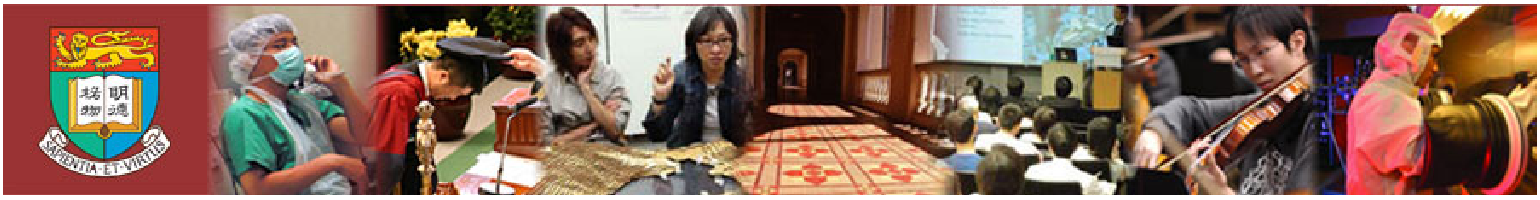

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Quantitative Assessment of Medical Student Learning through Effective Cognitive Bayesian Representation

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Abstract

The changes of learning environments and the advancement of learning theories have increasingly demanded for feedback that can describe learning progress trajectories. Effective assessment should be able to evaluate how learners acquire knowledge and develop problem solving skills. Additionally, it should identify what issues these learners have during the learning processes and why they have these issues. This study depicts visual representations of cognitive tasks as crucial points to connect learning and assessment. This study is an exploration of these cognitive tasks in complex learning environments and a quantitative representation of these measureable objects in cognitive structures.

Keywords: cognitive task, structural representation, cognitive structures and processes, cognitive assessment, Bayesian network, knowledge modeling, measurable objects, knowledge states, medical learning, cognitive feature

1. Introduction

The assessment of complex learning tasks is a challenge for assessors and researchers. Assessing clinical learning of medical students is such a case where the learning tasks are complex, dynamic and without pre-arranged scenarios. For example, medical students in their clerkship in a hospital emergency room practice how to manage emergency cases under the supervision of a resident or attending doctor. When the medical students usually manage patients they cannot anticipate the patients' symptoms and understand clinical prognosis. In such kinds of complex learning situations, the assessors have difficulty evaluating medical students' acquisition of clinical knowledge, development of problem solving skills and situated performances. One critical issue is deficiencies of structural representation of clinical tasks. Stated differently, in a complex clinical task, chairperson, assessor and medical students cannot develop a logical and clear structural representation of the learning tasks.

In this study a professor and a group of medical students discussed deteriorating patient case through a video-tape-based instruction. After observing the clinical case all students were interviewed via semi-structured interview guide by a group of researchers. The protocol were transcribed and analyzed based on cognitive task analysis techniques (Clark & Estes, 1996). A structurally cognitive model was developed and was further visually represented by using Bayesian network model (Barber, 2012; Conrady & Jouffee, 2011; Koller & Friedman, 2009). Student's conceptual knowledge and problem solving skills are assessed. Assessment based on the structural presentation model can inform a) students to know their strengths and weakness when they manage the patient, b) chairperson to understand medical students' progresses and problems and c) assessors that the assessment information is dynamic and diagnostic.

2. Literature Review

Effective representations of learning tasks can anchor and structure cognitive behavior (Zhang & Norman, 1994). Structural representations can provide learners with cognitive trajectories (Lajoie, 2003) and can allow assessment of learning processes (Lu & Zhang, 2013a, 2013b). In other words, an effective representation establishes a potential theoretical basis for the assessment.

The effectiveness of the cognitive task representations is, to a large extent, dominated by the characteristics of the task itself. The cognitive task can be well-structured and can consist of a set of subtasks. These subtasks exhibit well-graded knowledge structures (Falmagne & Doignon, 2011).

However, most cognitive tasks are not well-structured. There are several characteristics about them: (a) there are overlaps between subtasks, (b) a cognitive task can be expressed in a latent variable, which is further divided into more latent/evidential variables, (c) the presentation from latent to evidential variables is not solely through one path, and (d) such a cognitive path is usually explored by cognitive analysis techniques.

This study includes an examination of the structural representations of the cognitive tasks which are not normally well-structured. These tasks are involved in a medical learning activity called "the deteriorating patient." Representations include cognitive structures and processes. Cognitive structures are embedded in learning spaces (Falmagne, & Doignon, 2011) and concrete learning events are represented as trajectories within these spaces. Cognitive theories can be used to represent concrete learning events in order to understand learning trajectories and progress; these theories can also provide evidence for diagnostic assessment. Learning trajectories are represented in network structures and learning processes, in Bayesian networks (Darwiche, 2009; Koski & Noble, 2009; Mittal & Kassim, 2007; Pearl, 1988, 2009).

From a cognitivist perspective, the acquisition of knowledge and the development of problem solving skills can be examined by observing the psychological and behavioral features of human performance (Chipman, Schraagen, & Shalin, 2000). Evidence of learning can be elicited from cognitive task performances, which are useful in tracing learning and establishing effective assessment (Hollnagel, 2003).

With recent developments in learning environments (such as web-based and on-line learning systems), complex cognitive tasks are coming to dominate learning and assessment processes (Zhang & Frederiksen, 2007; Zhang & Lu, 2012). The assessment of learning processes requires information and feedback on the learning trajectories of individual learners. Defining, developing and representing learning tasks are crucial for connecting learning and assessment. Conventional assessment procedures, such as multiple choice questions, are ineffective because of the lack of construct validity. Furthermore, sets of test items randomly selected from banks cannot represent expected knowledge structures and conventional test items cannot characterize complex learning task structure (Clark, Yates, Early, & Moulton, 2010; Falmagne & Doignon, 2011).This study explores cognitive tasks in a complex learning environment, elaborates these tasks into measureable objects, and represents them in cognitive structures.

3. Research Questions

The critical issue is that assessors and supervisors are not able to properly assess medical students' learning progress because the learning environments and tasks are complicated. We intend to develop structural representation as a cognitive assessment model based on the cognitive task analysis. A Bayesian network is used to represent the cognitive assessment model. Thus, the following research questions can be addressed:

1) How is the structural representation model used to represent medical student learning tasks?

2) How is the Bayesian network used to provide dynamic assessment information?

3) How are the students' knowledge and problem solving skills assessed diagnostically?

4. Theoretical Framework

Cognitivist perspectives examine the progress of learners in terms of cognitive structures and processes (Zhang & Leung, 2007). Acquiring knowledge and developing problem solving skills are accounted for by examining structural representations. Also, learning progress can be examined by depicting moment-by-moment changes in cognitive processes, and by identifying errors in cognition and performance (Lajoie, 2003).

4.1 Cognitive Task Representations and Assessment

Cognitive tasks are usually defined as a series of objects which are implicitly contained in a learning environment (Clark & Estes, 1996). These cognitive tasks are "wrapped" into content knowledge of a given domain. In a pedagogical context, the instructor and learners rarely place the focus on appropriate cognitive tasks. Instructors are able to target some contents, but they do not precisely tailor the content to knowledge categorization and different problem solving features. In other words, instructors cannot elaborately design cognitive tasks for both (Early, 2007). At the end of a learning period, instructors collect pieces of content knowledge arbitrarily or randomly to develop them into test items. Learners' response to these items can be represented at a score level. However, these scores do not report what knowledge these learners acquired, what problem solving skills were developed, what kind of errors were made, and what reasons led to these problems. No progressive details in the learning process can be recorded and recognized. Thus, an effective representation of a cognitive task in learning is a crucial step towards establishing an assessment that reports diagnostic information of knowledge acquisition and skill development.

4.2 Cognitive Task Analysis and Influencing Factors

Researchers seek to examine learning tasks from diverse angles. Chipman, Schraagen, and Shalin (2000) described learning tasks in terms of a covert-overt continuum. The covert learning tasks, the main focus of cognitive tasks in this study, involve unobservable knowledge corresponding to psychological activities, thought processes, and goal structures, whereas overt learning tasks involve observable performance.

Cognitive task analysis is a method for specifying the covert cognitive structures and processes that are associated with overt task performance (Clark & Estes, 1996; Gray, 2000; Prasanna, Yang, & King, 2009). According to Redding (1992), cognitive task analysis contains three steps: (1) develop visual representations of knowledge structures, (2) describe cognitive processes underlying performance, and (3) determine implications of results. Olson and Biolsi (1991) argue that cognitive representations are critical for conceptual and performance features of cognitive task analysis. Multivariate techniques, such as multidimensional scaling, can characterize quantitative features of cognitive representations (Rider & Redding, 1993). Researchers have suggested various frameworks, such as representing problem solving skills and strategies (Redding, 1995), knowledge structures and measurement modeling (Benysh, Koubek, & Cakvez, 1993), and knowledge modeling classification (Essens, Fallesen, McCann, Cannon-Browers, & Dorfel, 1994).

4.3 Hierarchical Cognitive Task Analysis and Structural Representations

Hierarchical cognitive task analysis is widely used in the Learning Sciences (Clark, Feldon, van Merriënboer, Yates, & Early, 2006, 2007; Merkelback & Schraagen, 1994; Stemler, 2001) and is effective in eliciting and representing knowledge and performance. It is often used to examine learning trajectories (Jonassen, Tessmer, & Hannum, 1999). Hierarchical cognitive task analysis involves: (1) describing the cognitive tasks and sub-tasks, (2) clarifying knowledge (declarative, procedural, strategic, and schematic), and (3) providing a theoretical and evidential framework for constructing performance assessments and evaluation.

5. Methodology

5.1 Rationale

This study uses cognitive task analysis and structural representations to investigate a medical learning task. The "deteriorating patient" task requires structural representations to identify the evidential variables needed to examine the learning trajectories and individual learner's progress. Cognitive models are used to characterize learning trajectories. Cognitive task analysis delineates the steps from learning tasks to quantitative structural representations.

5.2 From Learning Tasks to Measurable Objects

The essential parts of structural representation are evidential and explanatory variables. Measureable objects are recognized from cognitive tasks. The variables, as the elements of structural representation, are developed from measurable objects. The measurable objects function as a "transformation device" from qualitative to quantitative cognitive information.

The notion of measurable objects originated in software engineering as entities with quantitative characteristics (Bansiya & Davis, 2002). A similar notion occurs in educational research as physical objects with qualitative characteristics (Boulet, 2007). In this study, measurable objects have both quantitative and qualitative characteristics.

5.3 Developing Structural Representations

A number of steps are involved in using cognitive task analysis to develop structural representations. The following steps specify a procedure for applying cognitive task analysis.

1) Cognitive tasks in a given learning environment.

The cognitive task in this study involves solving a medical problem in order to stabilize an emergency room patient who is deteriorating.

2) Cognitive framework

The hypothesis and theories are used in the analysis. In a medical learning situation, students explain how they collected patient information.

3) Cognitive task analysis techniques

Knowledge components were recognized at a fine grain level. Protocol analysis of cognitive task analysis is used in eliciting knowledge components.

4) Transform collected information into measureable objects

Data are coded by rules and raw data are elicited via rubrics to transform information into measurable objects.

5) Develop evidence variables and explanatory variables

Variables are defined based on measurable objects. Overt evidential variables are developed from measurable objects and covert explanatory variables, from evidential variables.

6) Structural representation

After developing evidence variables and explanatory variables, structural representations are assembled based on hypotheses and theoretical considerations.

7) Quantitative model of the structural representations

Statistical techniques, such as structural equation modeling, multilevel analysis and Bayesian networks can be used to change qualitative structural representations into quantitative structural representations.

8) Knowledge state patterns following dynamic trajectories.

Certain statistical techniques can be used dynamically to represent learning trajectories or knowledge state patterns. The Bayesian network is an effective tool to update learning progress level instantaneously.

6. Analytical Model

An analytical model was developed based on the procedural steps.

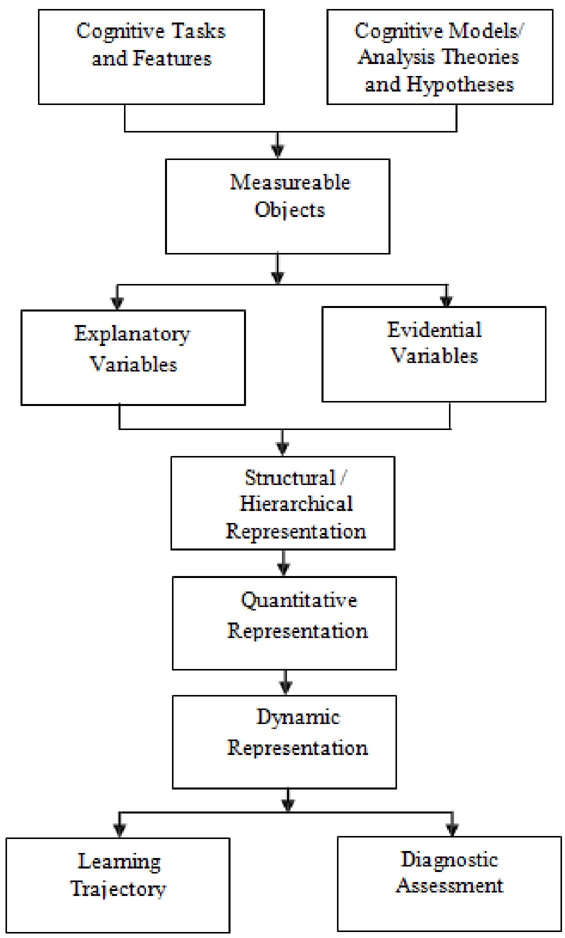

Figure 1. Procedural steps of cognitive tasks analysis

Figure 1 illustrates the relationships in cognitive task analysis components for a quantitative structural representation of a medical learning task, in terms of a Bayesian network.

7. Data Sources in Medical Learning

7.1 Participants

Thirteen third-year medical students volunteered to solve a videotaped clinical case taken from a clinical teaching session that was based on a simulated emergency medical scenario, called the "deteriorating patient." The 10-minute video clip shows one learner partially solving the case and a physician and his students dealing with a deteriorating patient in an emergency room. The 13 participants were asked to complete the tasks by observing the problem solving scenario and were then asked: "If you were the doctor in the emergency room. What would you do…?"

7.2 Protocol Cognitive Tasks Analysis

Participants were required to think aloud. The think aloud protocols require students to say what they would have done to solve the problem after watching the video clip. Idea unit analysis (Frederiksen, 1986; Ayala, Yin, Shavelson, & Vanides, 2002) is an analytical technique for extracting variables from cognitive tasks. Participants' think-aloud protocols were recorded and transcribed, then the transcribed texts were analyzed (Elm, Potter, Gualtieri, Easters, & Roth, 2003; Ayala, Yi, Shavelson, & Vanides, 2002) so that participants' clinical reasoning processes could be identified. Idea units were decided based on theoretical constructs, which can function as criteria for extracting evidence variable values and model components for presenting different aspects of competency. Idea units connected both evidential data and theoretical constructs. Due to the length of the transcript, it would be too time-consuming to analyze the entire text. Two independent raters evaluated a selection representing 25% of the entire total protocol. Percentage of agreement on all categories ranged from 78-92%.

8. Cognitive Models and Bayesian Representation

8.1 Cognitive Models and Measurable Objects

Cognitive models can be represented as hierarchical structures and Bayesian networks are appropriate techniques for quantitatively representing cognitive models as configurations of evidence and explanatory variables. Evidence variables collect evidence from cognitive tasks. Explanatory variables are theoretical constructs representing observable judgments from think-aloud protocols.

8.2 Evidence Variables

In hierarchical cognitive models, evidence variables are on the bottom layer and are used to extract variable values from the data via idea unit analysis. There are ten evidence variables in this study.

1) Identifying Relevant Information: Students list related information for diagnosis or further actions. Patients may manifest many symptoms and focusing on the relevant symptoms is crucial for making decisions, especially when time is a factor in life and death situations, e.g.: "He is also hypertensive, he had infarcts before").

2) Situation Awareness: This variable is especially important to solve naturalistic problems. Patients may have more than one problem and consequently it is important to recognize or express concern for the most pressing problem. A patient may have been in a motor vehicle accident and a student might say: "I would worry about him having any internal [bleeding]."

3) Making Judgments: Students express their opinions and give a diagnosis, for example: "I would think he is hypoglycemic."

4) Evaluating: Students give a rationale for a judgment, opinion, or action, e.g., "I would also ask for a carotid doppler to see if it could be a stroke causing that…because he has bilateral carotid bruits."

5) Metacognition: It is an advanced cognitive process which assesses and analyzes evaluations and judgments, for example: "I'm worried about the pressure, because I think he'd be tachycardic; he'd be sweaty, he'd be all of those things. But I do not think he'd have high blood pressure."

6) Taking Patient History: Students intend to collect more information about patient history. The purpose is to find evidence to support current problem solving and reasoning, such as: "I would like to know his meds."

7) Physical Examination: Students intend to collect more information through physical examination, e.g.: "I would ask for blood pressure on both arms and I would ask for pulses on all four limbs."

8) Doing Laboratory Tests: Students intend to collect more information through laboratory tests, such as blood sugar.

9) Giving Medication: This is a cognitive action that the medical student would take after a judgment was made,

such as: "…Just give him D50, as quickly as you can."

10) Monitoring Patient: This is a more general action that might include management, observation and control of patient situation, for example: "Give oxygen…

8.3 Developing Explanatory Variables

Explanatory variables occupy two layers in the hierarchical cognitive model. It is more convenient to describe the explanatory variable from the very bottom level, which is close to the evidence variables. As the model is completed, the information of the explanatory variables will be transferred from the top explanatory variable to the evidence variables.

8.4 Upper and Lower Level Explanatory Variables

As soon as those evidence variables are defined, the lower explanatory ones have to be developed. The lower level means that the explanatory variable is closely connected to the evidence one, but they are not observed from the data set or they have to be updated by evidence variables. Ten evidence variables have been grouped into four categories. The four variables are: Recognizing Information, Deep Cognition, Collecting Patient Data, and Managing the Patients.

Identifying Relevant Information and Situation Awareness share a common feature: Recognizing Information. It is obvious that the latter concept indicates the first step in medical problem solving. Making Judgments, Evaluation, and Metacognition consist of Deep Cognition, which reflects the second step, following Recognizing Information. Taking Patient History, Physical Examination, and Doing Laboratory Tests are composed of Collecting Patient Data in the past, present, and future time points. Giving Medication and Monitoring the Patient consist of Managing the Patients. Collecting Patient Data and Managing the Patients share a common feature: Cognitive Action. Thus, the Cognitive Feature Theory model consists of three sub-models: Recognizing Information, Deep Cognition, and Cognition Action; these represent three cognitive process aspects and demonstrate a sequential trajectory. The trajectory presents a natural cognitive process as medical students solve a clinical emergency problem. However, Cognitive Action cannot be directly observed; it can only be measured by instantiating the variables of Collecting Patient Data and Managing the Patients. In brief, the upper level of explanatory variables represents an advanced level of clinical cognitive process.

8.5 Initializing Values in the Cognitive Bayesian Network

In this cognitive Bayesian network, students' skills in solving a deteriorating patient problem are expressed as both explanatory and evidential variables. Technically these variables are called nodes. The relations between variables are connected by the arcs which represent causal relationships. Initializing the estimates of the nodes is a necessary step which provides a probabilistic basis for each variable (i.e. node) of the cognitive Bayesian network. In other words, the evidential variables, students' observable behaviors and cognition in solving the deteriorating patient problem cannot be updated without the initialized values.

There are several ways to acquire the estimates of the network nodes, which include educated guesses (based on expert beliefs and experience), average values from students' previous records, and estimates based on student performances in similar tasks. Since there are no records from other students in this study, estimates were based on expert belief and the literature in the field. In a Bayesian network, the top node is called the parent node and the following nodes are called children nodes. We assume that the probability a student successfully accomplishes the Cognitive Feature is 0.67; therefore the probability of failure is 0.33. For other nodes (variables), we also assume that the probability a student completes a given node is 0.67, otherwise it is 0.33. This is also called conditional probability (Koski & Noble, 2009; Korb & Nicholson, 2011). We expect that the initialized value of each node is close to the student's probabilistic level. If the initialized value is not close to the expected value, it can be corrected through updating the records until it approaches the expected value (Woolf, 2009).

8.6 Brief Description of Entire Cognitive Model

The entire cognitive model is presented in Figure 2; it consists of three cognitive aspects: Recognizing Information, Deep Cognition and Cognitive Action. These aspects represent clinical cognitive processes. This level in the model has played an important role in the entire hierarchical cognitive model.

These three aspects represent a general competency of clinical problem solving, called cognitive feature trajectory (CFT) in the graph model. Recognizing Information directly connects to two evidence variables. Deep Cognition is composed of three evidence variables. Cognitive Action consists of two sub explanatory variables: Collecting Patient Data and Managing the Patient. Collecting Patient Data is updated by three evidence variables; Managing the

Patients is updated by two evidence variables. Finally, Recognizing Information, Deep Cognition and Cognitive Action are composed of cognitive feature theory in the graph model.

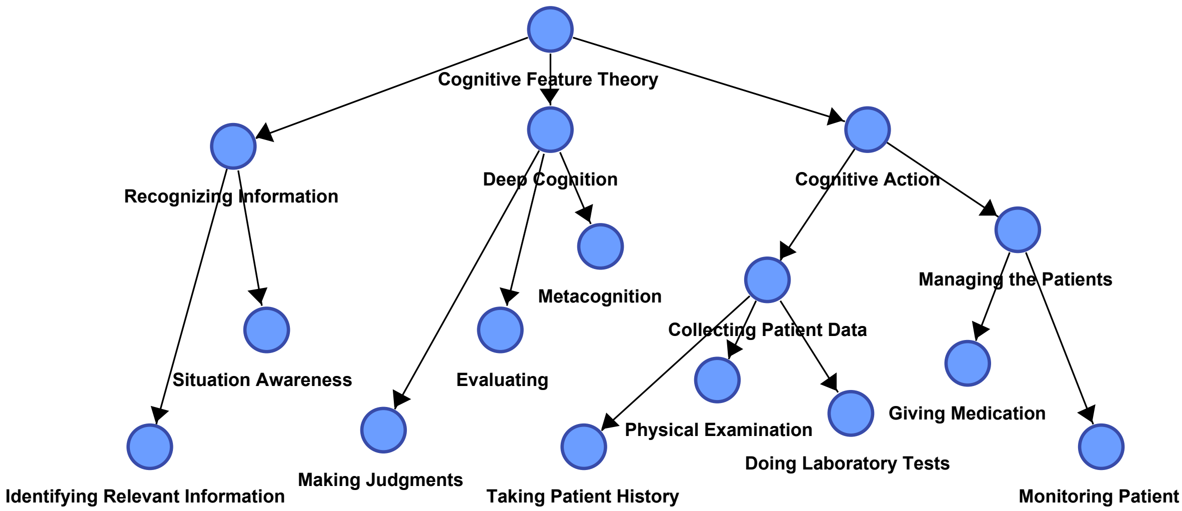

Figure 2. Cognitive feature trajectory model in a clinical process

9. The Bayesian Network Cognitive Model

There are ten evidence variables which can be used to update the entire cognitive model. A random sampling method is applied to test evidence states from one true evidence to ten true evidence observations. The true status means the variable acquires a positive value based on the student's think-aloud text. In order to reduce the tedious process of the test, the random process starts from a zero mastery model, which means that the 10 evidence variables do not represent any positive values. The student masters zero evidence variables. At the next step, the simulated data of the evidence variables demonstrates mastery of one, two, and three evidence variables until it completes the mastery model fully; this means the student masters all ten evidence variables. The mastery statuses of problem solving processes are listed in Table 1.

Table 1 demonstrates the relations of various instantiated evidence variables and explanatory variables. The most important column is Cognitive Feature, which indicates the general level of the problem solving processes. When only one positive evidence is in the model, the Cognitive Feature value is 0.2181 and then increases as the evidence increases. When all 10 positive evidence fills in the model, the Cognitive Feature value is 0.7819. The probabilistic range is from 0.2181 to 0.7819, which provides a scale to differentiate between various cognitive feature levels.

Table 1. Updating probabilities of random evidence combination of problem solving process

Number of Positive Evidence	Cognitive Feature	Recognizing Information	Deep Cognition	Cognitive Action	Collecting Patient Data	Managing the Patients
0	0.2181	0.1554	0.0860	0.2181	0.0860	0.1554
1	0.2403	0.1604	0.0891	0.2981	0.0972	0.4314
2	0.2597	0.1647	0.0919	0.3681	0.3074	0.4551
3	0.3249	0.1793	0.2942	0.3899	0.3141	0.4626
4	0.4229	0.4738	0.3241	0.4229	0.3241	0.4738
5	0.4617	0.4869	0.3359	0.5383	0.6641	0.5130
6	0.5477	0.2290	0.8812	0.5577	0.3652	0.7945
7	0.7161	0.6299	0.9048	0.5450	0.1317	0.7917
8	0.6974	0.8257	0.7126	0.6821	0.9000	0.5619
9	0.7657	0.8409	0.9117	0.7233	0.7204	0.8315
10	0.7819	0.8446	0.9137	0.7819	0.9140	0.8446

10. Students' Cognitive Feature and Assessment

10.1 Classification of the Students' Cognitive Feature and Measures

Measures can be defined in different ways. One of the measures is based on the range of the entire probability and theory-driven categories. For example, if a researcher believes three categories are appropriate, e.g. lower, middle and high, the researcher can define the measure distances as three intervals: (a) $0 \leq x \leq 0.33$, (b) $0.33^{+} \leq x \leq 0.67$, and (c) $0.67^{+} \leq x \leq 1.00$. However, the different distributions of given specific data sets are not considered in the above measures. If the categories are not sensitive to the given data sets, the categorical validity will be weak.

The second measure can be defined in terms of the practical range of each data set. In other words, we entertain the lowest and highest values of a random variable. This measure can effectively describe the classification of a set data. If there are *n* categories, the classification will be defined mathematically,

$$X_c = R_p / n$$

Where X_c is the interval of the classification, R_p is the range of the probability values of a given data, and n is the number of classification. We assume the lower, middle, and high are appropriate classifications in our case. So here *n* is equal to 3.

The third measure can be defined in terms of the practical range of each data set and

weighted βs. Regardless of how we consider the weights from any theory and related evidence from data-driven reports, a set of weight βs can be incorporated into the classification. Thus, the classification will be defined mathematically,

$$X_{ci} = \beta_i R_p / n$$

Where i is from 1 to n.

$$\sum \beta_i = 1.$$

In this study, we have chosen the second measure because this is a data-driven study. We have no theories to refer to, but the measure is based on what was discovered from an analysis of the data. Therefore, the second measure is an appropriate measure in determination of the classification.

Students' problem solving proficiencies are represented by explanatory variables in Table 2, namely Recognizing Information, Deep Cognition and Cognitive Action. The probability values represent students' achievement in each explanatory variable.

Table 2. Students' cognitive features of problem solving

Subject number	Cognitive Feature	Recognizing Information	Deep Cognition	Cognitive Action
1	0.5258	0.7942	0.7509	0.7398
2	0.4295	0.4295	0.5087	0.5327
3	0.4473	0.4364	0.7268	0.5821
4	0.4366	0.4844	0.5095	0.6092
5	0.4280	0.5305	0.5088	0.6521
6	0.4276	0.5363	0.5145	0.6893
7	0.4323	0.5231	0.4693	0.6219
8	0.4409	0.7320	0.5100	0.5707
9	0.4377	0.7698	0.5059	0.6804
10	0.4321	0.5332	0.4790	0.6867
11	0.4111	0.5661	0.7282	0.7151
12	0.4289	0.7671	0.5023	0.6547
13	0.4323	0.7451	0.5101	0.6815

10.2 Students' Cognitive Feature Categories

There were 13 participants in the study. In Table 3, Cognitive Feature presents a general cognitive level in solving a deteriorating patient problem based on these students' data. Recognizing Information, Deep Cognition, and Cognitive Action represent three different aspects. The probabilities beneath the four columns of cognitive terms quantitatively describe these features. Cognitive Feature can be directly used to represent general "rich" level of problem solving processes, while three sub-categories emphasize different aspects. In other words, there might be similar values of Cognitive Feature for each subject, but the weights of the three sub-categories are probably different. The L, M and H represent lower, middle and high, three skill levels of problem solving processes. The values are probabilities that indicate the extent to which the judgment of levels can be trusted. These levels provide suggestions to researchers and students and indicate what kinds of information, at what levels, and what is useful in a problem solving process, such as clinical information collection and application processes.

Table 3. Group distribution of subject members in four cognitive categories

Group	Cognitive Feature	Recognizing Information	Deep Cognition	Cognitive Action	Subject Number
A	L	L	L	L	1, 9, 12
B	M	L	L	L	5, 6, 7, 10, 11
C	M	L	M	L	4, 8, 13
D	M	M	M	L	2
E	M	M	H	L	3

Based on the results in Table 3, the Cognitive Feature can be categorized into 2 general groups: M and L group. The M group subjects demonstrate that their features applied much richer effective information in clinical cognitive process; the L group indicates less information used in the process. The Recognizing Information group represents the majority of L level and some M level. Deep cognition category represents all three levels. Cognitive Action expresses L level in all groups.

There are five patterns based on the combination of each explanatory level. Groups D and E present relatively intensive information searches, interpretations, and application competencies. We can also observe that the categories in Cognitive Feature and in its sub-cognitive categories are not completely identical. In other words, a high score in a sub-category does not indicate higher or lower scores whether in general or in other subcategory cognitive processes. Thus, the distribution of the values in each column can provide diagnostic information to the students. Based on professors and other experts' experiences, suggestions of how to strengthen student competency in collecting effective clinical information might be provided.

11. Conclusions and Future Work

This study presents a cognitive task representation in medical learning domains. These cognitive tasks are not well-structured, but are embedded in a medical learning context. The learning objectives cannot exhibit explicit knowledge structure and states (Falmagne & Doignon, 2011). The authors discovered the effective cognitive task representation, which reflected the features of medical students' learning. The cognitive feature components can be referred to further develop well-structured cognitive tasks in similar learning purposes in medical learning domains. Such a cognitive representation structure is also used as a data-driven alternative assessment framework, such as cognitive diagnostic assessment, performance assessment and dynamic assessment (Lajoie, 2003).

This study explores a cognitive process indicating how medical students recognize information, experience deep cognition, and take actions in a simulated emergency medical situation. The cognitive process describes students' clinical information collection and application process. A general explanatory variable has been defined as Cognitive Feature. The Cognitive Feature consists of three cognitive explanatory variables sequentially: Recognizing Information, Deep Cognition, and Cognitive Action. In order to further examine the cognitive feature, a hierarchical cognitive model has been established through the analysis of think-aloud protocols. The explanatory variables of the cognitive feature trajectory cannot be observed. There are potential variables for explaining students' different features in clinical problem solving processes. Ten evidence variables are developed through the idea unit data analysis. These instantiated evidence variables are used to update the entire model.

A Bayesian network was applied to propagate the information from evidence to explanatory variables. A set of simulated network data provides a scale that allows knowing the variation of the students' levels in clinical information collection and application. Cognitive Action results indicate a lower value. Although there are some lower and some intermediate values in Recognizing Information, there is large variation of values in Deep Cognition. These patterns can provide differential information to analyze different stages in a problem solving process. At the first stage in the sequential cognitive feature trajectory, most students focus on the information recognition. They have to find and select related information with the clinical case. At the second stage of the cognitive feature trajectory, the model presents a variation of patterns, such that five groups fall into three levels in Deep Cognition. This stage provides students with more thinking space in making judgments, evaluating, and using metacognition. It is challenging for students to make decisions and to take cognitive action in the format of a short video clip. It is reasonable that students can contribute more in the cognitive action category if they have more opportunities to search for information from available resources, such as electronic clinical libraries or to seek help from the clinical tutor in regards to the clinical case scenario.

In brief, the hierarchical cognitive model, a quantitative cognitive task representation, has effectively identified different types of students' competencies in problem solving processes, based on a verbal protocol analysis. The model provides moment-by-moment information differentiation for both students and cognitive feature categories in two dimensions. From a student learning dimension, we can observe student cognitive trajectory across these cognitive components. Differences between cognitive variables can be examined based on cognitive feature components. The cognitive Bayesian network will be more robust in differentiating different student groups and cognitive feature categories with updating evidence by the Bayesian network learning.

The cognitive construct is established by theory-driven analysis. Therefore, the construct validity should be further explored with extended clinical data. After all, there are only 13 medical students providing think-aloud data based on a short video clip. Exploratory factor analysis and cluster analysis can be employed to examine the data structure and construct validity as the number of participants and quantity of data increase.

The quantitative structural representation of cognitive tasks in complex learning domains provides researchers and instructors with a cognitive tool for both learning and assessment purposes. It allows them to observe students' learning behaviors cognitively and assess students' progress diagnostically following a dynamic path. Based on cognitive feature trajectory model in the clinical process and students' cognitive features of problem solving the professor can observe each student's progress and obtain assessment information at different levels of the cognitive categories.

12. Limitations

The study was completed with 13 students' data. The conclusion and suggestions are limitedly generalized to different clinical settings and learning environments due to the small sample size. However, the cognitive Bayesian representation model can be used as an alternative assessment model in the similar learning environments.

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