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The relationship between cognitive engagement and students' performance in a simulation-based training environment: an information-processing perspective

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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.

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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 et al., 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 (B. A. 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

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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 (Järvelä et al., 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 et al.'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 et al. (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 et al. (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 et al. (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-regulate interest, structure-dependent engagement (trying all available operational options regardless 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 et al., 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 recipience 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 1, 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.

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 h-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

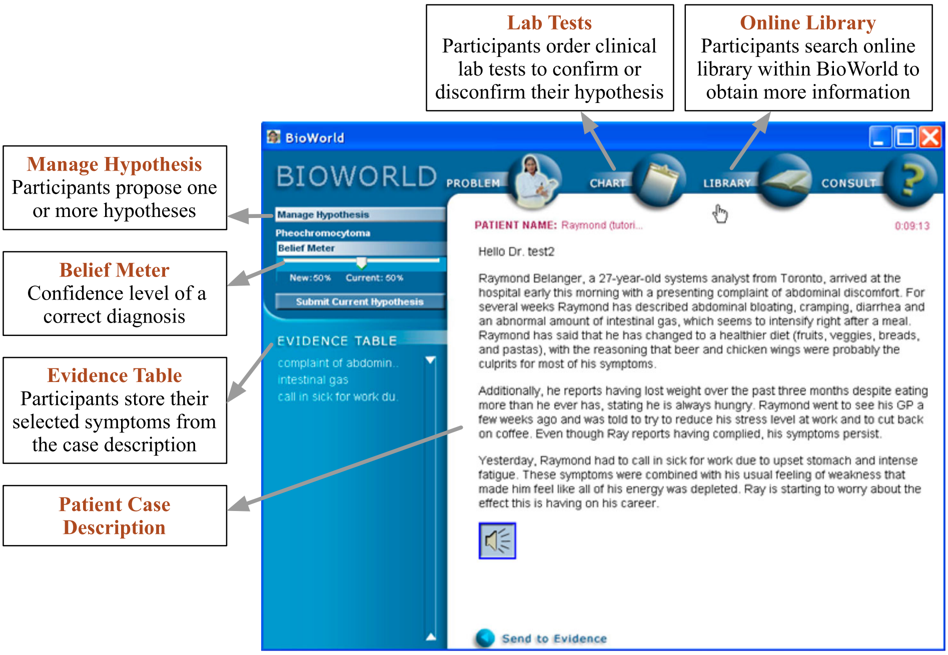

Figure 1. The interface of BioWorld system.

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. 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 1). 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 M*plus* 7.4 using a maximum likelihood (ML) estimation via the expectation maximization (EM) algorithm. 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 et al., 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 et al., 2013). The algorithms for the three model fit indices are:

$$\text{AIC} = -2LL + 2\,p \tag{1}$$

$$\text{BIC} = -2LL + \; p* \ln{(N)} \tag{2}$$

$$\text{Adjusted BIC} = -2LL + p* \ln{(N*(N+2)/24)} \tag{3}$$

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 et al., 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 et al. (2004), which is well-known as the BCH approach, to control classification errors in the process of estimating class differences in distal outcomes. In particular, the BCH approach performs a weighted analysis of variance (ANOVA), and the weights are inversely related to the classification error probabilities (Bakk et al., 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 1. As aforementioned, we took the two classes of information processing activities as the input variables for latent profile analysis. Results in Table 2 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 et al. (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.

As shown in Table 3, 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.

In the same vein, the results of the latent profile analysis displayed in Table 2 showed that the 3-cluster solution was also optimal for the Cynthia case. A thorough examination of the means of the

Table 1. 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 2. Fit indices for different models with the number of clusters ranging from 2 to 6.

Case	Model	AIC	BIC	Adjusted BIC	*p* BLR	*p* LMR	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.

acquisition and transformation activities in Table 3 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 et al. (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 4, 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 3. The three clusters of cognitive engagement profiles identified by latent profile analysis.

			Acquisition		Transformation	
Case	Group	No.	*M*	*SD*	*M*	*SD*
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

Table 4. Pairwise comparisons of diagnostic confidence and efficacy.

Case	Index	Group	Mean	SE	Chi-Square (*p* value)		
					1	2	3
Amy		1	.80	.03	–		
	Confidence	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 et al., 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 et al., 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 et al., 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 et al., 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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Data availability statement

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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Appendices

Appendix A

```
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;
   OUTPUT: tech1 tech11 tech14;
   SAVEDATA:
      FILE = class.txt;
      SAVE = cprob;
      FORMAT = free;
```

Appendix B

```
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);
       AUXILIARY = y4(bch);
   ANALYSIS:
       TYPE = mixture;
```