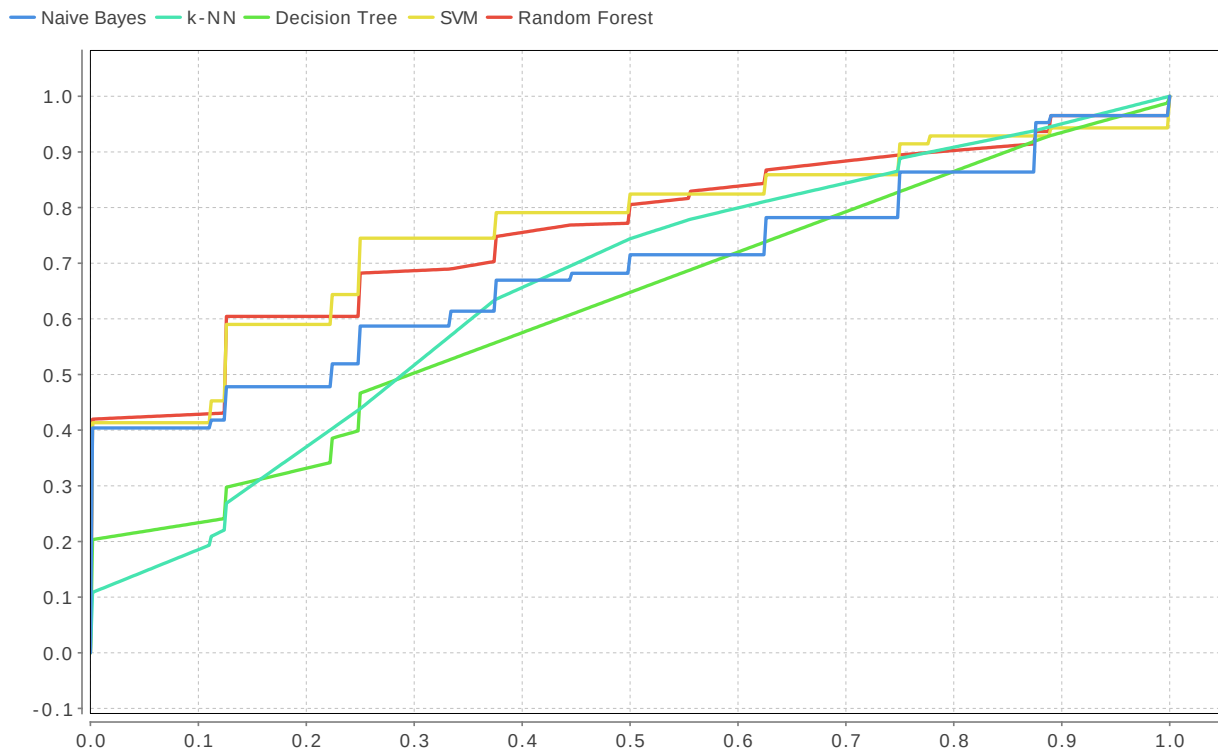
truth. In particular, we used a 10-fold cross-validation during the training process to avoid overfitting and to check the generalization ability of the models. Since the training and the validation processes are repeated 10 times with different subsamples, the method can produce reliable and unbiased results on small datasets (Bengio & Grandvalet, 2004). The results of the 10-fold cross-validation of the five models were shown in Table 14. Specifically, the results showed that the model evaluation metrics of both accuracy and precision of the SVM (Support Vector Machine) were larger than that of the other models. In addition, the AUC results also suggested that the SVM model demonstrated the best overall capacity for distinguishing classes among all of the five algorithms. Notably, the AUC value of the SVM model was .801, which is excellent according to Mandrekar (2010). Moreover, we compared the ROC curves of different models (see Figure 6) which indicated that the SVM model performed best in general.

Table 14

10-fold Cross Validation of Different Models in Predicting Cognitive Engagement

Model	Accuracy (%)	Precision (%)	AUC
Naïve Bayes	64.85	73.24	.684
k-NN	65.29	67.65	.719
Decision Tree	62.98	81.83	.589
Random Forest	72.54	80.12	.780
SVM	74.82	83.41	.801

Note: k-NN = k-Nearest Neighbor algorithm, SVM = Support Vector Machine, AUC = Area Under the Curve. AUC is an indicator of the overall performance of a classification model. An AUC above .70 is considered acceptable. Accuracy = Number of correct predictions / Total number of predictions. Precision = True Positive / (True Positive + False Positive).

Figure 6*ROC Curve to Comparing the Performance of Classification Models*

Note: The ROC curve was plotted with true positive rate (the vertical axis) against false positive rate (the horizontal axis). True positive rate = True Positive / (True Positive + False Negative). False positive rate = False Positive / (False Positive + True Negative). A model with perfect skill is represented by a line that travels from the bottom left of the plot to the top left and then across the top to the top right.

(2) How do high and low performing groups allocate their cognitive engagement in the problem-solving process?

To address this question, we first partitioned each student's problem-solving process into surface and deep learning segments based on the coding scheme shown in Table 10. Specifically, students' problem-solving processes were coded into 200 surface and 190 deep learning segments. We further split each segment into 10-s intervals, which yielded 10,541 and 4,609

intervals for surface and deep learning, respectively. For each 10-s interval, we used the SVM model to predict students' cognitive engagement states (i.e., engaged or less engaged) based on the 17 facial features extracted from corresponding intervals. In total, there were 7,419 and 3,122 intervals that were modeled as engaged and less engaged states respectively when performing surface learning behaviors. Meanwhile, 3,143 and 1,466 intervals were identified as engaged and less engaged states respectively as students conducted deep learning behaviors. Regarding each student's cognitive engagement level during surface learning, it was calculated as the proportion of engaged states to total states. In the same vein, we calculated the cognitive engagement level for each student when they engaged in deep learning behaviors.

We compared the differences in cognitive engagement levels between high and low performers in general and for the periods when they engaged in shallow and deep learning. As aforementioned, high performers were those who provided a correct diagnosis and low performers were those who failed to diagnose the case correctly. Since we adopted the experience sampling method to collect information on students' situational cognitive engagement in problem-solving, we used the mean of the three self-reports to represent an individual's overall engagement level. As shown in Table 15, there was no significant difference in students' self-reported engagement in general between high and low performers. There was also no difference in cognitive engagement levels between high and low performing groups as they engaged in shallow learning behaviors. Nevertheless, high performers demonstrated significantly higher levels of cognitive engagement ($M = .82$) than low performers ($M = .64$) when performing deep learning activities, $t(55) = 3.68, p = .001$. The effect size for the difference was large, with Cohen's $d = .88 > .80$ (Cohen, 1988).

Table 15*Differences in Cognitive Engagement Levels Between High and Low Performers*

Engagement	Performance	<i>M</i>	<i>SD</i>	<i>t</i>	<i>df</i>	<i>p</i>	<i>Cohen's d</i>
General level	High	3.64	.50	.44	55	.659	.12
	Low	3.57	.63				
Shallow learning	High	.75	.21	1.75	55	.085	.48
	Low	.65	.22				
Deep learning	High	.82	.13	3.68	55	.001**	.88
	Low	.64	.24				

*Note: ** $p < .01$*

Discussion

In this study, we examined whether or not students' cognitive engagement can be predicted by their facial behavioral cues. Unlike previous studies that have used a broad term of engagement in exploring automated measurement possibilities from students' facial behaviors, we used situational cognitive engagement data that was collected at the moment using an experience sampling method. The situational cognitive engagement data served as the grounded truth measure, and from that data we built a specific model for tracing students' cognitive engagement from their facial behavioral cues. Another notable difference between our study and previous research is that we took three categories of facial behavioral cues (i.e., eye gaze, head pose, and facial action units) into consideration, whereas most studies investigated only facial action units when developing automated measurement of engagement (Grafsgaard et al., 2013; Monkaresi et al., 2016). Moreover, a strength of this study is that we used the OpenFace, instead of the CERT (Littlewort et al., 2011), to extract facial behavioral cues from recorded videos. The

OpenFace applied the same techniques (i.e., face recognition with deep neural networks) that were used in Facebook's DeepFace and Google's FaceNet systems (Amos et al., 2016). Findings from this study revealed that students' facial behavioral cues were effective indicators of their cognitive engagement states. In particular, we found that the SVM (Support Vector Machine) model demonstrated excellent capacity for distinguishing engaged and less engaged states when 17 informative facial features were added into the model. In addition to the locations of head and eyes with respect to the camera, the selected 17 facial features included the behaviors of looking left-right, turning or tilting head to the left and right, as well as the facial action units of AU01(inner brow raiser), AU04 (brow lowerer), AU14 (dimpler), AU17 (chin raiser), AU20 (lip stretcher), AU23 (lip tightener), AU25 (lips part), and AU45 (blink). Since no studies have predicted cognitive engagement from eye gaze and head pose in the context of clinical reasoning, it is our contention that students may feel distracted if they look left-right or turn their heads left-right. As for head tilt, it usually indicates the occurrence of a range of cognitive mental states such as concentrating and thinking (El Kaliouby & Robinson, 2005). Moreover, our finding is partially consistent with the research of Grafsgaard et al. (2013), who found that AU01 and AU04 were predictors of student engagement, whereas AU14 predicted task performance and learning gains. In addition, our research corroborated the findings of Thomas and Jayagopi (2017), who found that AU17 was among the top facial features to predict student engagement in classrooms. According to Whitehill et al. (2014), AU45 was negatively correlated with engagement. In sum, the present study extends previous research on engagement detection in that it provides significant methodological insights regarding the automated measurement of cognitive engagement in the context of clinical reasoning. Students' facial behaviors, which are widely adopted to analyze students' facial expressions and emotions, can also provide continual

assessments of cognitive states at fine-grained temporal resolutions throughout the problem-solving process (D'Mello et al., 2017).

The novel approach of measuring cognitive engagement from facial behavioral cues can inform the design of intelligent tutoring systems (ITS), student assessment, and instructional interventions significantly. For one, students' facial behavioral cues provide another channel of data for the ITS community to build automatic engagement recognition systems. Such systems allow the delivery of real-time, automatic feedback based on an individual's engagement state that goes beyond log file indicators on student interactions. BioWorld, as an ITS, is no exception. For student assessment, the cognitive engagement recognition technique described in this study provides a feasible and economical solution to track the cognitive engagement of a substantial number of students, as they watch video lectures in technology-rich learning environments with their facial behaviors being recorded via a computer webcam. In doing so, many important questions pertaining to students' interactions with video lectures can be addressed. For example, what types of video lectures do students engage in most? Which parts of a specific video distract students from their studies? Hence, instructors can change teaching strategies accordingly based on the overall quality of students' cognitive engagement. Instructors can also provide personalized feedback or interventions to prevent certain individuals from disengagement.

Furthermore, this study found that high performers did not differ significantly in the general level of cognitive engagement with low performers. This finding was inconsistent with previous research proposing that cognitive engagement was positively associated with perceived learning and actual learning outcomes (Chen, 2017; Galikyan & Admiraal, 2019; Xie et al., 2019). We highlighted this finding because researchers tended to anticipate the contrary, which we believed would simplify the research on cognitive engagement and did not help to develop a

deep understanding of the complex process of how cognitive engagement was initiated, monitored, and regulated in learning. For example, Whitehill et al. (2014) explored the correlations between students' perceived engagement and learning gains as they completed a cognitive training task. It is noteworthy that they used two approaches to measure students' engagement. They asked human observers to review and rate the recorded videos for the appearance of engagement per ten seconds. Meanwhile, they used machine learning to develop automated engagement detectors from students' facial expressions. However, they found that engagement was not significantly associated with learning gain, using either human labels or automatic engagement judgments. Whitehill et al. (2014) stated that "the lack of correlation between engagement and learning was somewhat disappointing (p. 96)". It is our argument that cognitive engagement may develop as a function of learning phases, which could help explain the findings of Whitehill's et al. (2014) research and those with similar results. In addition, cognitive engagement is context dependent. Take this study as an example. Medical students are high-functioning in solving clinical problems, which can explain the non-significant difference in cognitive engagement between high and low performers.

An alternative explanation, as supported by the findings of this study, is that students can purposely regulate their cognitive engagement in the problem-solving process. In particular, we found that there was no significant difference in cognitive engagement levels between high and low performers when they performed shallow learning behaviors. However, high performers showed a significantly higher level of cognitive engagement than low performers when conducting deep learning behaviors. These findings were partially in line with the research of Greene et al. (2004), which argued that deep learning strategies led to greater achievement over shallow strategies. High performers did not sustain a higher level of cognitive engagement over

time than low performers but rather they regulated their cognitive engagement in a way that promoted deep processing of information (Cleary & Zimmerman, 2012; Galikyan & Admiraal, 2019). Future theoretical orientations on cognitive engagement may benefit from a dynamic perspective of this construct, the lens of self-regulation, and resource-depletion theories (Vohs et al., 2005). While theoretically important, these findings are also practical in that medical educators should allow the presence of shallow engagement in certain periods of clinical reasoning, since shallow engagement is not always dysfunctional and detrimental to performance. Moreover, medical practitioners should be aware of the points where high levels of cognitive engagement contribute most to clinical problem solving so that they can design instructional scaffoldings accordingly.

Although this study was exploratory in nature, it raised a number of promising opportunities for future research. First, much work remains to be done, especially those from the field of educational neuroscience, to clarify the mechanisms of AUs and their connections to engagement. Moreover, this study opens up new areas of research on the pattern of changes in cognitive engagement since the grain size of facial behavioral cues enables researchers to measure small contextual variations in engagement over a learning event. For example, Rotgans and Schmidt (2011) hypothesized that a wave-like pattern of students' cognitive engagement could emerge during a 1-day PBL (problem-based learning) event. Nevertheless, they found that students' cognitive engagement increased significantly and consistently as they progressed with their learning in PBL. Clearly more research is needed to examine the relationships between cognitive engagement patterns and task features. Furthermore, we situated our study in a simulation environment whereas future studies need to locate empirical evidence for the regulation of cognitive engagement within authentic classrooms or workplaces. In addition,

future studies may expect a performance improvement in the predictive model when more features (e.g., eye movements of fixation and saccades, body postures, and hand gestures) are considered along with facial behavioral cues. As noticed by Miller (2015), the eye-mind-engagement assumption (i.e., the length of visual fixation on an object reflects student engagement) was theoretically valid, and there was also empirical evidence to support this assumption. Lastly, it would also be interesting to explore the possibility of examining the interplay between cognitive engagement and other motivational and emotional factors in an automated fashion with fine-grained size.

Conclusion

This study extends the literature on students' cognitive engagement in both methodological and theoretical dimensions. First, the current study presented a novel methodological approach for measuring cognitive engagement from students' facial behavioral cues by leveraging the affordance of computer vision and machine learning techniques. In addition to our methodological contributions to the field, this study advanced the theoretical development of cognitive engagement. Specifically, we used the novel measurement methodology to explore differences in cognitive engagement between high and low performers as they performed either shallow or deep learning behaviors. Our results suggested that researchers may need to shift their focus from examining whether students are engaged or not to how students regulate their engagement in learning or problem-solving, in order to develop a deep understanding of students' decision-making processes and to provide instructional interventions accordingly. Along with the novelty in the research of automated measurement of cognitive engagement, as well as the contributions of empirical evidence to the theoretical framing of self-regulation of engagement, there are limitations to this study. Although we used

10-fold cross-validation to increase the robustness of our training models, the generalizability of the machine learning models and the SVM in particular cannot be guaranteed for students in different age groups and for different problem-solving contexts. In addition, students might manage their facial expressions and gestures in the problem-solving process as they were aware of the webcams that were recording their faces and behaviors. Another limitation is about the homogeneity of the participants with respect to their race and academic background. Given that cognitive engagement is a context-specific construct, a different cohort of participants is needed to verify the generalizability of our findings in other disciplines. For example, it would be fruitful to examine the differences in cognitive engagement and facial behavioral cues between medical and non-medical students. Moreover, the nonexperimental nature of this study prevents us from making causal inferences. Despite these limitations, this study lays the foundation for future advances in understanding the regulation of cognitive engagement and in cultivating efficient problem solvers.

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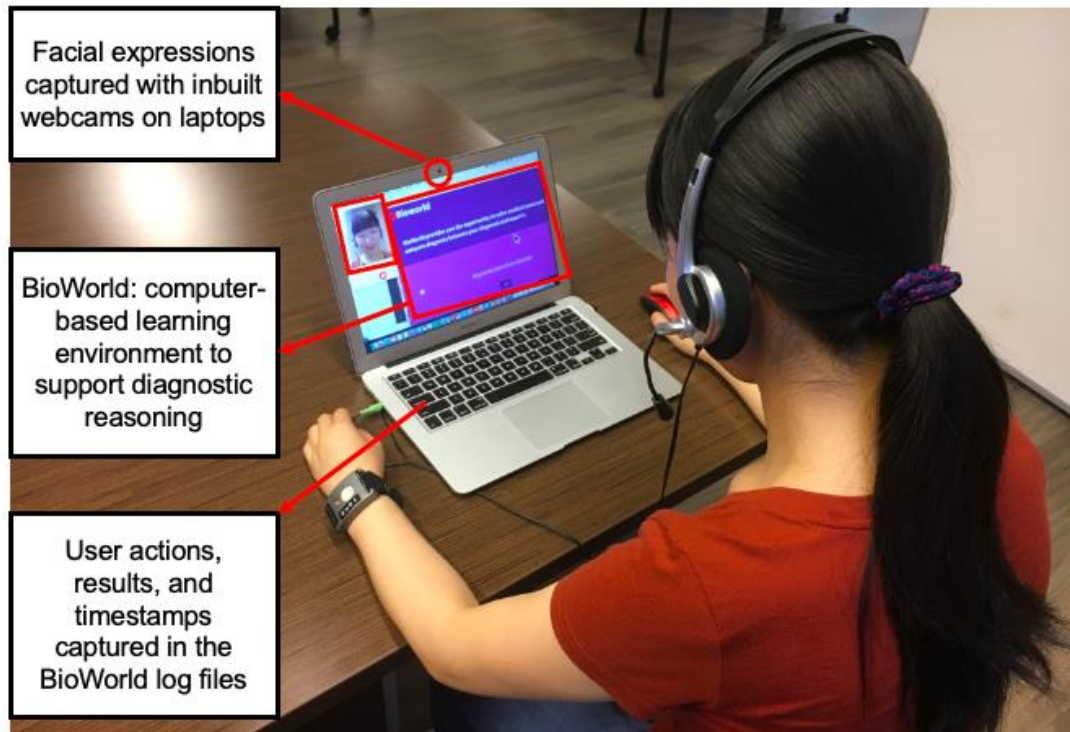
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Appendices

Appendix D

An Illustration of the Data Collection Settings



Chapter 6. Final Discussion

Research on cognitive engagement typically emphasizes the need to increase and maintain students' cognitive engagement to achieve learning goals (Chi & Wylie, 2014; Corno & Mandinach, 2004; Eccles, 2016; Finn & Zimmer, 2012; Fredricks et al., 2004; Furlong & Christenson, 2008; Zusho, 2017). While this research tradition continues to attract scholarly attention across disciplines, what is overlooked is the fact that students do not always need to raise their cognitive engagement to accomplish a learning task. Instead, students can strategically allocate an *appropriate* amount of mental effort on different types of learning strategies, which we framed as the self-regulation of cognitive engagement. However, the lack of theoretical frameworks on this topic has led to a fragmented body of research regarding how cognitive engagement dynamically changes across the SRL process (Azevedo, 2015; Boekaerts, 2016; Cleary & Zimmerman, 2012; D'Mello et al., 2017; Eccles, 2016). Moreover, a key issue that plagues the research of cognitive engagement is the lack of agreement among researchers about the nature of this construct (Azevedo, 2015). For instance, cognitive engagement has been conceptualized as either the mental involvement in learning, use of learning strategies, motivations (e.g., interest, willingness to learn, control of schoolwork), or their combinations. Furthermore, as discussed in Chapter 3, the current studies vary radically in how they measure cognitive engagement. In sum, there is a pressing need to address the theoretical and methodological difficulties surrounding the nature, definition, and measurement of cognitive engagement and its role in SRL, and to place the study of self-regulation of cognitive engagement within a unifying theoretical framework.

The purpose of this dissertation was to address these gaps by proposing an integrative model of SRL engagement to clarify the changes of cognitive engagement in SRL, to guide studies on students' self-regulation of cognitive engagement, and to identify meaningful

directions for future research. To move this field forward, this dissertation also aimed to increase our knowledge on the measurement of cognitive engagement. The work presented in this dissertation fulfilled these goals and offered unique contributes to advance the field.

Contributions

Theoretical Contributions

This dissertation makes several important contributions to the theoretical understanding of cognitive engagement in SRL. In Chapter 2, we synthesized current perspectives and findings concerning the nature of cognitive engagement in learning contexts. We revealed four important features of cognitive engagement: (1) it changes over time; (2) it is context-dependent; (3) it comprises of both quantitative and qualitative dimensions, and (4) it occurs consciously or unconsciously. Moreover, we compared the similarities and differences between cognitive engagement and SRL from a theoretical perspective. In doing so, we clarified some ambiguities about the relationships between cognitive engagement and SRL that remained in the literature. Furthermore, we provided an analytical review of the three prominent frameworks that have investigated cognitive engagement within the frameworks of SRL. Specifically, the three frameworks include the elaborated model of SRL (Butler & Winne, 1995), the theoretical framework of self-regulatory engagement (Cleary & Zimmerman, 2012), and the integrative model of student learning (Zusho, 2017). The analyses of the existing literature resulted in our proposal for an integrative model of cognition engagement and SRL that further clarifies the functioning of cognitive engagement in different SRL phases and subprocesses.

In Chapter 3, we synthesized the current practice in measuring cognitive engagement. Although the overarching purpose of this manuscript was to critically review and analyze the measurements of cognitive engagement, it also enables researchers to develop a solid

understanding of the research base about cognitive engagement. The manuscript provides researchers with a better understanding of the indicators, antecedents, and manifestations of cognitive engagement by exploring the theoretical considerations and rationales that underlie the design of cognitive engagement measurement methods. Chapter 3 provides researchers with a more nuanced understanding of cognitive engagement by presenting the theories that have influenced the operationalization of the construct and thereby its measurement.

Chapters 2 and 3 laid the groundwork for the empirical studies of this dissertation, i.e., Chapters 4 and 5. In the two empirical manuscripts, we found evidence that high-performing students can strategically regulate their cognitive engagement in SRL. In the first empirical manuscript (Chapter 4), we adopted an information-processing perspective to examine the forms of cognitive engagement students displayed in clinical reasoning and their relationships with students' diagnostic performance. Specifically, we differentiated two types of clinical reasoning behaviors, i.e., information acquisition and information transformation. We investigated how students allocated their effort to these two types of behaviors in tasks of varying complexity. Findings from this chapter revealed that students who were more cognitively engaged in information transformation behaviors performed better than those relying on information acquisition behaviors. Moreover, our findings suggested that cognitive engagement varies as a function of environmental complexity and students' preferences for information processing strategies.

The findings in Chapter 5 afford us a better understanding of how students self-regulated their cognitive engagement in problem-solving. While it seems reasonable to assume that increased cognitive engagement leads to expected performance, we found that there was no significant difference in the overall level of cognitive engagement between high and low

performers. Instead, high performers strategically allocated more mental effort on deep learning behaviors than low performers (Cleary & Zimmerman, 2012; Galikyan & Admiraal, 2019).

These findings point to the importance of examining the self-regulation of cognitive engagement, which complements the current research in the literature that emphasizes facilitating and maintaining cognitive engagement in learning or problem-solving.

Methodological Importance

In addition to its theoretical contributions to the literature, this dissertation has also methodological importance. In Chapter 3, we provided a critical review of the instruments and techniques used to measure cognitive engagement. We highlighted the strength and weaknesses of each type of cognitive engagement measurement method, including self-report scales, observations, interviews, teacher ratings, experience sampling method, eye-tracking, physiological sensors, trace analysis, and content analysis. One conclusion from this review is that researchers should clearly define cognitive engagement and be aware of the theoretical foundations underlying that definition before measuring the construct of cognitive engagement. Another conclusion of Chapter 3 is the need to measure cognitive engagement at a fine-grained size with multimodal, multichannel data. We proposed that a multimethod approach to measuring cognitive engagement is a necessity for future empirical studies.

In addition, we found that students performed differently with different forms of cognitive engagement. Findings from Chapter 4 revealed that students used different forms of cognitive engagement in addressing clinical reasoning tasks, as suggested by latent profile analysis (LPA). As such, Chapter 4 informs the study design and analytical approaches of cognitive engagement in other contexts. It is also worth mentioning that we used the BCH approach in LPA, which was developed by Bolck, Croon, and Hagnaars (2004), to estimate the

differences in task performance among latent classes of students. The BCH approach addresses the concern of classification inconsistency by viewing students' performance as a distal outcome of the latent profile model. A detailed discussion of the superiority of the BCH approach over traditional LPA can be found in Chapter 4, as well as the research of Ferguson et al. (2020).

Chapter 5 uniquely added to the range of measurement approaches of cognitive engagement by employing computer vision and supervised machine learning algorithms to infer students' cognitive engagement states from their facial behavioral cues. This work contributes methodologically to the automated detection of cognitive engagement in unique ways by: (1) taking eye gaze, head pose, and facial action units simultaneously into account when building the engagement-detection model; (2) combining the use of recursive feature elimination (RFR) and random forest (RF) algorithms to get unbiased and stable results regarding the selection of crucial facial features for detecting cognitive engagement (Granitto et al., 2006); and (3) measuring cognitive engagement at fine-grained temporal resolutions in clinical reasoning.

Limitations and Future Directions

Although this dissertation provides important theoretical insights into the self-regulation of cognitive engagement and it contributes original knowledge to the measurement and analysis of cognitive engagement in SRL, this dissertation is not without limitations. While the limitations and future directions for Chapters 2-5 are discussed within the respective chapter, there are overall limitations that need to be noted and addressed in future studies.

First, it is important to note that both Chapter 4 and Chapter 5 consisted of relatively small samples which may affect the external validity and generalizability of our study findings. In Chapter 4, we used latent profile analysis (LPA) to identify subgroups of students who demonstrated similar cognitive engagement patterns. Considering that little is known about the

needed sample size for appropriately detecting classes in LPA (Wang & Wang, 2020), it is reasonable to assume that the unbalanced class sizes in this study are largely due to the small samples. Similarly, an important limitation of Chapter 5 resides in the small number of instances for training machine learning models (MLM). To optimize the performance of MLM, they should be trained on large sets of data collected in certain conditions. However, it is nearly impossible to precisely estimate the minimum amount of data required for the training of MLM, given that there are no definitive criteria to predict the size of the data for machine learning algorithms. In Chapter 5, we were aware of this issue, and we made several efforts to address this issue by: (1) simplifying the classification of cognitive engagement states, i.e., engaged and less engaged; (2) using the 10-fold cross-validation to evaluate MLM; and (3) examining different performance metrics (e.g., accuracy, precision, and the AUC value). Despite of those efforts, future replication studies with large sample sizes would be valuable.

Moreover, the ethnic and cultural background of participants is overlooked in the current work, especially when it comes to building a machine learning model to predict students' cognitive engagement from their facial behavioral cues. In Chapter 5, we used the data of 59 participants, who all came from a top university in China, to train the engagement-detection model. Given the data source is not fully representative of real-world data streams, the quality of this machine learning model cannot be guaranteed if it is deployed to make predictions on other groups of populations. In addition, the cultural differences in students' facial expressions add more uncertainties to the capacity of the engagement-detection model (Elfenbein et al., 2007). In this sense, the current work is exploratory and findings from this work must be viewed with caution. Therefore, an important direction for future work is to recruit participants from diverse

ethnic and cultural backgrounds, enabling the underlying training data for machine learning algorithms reflect the principles of equity, diversity, and inclusion.

Other limitations pertain to the biases in the data collection and analysis processes. It is possible that the facial expression data that machine learning algorithms trained on contains biases (e.g., representation bias and measurement bias), which subsequently yield biased outcomes in predictions. In this dissertation, we used OpenFace to extract students' facial features in the clinical reasoning process; however, there is a lack of assessment of the efficiency of OpenFace in this problem-solving context. As an illustration, Fydanaki and Geradts (2018) evaluated the performance of OpenFace in relation to face verification, recognition, and clustering tasks on multiple forensic datasets. They found that OpenFace was inadequate for real-world application to forensics, although OpenFace had multiple advantages compared with other facial analysis toolkits. Moreover, the algorithmic design choices (e.g., the use of certain optimization functions and the decisions on threshold values) may bias the outcome of machine learning algorithms. The algorithmic bias is hard to be excluded from model training and evaluation since it lies in a range of factors, such as the complexity of the research problem, the number of categories to be predicted, and researchers' knowledge and expertise in the area. In future studies, it is important that researchers take different sources of biases seriously and take actions to mitigate or eliminate the effects of those biases on machine learning models.

Furthermore, the two empirical studies (Chapters 4 and 5) provided evidence supporting the self-regulation of cognitive engagement. Still more work is needed to directly answer the question: how does cognitive engagement dynamically change through different SRL phases? In Chapter 2, we proposed that cognitive engagement functions differently in different SRL phases. In the forethought phase of SRL (Zimmerman, 2000), students initiate their cognitive

engagement by planning the strategies needed to solve the task and corresponding effort on these strategies. Students maintain and monitor their cognitive engagement in the performance phase, whereas they evaluate and adjust their cognitive engagement in the self-reflection phase.

Therefore, one immediate and promising future direction is to validate the theoretical claims presented in the integrative model of SRL engagement. The many future directions proposed in Chapter 2 are still valid and worth exploring. Additionally, both Chapter 4 and Chapter 5 did not shed light on the core question as to why some students can strategically regulate their cognitive engagement while others cannot. Hence, future research should pay attention to the driving forces behind students' self-regulation of cognitive engagement, as well as to the internal and external factors that may affect students' cognitive engagement in SRL.

Another important direction for future research is to further develop the integrative model of SRL engagement presented in Chapter 2 by incorporating other types of engagement, for example, behavioral engagement, affective engagement, and social engagement (Finn & Zimmer, 2012). Only when a learning model accounts for the multidimensional aspects of learning (i.e., behavioral, cognitive, metacognitive, affective, and contextual aspects) can it be widely applied to address complex issues in education. This dissertation made an important step towards integrating the research domains of student engagement and SRL, but clearly more work is needed in this line of inquiry. Moreover, the proposed integrative model of SRL engagement contains several ambiguities in its current form. Most notably, this model views students' motivation beliefs and emotions as either the antecedents or facilitators of their cognitive engagement in the SRL phases; however, much additional work remains to be done to illustrate the roles of different motivational and emotional factors in the process of self-regulation of cognitive engagement. Example research questions include: How do self-efficacy, outcome

expectation, task value, interest, and achievement goal orientation affect students' cognitive engagement in SRL? Does students' emotion variability affect the functioning of cognitive engagement in different SRL phases? What are the relationships between students' self-regulation of cognitive engagement and discrete academic emotions in tasks of varying complexity? The answers to these questions will have direct practical implications for the design of related training programs and scaffolding strategies.

Finally, both Chapter 2 and Chapter 3 concluded that a multimethod approach to measuring cognitive engagement will benefit future empirical studies. However, we merely relied on system log files, more specifically, students' digital trace of actions, to infer their cognitive engagement in Chapter 4. Azevedo and Gašević (2019) provided an excellent discussion of the issues and challenges of analyzing multimodal multichannel data about self-regulated learning with advanced learning technologies. For instance, it is challenging to temporally align multimodal multichannel data sources, especially when they are collected at different sampling rates and levels of granularity. Another challenge concerns the assessment of the level of accuracy and confidence in inferences because of lack of theoretical foundations. The same issues and challenges exist for the measurement of cognitive engagement with multimodal multichannel data. This dissertation provided limited guidance to address those issues and challenges. Therefore, there is room for research to improve the measurement of cognitive engagement with a multimethod approach.

Concluding Remarks

This dissertation makes important theoretical contributions to our understanding of how cognitive engagement dynamically changes across the SRL process. Importantly, this dissertation proposed a new theoretical model that integrates the two constructs of cognitive

engagement and SRL. In addition to providing novel insights into the mechanisms of self-regulation of cognitive engagement, this dissertation makes methodological advances by critically analyzing the current measurement methods of cognitive engagement, as well as by exploring advanced techniques to capture cognitive engagement. Moreover, findings from this dissertation provided empirical evidence for the design of learning environments and educational interventions aimed to promote effective regulation of cognitive engagement. This dissertation lays the groundwork for future studies on self-regulation of cognitive engagement.

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