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Examining the Interplay between Self-regulated Learning Activities and Types of Knowledge within a Computer-Simulated Environment

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Abstract

This study examines the temporal co-occurrences of self-regulated learning (SRL) activities and three types of knowledge (i.e., task information, domain knowledge, and metacognitive knowledge) of 34 medical students who solved two tasks of varying complexity in a computer-simulated environment. Specifically, we explored how task complexity affected the use of SRL activities, types of knowledge, and their interplays using epistemic network analysis (ENA). We also compared the differences between high and low performers. The results showed that the use of SRL activities, especially planning and monitoring, was more intensive in a difficult task compared to an easy task. Students also used more domain knowledge to solve the difficult task. For both tasks, domain knowledge and metacognitive knowledge co-occurred most frequently, followed by domain knowledge and planning. Nevertheless, the interplay of SRL activities and types of knowledge is generally different between the two tasks. Moreover, we found that high performers used significantly more metacognitive knowledge than low performers in the easy task. However, no significant differences were found between high and low performers in both tasks. This study helps shift the focus from solely examining SRL strategies or the use of knowledge to exploring the interplay of various SRL components. Moreover, this study lays the foundation for rethinking SRL competency in clinical reasoning and redesigning instructional models that highlight the acquisition of both knowledge and skills.

Notes for Practice

- While the role of self-regulated learning (SRL) is widely acknowledged in medical education, less is known about the temporal interplays between SRL activities and different types of knowledge.
- This study shows how the temporal co-occurrences of SRL activities and knowledge types were associated with students' performance differences.
- Domain knowledge was central to the problem-solving process, regardless of the task complexity.
- The interplay between SRL activities and knowledge types, instead of SRL activities per se, matters to students' clinical reasoning performance.
- Medical instructors should redesign instructional models that support the development of clinical reasoning skills as well as the acquisition of different types of knowledge.

Keywords

Epistemic network analysis, self-regulated learning, types of knowledge, temporal co-occurrence, computer-simulated environment

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1. Introduction

An important goal of contemporary medical education is to help students develop self-regulated learning (SRL) skills so that they can continue learning independently in their professional life after graduation (ten Cate et al., 2004). Specifically, SRL refers to a dynamic and recursive process whereby students manage the behavioural, cognitive, metacognitive, and affective aspects of learning towards the fulfillment of personal goals (Boekaerts et al., 2005; Greene & Azevedo, 2007; Li, Zheng, Huang & Xie, 2022; Pintrich, 2004; Schunk & Greene, 2017; Winne & Hadwin, 1998; Zimmerman, 2000). The field of SRL typically emphasizes how students use a variety of strategies to control, monitor, and adjust the multidimensional learning process in goal-oriented tasks (Schunk & Greene, 2017). In comparison to the research on SRL strategies, the role of different knowledge types (e.g., domain knowledge and metacognitive knowledge) in SRL is underexplored (Moos & Azevedo, 2008).

This study examines the temporal interplay between knowledge categories and SRL activities. We situate this study in the context of clinical reasoning, where there has been a growing call to examine medical students' SRL competency (Artino et al., 2011; Cleary et al., 2016; Lajoie et al., 2018; Li et al., 2021). In clinical reasoning, medical practitioners or students diagnose patients by inquiring about the patient's symptoms and life experience, performing medical lab tests, and proposing one or more diagnostic hypotheses. They link each piece of evidence to each hypothesis to make a final diagnostic decision (Eva, 2005; Li, Zheng & Lajoie, 2020). As such, clinical reasoning involves processing different types of information (e.g., patient information, domain-specific knowledge, and self-knowledge) and critical thinking and reasoning skills. Surprisingly, no model of clinical reasoning has included knowledge categories in explaining students' diagnostic performance (Kiesewetter et al., 2016). For instance, ten Cate et al. (2004) proposed a learning-oriented teaching (LOT) model to guide instructional designs in clinical teaching. The LOT model consists of four components, cognition, affect, metacognition, and the amount of guidance needed. In the integrated model of clinical reasoning, Marcum (2012) described clinical reasoning using a dual-process theory of cognition and metacognition theory. However, neither model took students' use of knowledge into account. This is perhaps because whether the knowledge base of medical practitioners influences clinical reasoning performance is no longer the question. However, much less is known about how different types of knowledge relate to diagnostic outcomes (Klein et al., 2019). The lack of understanding of the use of different types of knowledge in clinical reasoning is a gap that must be addressed in order to provide guidance on the design of quality instructions and training.

Moreover, empirical research on the interplay between the use of SRL activities and knowledge categories in tasks of varying complexity, especially in the context of clinical reasoning, is limited (Kiesewetter et al., 2016). This study attempts to fill this gap by examining the co-occurrences of SRL activities and knowledge categories during clinical reasoning. We also investigate how task complexity influences the relationship between SRL activities and knowledge types.

2. Theoretical Background

2.1. Types of Knowledge in Self-Regulated Learning

According to Winne (2018), "SRL is a nexus of information types and types of information processing ranging across academic content at a lower object level and tactics used for learning academic content at a higher metalevel" (p. 12). At the object level, there are two types of information concerning a task. One type of information is "in" the task (i.e., task information), represented by a flow of meaningful messages. The other is "about" the task, i.e., domain knowledge. Specifically, domain knowledge is useful information in a specialized discipline, profession, or activity. Students have different levels of prior domain knowledge based on their conceptual understanding of the domain, relevant experiences, values, and insights. At the metalevel of information processing, Winne (2018) highlights the knowledge of study tactics and strategies, conceptualized as one type of metacognitive knowledge by Pintrich (2002). Particularly, Pintrich (2002) argued that there were three types of metacognitive knowledge: (a) strategic knowledge (i.e., knowledge of general strategies for different tasks); (b) knowledge about cognitive tasks (i.e., the conditions under which study strategies might be used, and the extent to which those strategies are effective in a specific task); and (c) self-knowledge. It is noteworthy that self-knowledge refers to an individual's awareness of their own strengths and weaknesses in a task (Pintrich, 2002). Students acquire self-knowledge as they reflect on learning or problem-solving processes concurrently or retrospectively.

Moreover, Kiesewetter et al. (2016) contended that metacognitive knowledge also includes one's consciousness about information and state of cognition. This type of knowledge emerges as students make summaries and assessments of information, compare new information with the mental representation of a task, and evaluate their actions in the process of learning or problem-solving (Kiesewetter et al., 2016). In sum, the SRL process involves three dominant types of information or knowledge: task information, domain knowledge, and metacognitive knowledge, although researchers have not reached a consensus on their subcomponents.

The use of domain knowledge and metacognitive knowledge are said to be positively related since students with a higher level of metacognitive knowledge have higher recall of what they learned about a specific topic (Winne & Hadwin, 1998). Domain knowledge provides students with the background needed to interpret learning or problem-solving contexts and, as such, lays the foundation for any metacognitive considerations (Schwonke, 2015). However, the use of domain knowledge and metacognitive knowledge may be related to one's level of expertise or familiarity with a task. For instance, experts may use less metacognitive knowledge than novices because domain knowledge is sufficient to progress in learning or problem-solving for experts (Winne & Hadwin, 1998). Novices who know very little about a task might rely heavily on metacognitive knowledge and very little on domain knowledge.

Furthermore, task information may mediate the relationship between the use of domain knowledge and metacognitive knowledge. Winne (2018) pointed out that metacognitive processing could be easier than cognitive processing when task information is simple and straightforward. Accordingly, students may rely on metacognitive knowledge to solve an easy task. In contrast, they retrieve more domain knowledge than metacognitive knowledge from their long-term memory to address a complex task. However, more empirical research is needed to verify these relationships.

2.2. The Functioning of Knowledge in Self-Regulated Learning

There are SRL models that have considered the functioning of knowledge in SRL (Pintrich, 2004; Winne & Hadwin, 1998); however, the relationship between different types of knowledge and SRL activities remains unclear. For instance, Pintrich (2004) proposed a conceptual framework for SRL, which includes the phases of 1) forethought, planning, and activation, 2) monitoring, 3) control, and 4) reaction and reflection. It is only in the first phase of SRL that the activation of prior content knowledge and metacognitive knowledge is briefly mentioned (Pintrich, 2004). In the four-stage model of SRL, Winne and Hadwin (1998) viewed three types of knowledge (i.e., domain knowledge, knowledge of the task, and knowledge of study tactics and strategies) as cognitive conditions that support the occurrences of cognitive activities. Specifically, Winne and Hadwin (1998) contended that SRL occurs in four weakly sequenced phases, i.e., task definition, goal setting and planning, studying tactics, and adaptations to metacognition. The four SRL phases share the same cognitive architecture, conceptualized as the COPES by Winne and Hadwin (1998). The acronym COPES refers to the interaction of a learner's conditions (C), operations (O), products (P), evaluations (E), and standards (S) (Greene & Azevedo, 2007). Conditions are the internal and external resources available in learning or problem-solving, which come in two types: task conditions and cognitive conditions. In addition to the three types of knowledge, cognitive conditions also consist of an individual's beliefs, dispositions, styles, and motivation. Conditions influence how students use tactics and strategies to address a task (i.e., operations) and what criteria should be adopted (i.e., standards) for evaluating their learning processes or outcomes. Nevertheless, the four-stage model of SRL did not explicitly illustrate how each type of knowledge associates with the use of various cognitive and metacognitive activities.

In parallel with the absence of theoretical insights into the interplay of knowledge categories and SRL activities (e.g., planning, monitoring, and evaluation), empirical evidence is scattered and seemingly contradictory. For instance, Moos and Azevedo (2008) empirically examined the relationship between prior domain knowledge and college students' use of specific SRL processes (i.e., planning, monitoring, and strategy use) as students learned about the circulatory system with hypermedia. They found that prior domain knowledge was positively related to participants' monitoring and planning and negatively related to their use of strategies. Bernacki et al. (2012) examined the role of two prior knowledge variables, i.e., the declarative knowledge of text-based comprehension and the conceptual knowledge of situation model comprehension, in predicting SRL behaviours and learning outcomes. In line with Moos and Azevedo's (2008) research, Bernacki et al. (2012) hypothesized that "prior knowledge would predict increased monitoring, decreased strategy use, and increases in learning" (p. 158). However, Bernacki et al. (2012) found that prior knowledge did not affect any SRL behaviours except the monitoring process.

Moreover, prior declarative knowledge positively predicted two measures of learning outcomes (i.e., text-based and situation model learning scores), whereas prior conceptual knowledge negatively predicted situation model learning score. As for metacognitive knowledge, Griffin et al. (2013) distinguished the construct from metacognitive experiences and argued that pre-existing metacognitive knowledge only directly influenced the initial strategy selection during planning. Metacognitive knowledge does not necessarily entail monitoring and regulation activities in the learning process. Instead, the internal metacognitive experience associates with the monitoring processing and, consequently, the regulation operations (Griffin et al., 2013). To our knowledge, no study has simultaneously examined the associations of different types of knowledge with

SRL strategies, especially in technology-rich learning environments. Consequently, how the interplay between knowledge types and SRL strategies associates with students' performance has yet to be explored.

2.3. Self-Regulated Learning and Think Aloud

To examine the temporal patterns of association among SRL activities and types of knowledge, SRL should be treated as temporal events that unfold over time throughout a learning or problem-solving session (Azevedo & Gašević, 2019; Li, Du, et al., 2020; Li, Zheng & Lajoie, 2022). Envisioning SRL as a series of events requires researchers to capture SRL at a fine-grained size using appropriate data collection techniques. Specifically, the research community of SRL has widely applauded the use of online trace methods, such as log files, think aloud protocols, eye-tracking, physiological sensors, and classroom discourse, to gain insights into the SRL process as it occurs and changes from moment to moment (Azevedo & Gašević, 2019; Greene et al., 2017). For this study, we used think aloud protocol (TAP), which "involves asking participants to verbalize their thinking as they learn" (Greene et al., 2011, p 314). TAP provides a direct method to capture students' SRL activities and use of knowledge concurrently in learning and does not depend upon students' memory. Compared to other trace-based measurement methods, the inference for SRL processes is greatly simplified when using TAP.

Furthermore, think aloud is open-ended, meaning researchers are not restrained by a limited, predetermined set of SRL activities. TAP has been used to study cognitive and metacognitive processes in various learning tasks such as computer programming, self-regulated reading, mathematics, biology, and medical diagnosis (Hu & Gao, 2017; Lajoie et al., 2019; Moos & Azevedo, 2008). It is worth mentioning that TAP data is usually coded in a way amenable to quantitative analysis (Greene et al., 2011). The most used analysis strategy is coding-and-counting, whereby different categories of codes are compared by descriptive and inferential statistics. Recent advancement in analyzing TAP data, such as epistemic network analysis (Shaffer et al., 2016; Shaffer & Ruis, 2017), provides an alternative to revealing patterns of association among codes. Specifically, epistemic network analysis helps researchers develop an understanding of the temporal dynamics of variables of interest.

2.4. Epistemic Network Analysis

Epistemic network analysis (ENA) is a learning analytic technique that allows researchers to model temporal patterns of association among a relatively small, fixed set of elements (e.g., knowledge, values, and learning behaviours) and to visualize those connections in the form of network graphs (Shaffer et al., 2016; Shaffer & Ruis, 2017). According to Csanadi et al. (2018), ENA can "(1) capture, (2) visualize, (3) quantitatively compare patterns of learning activities across conditions, and (4) be used with smaller datasets" (p. 426), thereby making it superior over traditional coding-and-counting-based analyses when dealing with verbal data. Specifically, nodes and edges are represented in an epistemic network. Nodes refer to the variables of interest, usually highly dynamic and interdependent elements of a system. For our purpose, nodes are SRL activities and three types of knowledge, i.e., task information, domain knowledge, and metacognitive knowledge. We describe the SRL activities further in the method section. Edges reflect the relative frequency of co-occurrence between two nodes (Csanadi et al., 2018). Thus, by constructing an epistemic network from raw coded data, researchers can get an immediate understanding of a student's learning or problem-solving patterns.

Moreover, ENA provides researchers with the mean network for a group of students by averaging the connection weights across individual networks. As such, researchers can compare group differences in networks. Networks may also be compared using network difference graphs, i.e., comparison networks. A comparison network is calculated by subtracting the weight of each connection in one network from the corresponding connections in the other.

2.5. The Current Study

The main purpose of this study is to examine the temporal co-occurrences of SRL activities and types of knowledge using ENA. This study investigates the interplays of SRL activities and knowledge types, which could generate new knowledge that may be otherwise unobtainable from examining solely either SRL strategies or the use of knowledge in SRL. In this regard, this study has significant theoretical importance. We also examine how the interplay among SRL activities and knowledge types is related to students' performance so that new insights can be obtained into the factors that lead to performance differences. Therefore, this study also has practical implications.

Furthermore, we consider task complexity, given that it is a crucial aspect of task conditions and can influence students' preferences of SRL strategies and the use of different types of knowledge in problem-solving (Winne, 2018). As aforementioned, we situate this study in the context of clinical reasoning since little is known about the relationships among knowledge categories, SRL activities, and task complexity in this context. This study attempts to fill this gap by addressing the following research questions: (RQ1) Does task complexity associate with students' use of SRL activities, types of knowledge, and their interplay during clinical problem solving within a computer-simulated environment? (RQ2) Are there any differences in the SRL activities and types of knowledge between high and low performers?

For the first research question, we hypothesize that students will perform more SRL activities in a difficult task compared to an easy task. A difficult task also triggers more use of knowledge (i.e., domain and metacognitive knowledge) than an easy task. Since this study is one of the first to examine the interplay among SRL activities and types of knowledge in the context of clinical reasoning, we cannot propose directional hypotheses. We assume that the epistemic network of a difficult task differs from that of an easy task in terms of the connections and strengths among its network nodes. For our second research question, we hypothesize that high performers perform more SRL activities than low performers. In line with the research of Kiesewetter et al. (2016), there will be no significant differences in the use of different types of knowledge between high and low performers. Moreover, we hypothesize that high performers demonstrate different patterns of associations among SRL activities and knowledge types compared to low performers.

3. Method

3.1. Participants

A total of 34 participants (67.6% females) from a large North American University were involved in this study. Among the participants were 17 students involved in the institution's one-year preparatory medicine (Med-P) program. The other 17 had started their studies in the MDCM (Doctor of Medicine and Master of Surgery) program, which follows the completion of the Med-P program or an equivalent. Before participating in this study, all participants completed the prerequisite modules on Endocrinology, Metabolism, and Nutrition. They were all undergraduate medical students, with an average age of 23.3 (SD = 2.96). Ethical approval from the Research Ethics Board Office (REB) of the university was received for this study, and all students signed a consent form to participate with the understanding that they could terminate the study at any point in time if they so desired. Participants were asked to solve an easy clinical reasoning task and difficult one. Among the participants, 31 accomplished the two tasks, whereas one student only solved the easy task, and two students only solved the difficult task.

3.2. Learning Environment and Tasks

In this study, participants were tasked to diagnose two virtual patients (VP) at different levels of complexity in BioWorld (Lajoie, 2009), a computer-simulated environment designed for medical students to practise clinical reasoning skills (see Figure 1 for an illustration of the BioWorld interface). In BioWorld, students first read a patient case description to develop an understanding of the patient's history and symptoms. They then collect evidence to support a diagnosis of the patient's problem. Their evidence is posted in an evidence table, which serves as a metacognitive tool to help them monitor what and how much information is collected. Students can propose one or more diagnostic hypotheses, rate their confidence for each hypothesis (i.e., to what extent they believe the hypothesis is true), and order lab tests to confirm or disconfirm their diagnoses.

Moreover, students can search an online library within the system to gain more information about medical terms, tests, and procedures they are unfamiliar with. Afterward, students check evidence items and lab tests' relevance to their diagnostic hypotheses. They link evidence items and lab tests with corresponding hypotheses. After that, students submit a final diagnostic hypothesis and rank evidence items and lab tests based on their importance to the diagnosis. In the end, students write a case summary. It is noteworthy that the two cases were created by a panel of medical experts and learning scientists. Therefore, the two cases were practically sound and instructionally useful for medical educators. The correct diagnoses for the easy and difficult tasks were diabetes mellitus (type 1) and pheochromocytoma, respectively. Prior to the study, a medical professor also re-evaluated the tasks to ensure they were suitable for the participants.

3.3. Procedures

A training session was provided to help students get familiar with the BioWorld system through a researcher-guided practice case. Students were trained to conduct think alouds, which required them to verbalize their thoughts as they attempted to solve the case. Students were then asked to diagnose the two cases independently while thinking aloud. The order of patient cases was randomized to counterbalance its effect on the participants' problem-solving processes and performance. Think alouds were recorded in real time. Students were reminded to think aloud when there was a long silence. On average, students spent approximately 90 minutes in this study.

3.4. Performance

We classified students as either high or low performers depending on whether they provided a correct diagnosis. Specifically, 26 and 18 students correctly solved the easy and difficult tasks, respectively. They were identified as high performers.

Consequently, 6 and 15 students were identified as low performers who provided incorrect diagnoses when solving the easy and difficult tasks, respectively.

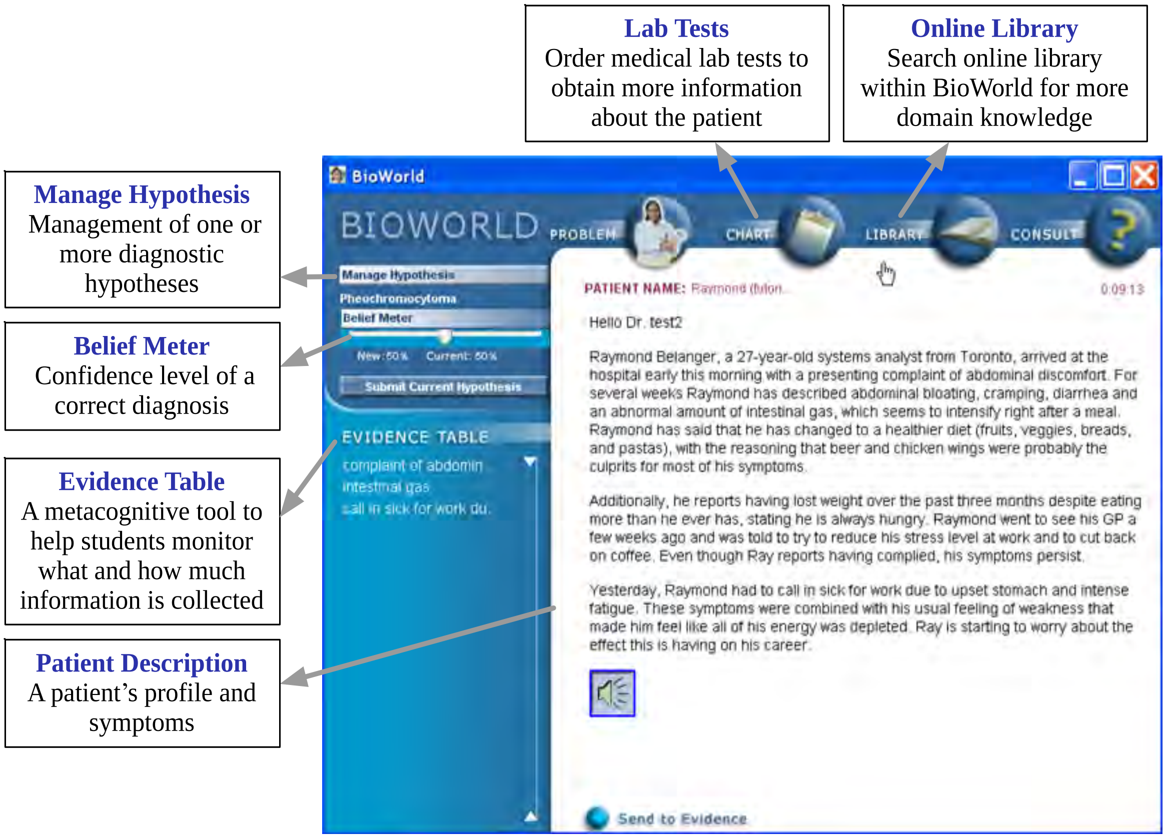

Figure 1. The main interface of the BioWorld environment

3.5. Data Processing and Analysis

For data processing, the recorded think aloud for each student was transcribed and then divided into idea units. Specifically, we used two types of strategies (i.e., topic representations and verbals) to segment the think aloud transcripts into units appropriate to our research context. Topic representation reflects an action or "assertion" made by the participants. Moreover, we considered the syntactic cues, such as sentences and pauses, to determine the boundaries of topic representations in the protocol. In addition, we used verbals as a unit for segmentation. Verbal is the language unit that conveys action, emotion, and existence. The verbal changes provided additional information about how the participants proceeded with continuous ideas and actions. Each segment generally addressed a particular instance of thought, intention, or action. An example of the segment was, "I'll do a neurological exam to see if there are peripheral neuropathies other than the visual problems, and I'll also do a visual exam." The three researchers performed the segmentation independently, whereby they could ask for help from the group when encountering difficulties in the segmentation. In particular, the think aloud protocols were segmented into 1,268 and 1,524 meaningful units for the easy and the difficult tasks, respectively.

Next, we coded students' SRL activities and types of knowledge from the think aloud protocols. See Table 1 and 2 for the coding schemes of SRL activities and types of knowledge, respectively. Specifically, the SRL activities coding scheme was based on the work of Meijer et al. (2006). They constructed a hierarchical taxonomy of metacognitive activities to interpret think-aloud protocols. Lajoie and Lu (2012) further adapted the hierarchical taxonomy of metacognitive activities to study SRL in the context of clinical reasoning.

Given that we investigated SRL from think-aloud protocols in the same context, the coding scheme was adequate for this study. We classified six SRL activities categories: orientation, planning, monitoring, evaluation, elaboration, and self-reflection. We differentiated three types of knowledge: task information, domain knowledge, and metacognitive knowledge.

It is noteworthy that the codes for both SRL activities and types of knowledge per se are mutually exclusive. However, having more than one SRL or type of knowledge code for an idea unit is possible.

Table 1. The Coding Scheme of Self-Regulated Learning Behaviours in Clinical Reasoning

Code	Sub-Code	Definition
Orientation (OR)	Hypothesizing (H)	Outlining a single or multiple diagnoses
	Identifying/repeating important information (IR)	Highlighting information in relation to the case
	Activating prior knowledge (APK)	Recalling information pertaining to the disease
Planning (PL)	Goal setting (GS)	Formulating a superordinate goal wherein multiple actions/plans are executed
	Sub-goaling: Form action plan (FAP)	Forming a plan to order lab tests/identify symptoms while formulating a diagnosis
	Sub-goaling: Looking for information (LI)	Forming a plan to search for information in the library while formulating a diagnosis
	Sub-goaling: Using an external source to get explanations (ES)	Requesting a consult from BioWorld while formulating a diagnosis
	Sub-goaling: Organizing thoughts by self-questioning (OSQ)	Asking questions to oneself in reference to the action plan being formulated
Monitoring (MO)	Claiming progress in understanding (CP −/+)	Mentioning that their overall understanding of the case improved (+). Alternatively, mentioning partial or lack of understanding (−)
	Found required information (FI −/+)	Mentioning that lab tests ordered were pertinent/abnormal (+) or non-pertinent/normal (−)
	Noticing unfamiliar word/term (NU)	Mentioning an instance of confusion attributed to terminology
	Noticing inconsistency, confusion, checking plausibility (NI)	Mentioning an instance of confusion pertaining to formulating their diagnosis
Evaluation (EV)	Checking (CH)	Reviewing the evidence, symptoms, and vital signs
	Verifying (V)	Claiming/proving/disproving something exists or is true
	Justifying (J −/+)	Justifying the probability of a hypothesis based on evidence items. The evidence items can be used to increase the likelihood of a particular diagnosis (+) or to decrease it (−)
	Concluding (CO −/+)	Make a conclusion about the virtual patient
Elaboration (EL)	Integrating information	Adding more information to existing information to create a more complex, emergent whole
	Connecting parts of text by reasoning (CR −/+)	Connecting different pieces of information in a logical way to form a conclusion or judgment
Self-Reflection (RE)	Self-questioning for reflection	Asking questions to oneself to check their understanding of certain contents or procedures
	Causal attribution	Attributional judgments about the results, such as whether poor performance is because of one’s limited ability or insufficient effort

Self-satisfaction	Self-satisfaction involves perceptions of satisfaction or dissatisfaction and associated affect regarding one's performance

Note. Meijer et al.'s (2006) framework adapted by Lajoie and Lu (2012).

Table 2. The Coding Scheme of Types of Knowledge

Types of Knowledge	Definition	Example
Task information	What a student can get from reading patient descriptions and symptoms.	She lost a lot of weight over only two months. Um, oh, and she's taking Valium.
Domain knowledge	Knowledge of a specific, specialized discipline, profession, or activity.	Why does she have high blood pressure since she's so young?
Metacognitive knowledge	Knowledge about study tactics and strategies, the conditional and contextual knowledge for cognitive tasks, and self-knowledge. It also includes consciousness about information and the state of cognitions.	That's my first idea … which I'm not sure if she has diabetes, but let's see

Note: The coding scheme was developed based on the research of Kiesewetter et al. (2016).

Regarding the coding procedure, four researchers discussed the coding schemes in detail and addressed all initial questions. After that, they randomly chose a think aloud protocol from the data set to practise the coding schemes. Three coders were then assigned 30% of the protocols in a way that two raters coded each protocol. It is worth mentioning that the first author randomly chose the protocols. The inter-rater reliability for SRL activities and types of knowledge were .620 and .608, respectively. Although the coding reliability is good (.60–.75) based on the research of Fleiss (1981), Syed and Nelson (2015) suggested that it should be larger than .70 to be considered acceptable. To increase the coding reliability, we discussed common questions thoroughly and refined the coding schemes further. Afterward, the coders were assigned another 10% of the protocols to code. We recalculated the inter-rater reliability for SRL activities and types of knowledge, which increased to .813 and .782, respectively. Finally, the three coders coded the remaining protocols independently.

To address our first research question, we compared the differences in the number of SRL activities and types of knowledge between the easy and the difficult tasks. We used ENA to construct the co-occurrence networks of SRL activities and types of knowledge for the two tasks. It is worth mentioning that a key variable for constructing an ENA is stanza, which indicates how to segment the data for analysis (Shaffer et al., 2016). If two codes fall within the same segment (i.e., one stanza) or neighbouring segments, they are considered temporally connected. In this study, stanza was defined as the idea unit in the think aloud protocols. In line with the research of Brückner et al. (2020), we set the window size as three, meaning that ENA counts the co-occurrences of codes among any three adjacent stanzas. The window size of three was also adopted in the work of Paquette et al. (2020), who examined SRL in an open-ended problem-solving environment. To plot the network graph created by ENA into a two-dimensional representation, we used SVD2 (singular value decomposition) for the y-axis to reduce the dimensionality of the graph. For the x-axis, we used MR1 (mean rotation) to align the centroids of the two tasks, following the practice of Brückner et al. (2020). In an epistemic network, the thickness of the arrows indicates the strength of the connections between codes. We visually compared the thickness of the arrows to identify the most salient connections within a network. We also generated a comparison network so that researchers can visually pinpoint the differences in the co-occurrence networks between the two tasks. Specifically, we performed ENA on our data using the ENA web tool (version 1.7.0) (Marquart et al., 2018). For our second research question, we first compared the differences in the use of SRL activities and types of knowledge between high and low performers as they solved each task. Moreover, we built the co-occurrence networks for high and low performers separately for each task.

4. Results

RQ1: Does task complexity associate with students' use of SRL activities, types of knowledge, and their interplay during clinical problem solving within a computer-simulated environment?

As shown in Table 3, students conducted significantly more SRL activities in the difficult task (M = 55.77) compared to the easy task (M = 46.55), t = -2.14, p < .05. With respect to the specific categories of SRL activities, students had significantly more planning and monitoring activities in the difficult task. Moreover, students applied significantly more knowledge to solve the difficult task (M = 57.13) than to solve the easy task (M = 47.81), t = -2.09, p < .05. There are no significant differences in the use of task information and metacognitive knowledge between the easy and the difficult tasks. Nevertheless, students used more domain knowledge to accomplish the difficult task compared to the easy task.

Table 3. Differences in SRL Activities and Types of Knowledge Between Easy and Difficult Cases

SRL activities & Types of knowledge	Easy		Difficult		*t*	*p*	Cohen's *d*
	Mean	SD	Mean	SD			
SRL activities	46.55	20.42	55.77	25.01	−2.14	.040*	.39
Orientation	9.35	6.41	9.65	6.30	−.25	.803	.05
Planning	9.81	4.30	13.61	7.39	−2.64	.013*	.48
Monitoring	7.42	3.59	9.81	4.80	−3.06	.005**	.55
Evaluation	10.16	5.55	11.42	7.40	−.96	.347	.17
Elaboration	3.00	2.73	2.77	2.35	.50	.620	.09
Self-reflection	6.81	4.72	8.52	5.12	−1.94	.062	.35
Types of knowledge	47.81	20.01	57.13	27.74	−2.09	.045*	.38
Task information	10.06	5.09	11.00	5.81	−.77	.448	.14
Domain knowledge	22.71	10.50	28.58	15.36	−2.26	.032*	.41
Metacognitive knowledge	15.03	9.85	17.55	11.64	−1.64	.112	.30

Note: *p < .05, **p < .01

Regarding the interplay of SRL activities and types of knowledge, there were strong interconnections between different types of knowledge for both tasks. Moreover, domain knowledge and metacognitive knowledge co-occurred most frequently, followed by domain knowledge and planning (see Figure 2). There was no difference between the easy and the difficult tasks regarding this pattern. However, there were points where the participants demonstrated different interaction patterns in the easy task from the difficult task, t (62.42) = 2.78, p = .007, Cohen's d = .69. The comparison network, which was generated by subtracting the weight of each connection in the network from the corresponding connections in another, tells a more in-depth story about how the easy task might differ from the difficult task in terms of the co-occurrence network. As shown in Figure 3, students made stronger connections to domain knowledge in the difficult task. In contrast, t showed more connections to task information, metacognitive knowledge, and evaluation elements in the easy task.

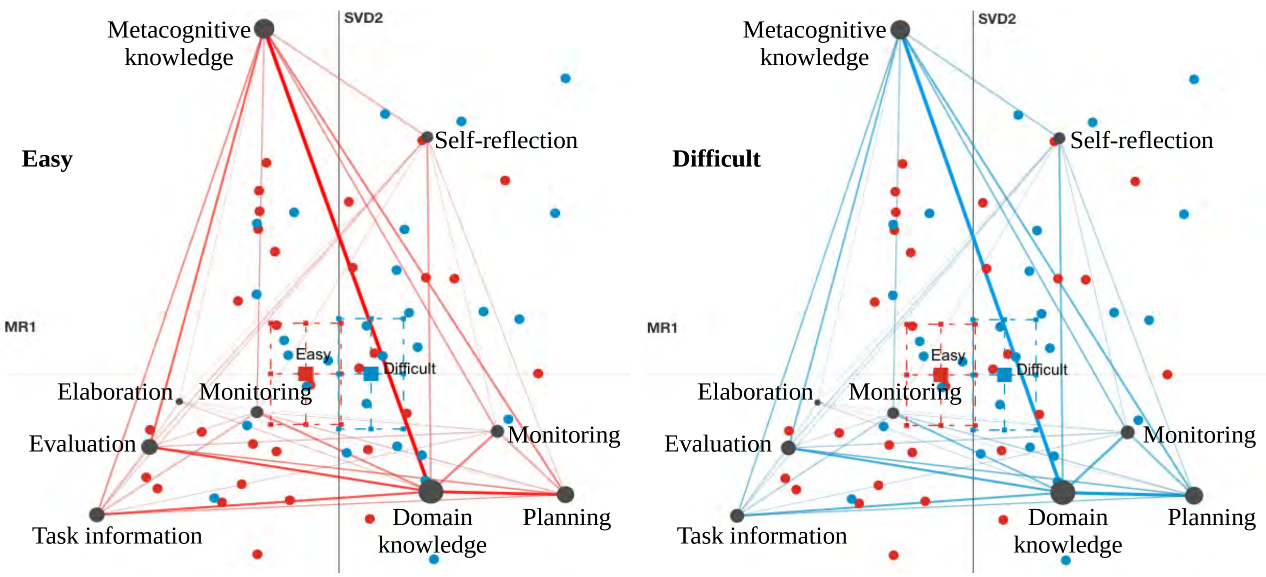

Figure 2. Mean networks of co-occurrences between SRL activities and types of knowledge for the easy (left) and difficult (right) tasks. *Note*: The red and blue circles represented the individuals who solved the easy and the difficult tasks, respectively. The coloured squares are the group means of the two task conditions, with 95% confidence intervals being outlined as dotted squares around the group means

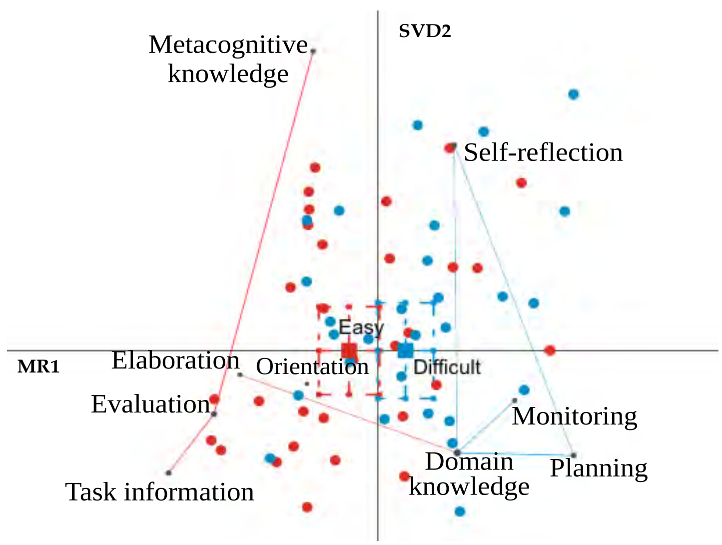

Figure 3. Comparison network between the easy (red) and difficult (blue) tasks

RQ2: Are there any differences in the SRL activities and types of knowledge between high and low performers?
We chose the Mann-Whitney U tests to compare the differences in the SRL activities and types of knowledge between high and low performers due to the small sample sizes, especially in the easy task. The results in Table 4 indicated that high performers applied significantly more metacognitive knowledge than low performers in the easy task, U = 25.00, p = .01. For the difficult task, there were no significant differences in the types of knowledge between high and low performers. Moreover, there were no significant differences in SRL activities between high and low performers for both tasks.

Table 4. Differences in SRL Activities and Types of Knowledge Between High and Low Performers

SRL activities & Knowledge types	Easy Task		*U*	*p*	Difficult Task		*U*	*p*
	Low	High			Low	High		

SRL activities	14.67	16.92	67.00	.595	14.63	18.97	99.50	.199
Orientation	16.08	16.60	75.50	.903	18.63	15.64	110.50	.373
Planning	15.00	16.85	69.00	.662	16.23	17.64	123.50	.677
Monitoring	14.42	16.98	65.50	.544	15.73	18.06	116.00	.491
Evaluation	16.00	16.62	75.00	.885	15.07	18.61	106.00	.293
Elaboration	19.75	15.75	58.50	.340	18.50	15.75	112.50	.405
Self-reflection	10.08	17.98	39.50	.062	14.03	19.47	90.50	.106
Knowledge types	13.92	17.10	62.50	.454	15.07	18.61	106.00	.294
Task information	20.08	15.67	56.50	.298	15.17	18.53	107.50	.318
Domain	15.25	16.79	70.50	.717	16.57	17.36	128.50	.814
Metacognitive	7.67	18.54	25.00	.010*	16.43	17.47	126.50	.758

Note: *p < .05, U = Mann-Whitney U test; values except those in the U and p columns are mean ranks.

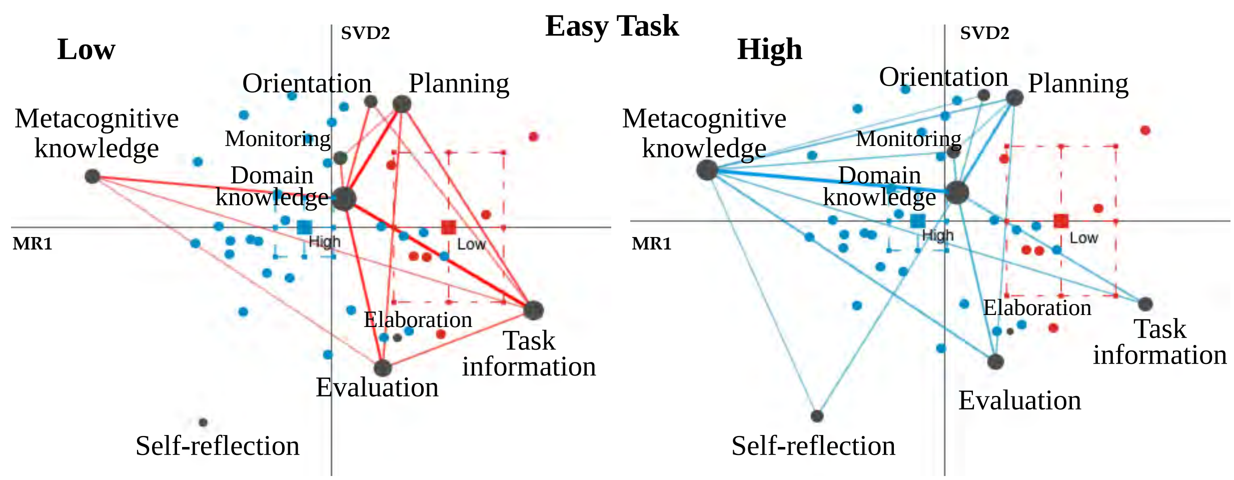

Figure 4. The networks of SRL activities and types of knowledge for the low (left) and high (right) performers in solving the easy task. *Note*: The red and blue circles represented low and high performers, respectively, while their group means are shown as coloured squares

An inspection of the networks of low and high performers suggested that they differed from each other in the x-axis of the network when solving the easy task, U = 7.00, p = .000, r = .91 (see Figure 4). As shown in Figure 5, high performers made more connections than low performers between metacognitive knowledge and domain knowledge, as well as between metacognitive knowledge and self-reflection. In contrast, low performers showed stronger connections between task information and other elements such as domain knowledge, planning, and evaluation than high performers.

Regarding the difficult task, the two performance groups shared similar patterns of connections (see Figure 6). There was a marginally significant difference in the x-axis of the network, t (30.62) = 1.98, p = .057, Cohen’s d = .69. The comparison network, as shown in Figure 7, suggested that high performers made stronger connections between self-reflection and all three types of knowledge than low performers. However, the comparison network should be interpreted with caution.

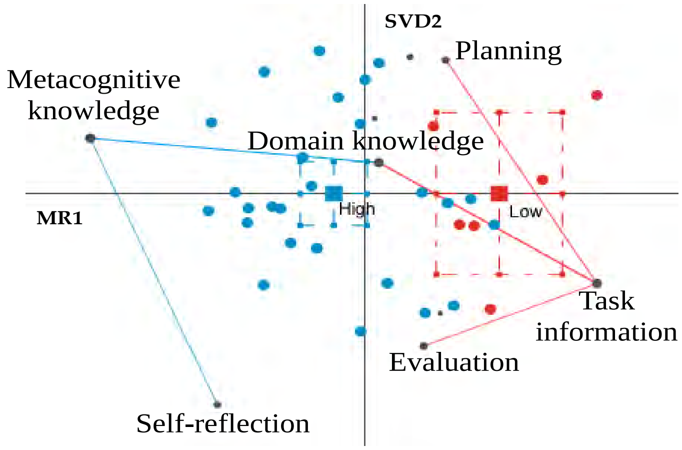

Figure 5. Comparison network between the low and high performers for the easy task

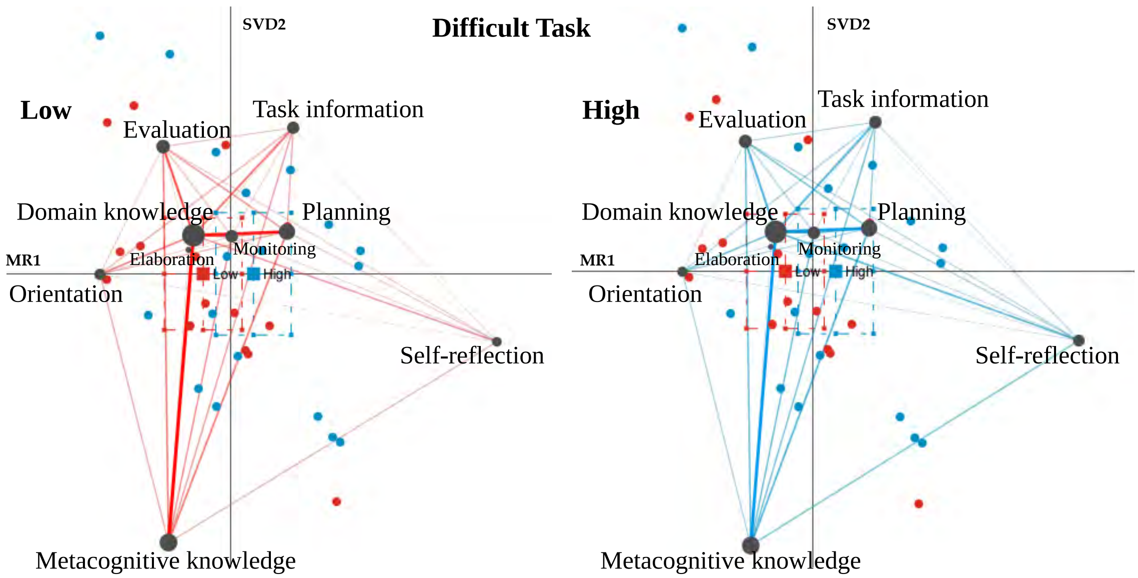

Figure 6. The networks of SRL activities and types of knowledge for the low (left) and high (right) performers in solving the difficult task

5. Discussion

In this study, we found that students used more domain knowledge to accomplish the difficult task compared to the easy task. This result makes sense as the design of a difficult task typically involves more declarative and procedural knowledge of a specific domain. We also found that students demonstrated more SRL activities in the difficult task than in the easy task. Specifically, the difficult task triggered more use of planning and monitoring activities than the easy task. This finding is partially in line with the research of Moos and Azevedo (2008). They revealed that students' prior domain knowledge was positively related to SRL planning and monitoring processes during a hypermedia learning task. According to Moos and Azevedo (2008), students with high domain knowledge could effectively regulate their learning by using planning processes since they have a well-established, interconnected knowledge base of the topic to generate thoughts and action plans. A high level of prior domain knowledge also allows students to monitor the details of their problem-solving processes. Our study revealed further that the use of domain knowledge has the same influence on students' SRL activities as students' prior domain knowledge.

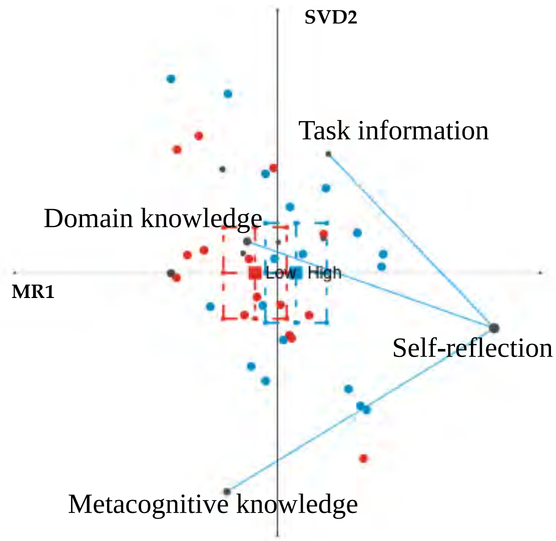

Figure 7. Comparison network between the low and high performers for the difficult task

Additionally, we examined the temporal co-occurrences of students' SRL activities and the use of knowledge to reveal problem-solving patterns. We found that domain knowledge was central to the problem-solving process, regardless of task complexity. This result can be explained by the fact that clinical reasoning relies extensively on domain-specific knowledge. Furthermore, for both tasks, domain knowledge and metacognitive knowledge co-occurred most frequently, followed by the co-occurrence of domain knowledge and planning. Nevertheless, task complexity was associated with the interplay of SRL activities and types of knowledge. Students generally made stronger connections to domain knowledge, planning, monitoring, and self-reflection elements in the difficult task.

In contrast, they showed more connections to the elements of task information, metacognitive knowledge, and evaluation in the easy task. In clinical reasoning, medical practitioners and students know the priori probability of a particular diagnosis when a patient case is presented (Eva, 2005; Zheng et al., 2021). They constantly adjust the probability of different diagnoses as more evidence items (e.g., patient symptoms and lab test results) are collected. This is typically called an "analytic reasoning" approach to diagnosis. However, a more general form of clinical reasoning is "non-analytic," which depends largely on one's experiences and feelings of familiarity (Eva, 2005; Li, Zheng & Lajoie, 2020). It is possible that students reasoned analytically in the difficult task while using non-analytic reasoning to solve the easy task.

Moreover, we found that high performers used significantly more metacognitive knowledge than low performers in the easy task. High performers may be more conscious of the clinical reasoning process than low performers and reach a better accuracy in the easy task. However, no significant differences were found in the three types of knowledge between high and low performers in the difficult task. This finding corroborated the study of Kiesewetter et al. (2016). They found that using different categories of knowledge (i.e., domain knowledge and metacognitive knowledge) was not associated with diagnostic accuracy. According to Kiesewetter et al. (2016), students' diagnostic performance is unlikely to be determined simply by knowledge but rather by integrating different categories of knowledge with cognitive actions. While we generally agree with Kiesewetter's et al. (2016) claim, our findings suggest that task complexity causes a difference in the relationship between the use of knowledge and students' performance.

Regarding the use of SRL activities between high and low performers, we did not find significant differences in both tasks. This is contrary to our expectations, given that a range of SRL studies across various disciplines had demonstrated the crucial role of SRL in reaching optimal performance (Boekaerts et al., 2005; Schunk & Greene, 2017; Zimmerman, 2008). One explanation is that students may differ in SRL processes other than the frequency distribution of SRL activities in certain contexts. Findings from this study suggested that the temporal co-occurrences of SRL activities and types of knowledge may account for students' performance differences. As an illustration, high performers made more connections than low performers between metacognitive knowledge and domain knowledge, as well as between metacognitive knowledge and self-reflection, when solving the easy task.

In contrast, low performers showed stronger connections between task information and other elements such as domain knowledge, planning, and evaluation than high performers. It is worth mentioning that these findings provided empirical evidence that supports the argument that metacognitive processing is easier than cognitive processing for high performers to solve an easy task (Winne, 2018). In an easy task, task information is in the hub of medical problem-solving for low performers. Concerning the difficult task, the two performing groups generally shared similar patterns of connections. However, a marginally significant difference was observed between high and low performers. High performers tended to make stronger connections between self-reflection and all three types of knowledge than low performers. While this finding should be interpreted with caution, it can be explained by the fact that self-reflection involves self-questioning, self-satisfaction, and adaptive inferences (Zimmerman, 2000). It is possible that students need to use different types of knowledge to support those SRL activities, and high performers have the competency to do so. Taken together, we argue that the interplay among SRL activities and types of knowledge, instead of SRL activities per se, matters to students' clinical reasoning performance.

In sum, this study contributes to the SRL literature by providing empirical evidence on how SRL activities and types of knowledge function together in students' clinical reasoning processes to account for their performance differences. We examined students' use of different types of knowledge as displayed in the problem-solving process instead of their prior domain and metacognitive knowledge. The distinction between students' actual use of knowledge and their prior knowledge is important since students may fail to retrieve information from long-term memory into their working memory. Moreover, this study helps shift the focus from solely examining SRL strategies or the use of knowledge to examining the interplay of various SRL components. Another substantial contribution is that we used ENA to uncover patterns of association among SRL activities and types of knowledge, which provided in-depth insights into the clinical problem-solving process. For example, we found that domain knowledge and metacognitive knowledge co-occurred most frequently, followed by the co-occurrence of domain knowledge and planning in tasks of varying complexity. This insight is otherwise unavailable without network analysis.

At a practical level, findings from this study could be used to inform the design of dashboards and intelligent tutoring systems. For instance, instructors could easily recognize students' clinical reasoning patterns from a learning analytics dashboard that displays the temporal relationship between SRL activities and different types of knowledge. An ENA can be made available to instructors using the incrementally accrued data during or at the end of a task. In doing so, instructors can provide early interventions to students if they rarely use metacognitive knowledge or deep SRL strategies. Instructors can also make a final diagnosis of students' learning patterns regarding the interplays among their use of different types of knowledge and SRL activities. By comparing the differences in the learning patterns between high and low performers, instructors develop an understanding of how to support low achievers to succeed. It is noteworthy that instructors are expected to provide scaffoldings according to the complexity of tasks.

6. Conclusion

In this study, we used a network-based analytic technique (i.e., epistemic network analysis) to examine the temporal co-occurrences of SRL activities and types of knowledge of medical students who solved two patient cases of varying complexity in a computer-simulated environment. This study makes theoretical, methodological, and practical contributions to the area of SRL in clinical reasoning. Nevertheless, this study is not without limitations. First, we asked the participants to solve two tasks of varying complexity, but students may perceive task complexity differently. Moreover, the findings of this research may be constrained by its sample size and the levels of task complexity. Lastly, the students were all from a highly competitive university, which may affect the generalizability of our research findings. Despite these limitations, this study lays the foundation for rethinking SRL competency in clinical reasoning and redesigning instructional models that highlight the acquisition of both knowledge and skills.

Moreover, several directions for future work arise from this study. One direction is to explore the underlying mechanisms for the co-occurrences of SRL activities and types of knowledge. Moreover, it would be interesting to examine how the relationships among knowledge types may affect the interplays between knowledge types and SRL activities. Another direction is to investigate the relationships among SRL activities and types of knowledge using different coding schemes. Additionally, McCarthy and McNamara (2021) identified four key dimensions of prior domain knowledge in relation to text comprehension (i.e., amount, accuracy, specificity, and coherence) in the Multidimensional Knowledge in Text Comprehension (MDK-C) framework. Accordingly, future research will be needed to assess how the interplay of different dimensions of domain knowledge influences students' performance. It would also be fruitful to consider students' motivation and emotion when examining the temporal interplay of different types of knowledge and SRL activities.

Declaration of Conflicting Interest

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