A Graph-Oriented Approach to Measuring Expertise- Detecting Structural Differences between Experts and Intermediates

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Abstract

For designing effective and tailored instruction, valid instruments that measure the level of expertise are necessary. We propose a graph-oriented approach for in-depth analyses of knowledge structures. Therefore, four measures of integration and encapsulation of knowledge structures were validated in an experiment. Participants (six experts and six intermediate students) recalled and explained the symptoms and laboratory data of a medical case description in the domain of cardiology. The results showed that the graph-oriented measures were more discriminative towards expertise-related differences than classic measures. Thus, our graph-oriented measures offer a more adequate and a more fine-grained analysis of knowledge structures.

Keywords: expertise, graph theory, knowledge encapsulation, knowledge integration.

Introduction

"Experts are made, not born" (Schraw, 2009). This citation nicely illustrates that the way from a novice to an expert can be characterized as a bumpy road of deliberate practice and effort (Ericsson, 2006). For supporting novices in developing their skills and knowledge, good and accurate shock absorbers, such as effective instructional explanations, are necessary. Thus, a deep understanding of expertise and its unique differences to novices' knowledge structures as a target state of novices' development is crucial for designing effective instruction (Nückles, Wittwer, & Renkl, 2005). Cognitive science provides a comprehensive picture about the patterns of knowledge structures that constitute expertise: the main findings suggest that experts primarily differ from novices in the nature of their knowledge structure; more specifically in the extent to which their domain knowledge is integrated and compiled. Knowledge integration can be described as principled knowledge, which is characterized as coherent and well-integrated domain knowledge (Chi, Feltovich, & Glaser, 1981). More specifically, novices tend to organize their knowledge around literal, superficial features, while experts organize their knowledge around abstract principles lying underneath the superficial features. These abstract principles allow for the integration of obviously divergent concepts and subcomponents into a coherent, tightly connected schema. As novices and intermediates do not come up with these abstract principles, they have more difficulties in recognizing patterns that fit together, as, for example, it is easier for a medical doctor to ascribe divergent symptoms like a loss of vision and a collapsing pulse to bacterial endocarditis, whereas novices and intermediates would not be able to intuitively ascribe these symptoms to a specific disease and would rather tend to "store" such details unconnectedly in long-term memory (Schmidt & Rikers, 2007).

The second distinctive feature of experts' knowledge is the degree of compilation. Knowledge compilation refers to the process by which persons transform declarative knowledge into productions and automate these productions by combination of these productions to larger units (Anderson, 1981). For instance, compared to intermediates, in order to medicate a flu, a medical doctor does not need to reason on the detail-level of pathophysiology, but rather operates on the macro-level of automated clinical knowledge, like "if the patient has symptoms A,B,C, then she has…", which allows the expert to omit reasoning steps when solving routine tasks (Koedinger & Anderson, 1990). But how does this compilation change the expert's knowledge structure? Boshuizen and Schmidt (1992) suggested that knowledge compilation resulted in the "subsumption of lower level, detailed propositions under higher level […] propositions." This reorganization of the knowledge structure is called knowledge encapsulation. For example, Rikers, Schmidt, and Boshuizen (2002) found that experts' knowledge structures were less detailed and they contained more encapsulated concepts compared to intermediates. In sum, developing expertise can be illustrated by progressing through a number of transitory stages that are characterized by the degree of integration and the degree of encapsulation of the knowledge structure (Schmidt & Rikers, 2007). To support learning, accurate and valid assessment strategies of these stages of knowledge structures are needed as a prerequisite for the design of effective and tailored instruction.

Measurement of Knowledge Integration and Knowledge Encapsulation

To have experts and intermediates elicit their knowledge, we used the classic procedure by Patel and Groen (1986) that consists of the following elements: *1)* Participants are provided with a medical case description, *2)* they accomplish a free recall task of the medical case description, *3)* explain the underlying processes that cause the disease, and *4)* provide a diagnosis for the case description. Whereas the free recall protocol allows for an insight into a participant's problem representation, the explanation captures the conceptual understanding of underlying patterns and the logical and semantic relations of the subject domain (Chi, 2006). For the analysis, the recall protocols and explanations were segmented into propositions, consisting of one relation and an ordered set of two concepts, containing the elementary idea units of the referring text base (Kintsch, 1988).

Classic indicators of knowledge encapsulation and knowledge integration

Based on the propositional segmentation of the recall protocols and the explanations, Rikers et al. (2002) used three different measures of knowledge encapsulation and knowledge integration. Knowledge encapsulation was measured by the number of *high-level inferences* a participant made during the recall of the case description. A high-level inference is a statement that compiles several reasoning steps into one statement. Therefore, each statement in the recall protocol was coded as a *1)* literal, *2)* paraphrased, *3)* low-level inferred, or *4)* high-level inferred proposition of the case description. Low-level inferences were based just on one statement in the case description, whereas high-level inferences merged several propositions of the case description into one inferential proposition. Consider the following propositional segmentation of a case description and a fictitious participant's recall (cf. figure 1). In this case, the participant merged seven propositions of the case description to one proposition and solely recalled that the man has endocarditis. Therefore, the proposition was coded as high-level inference.

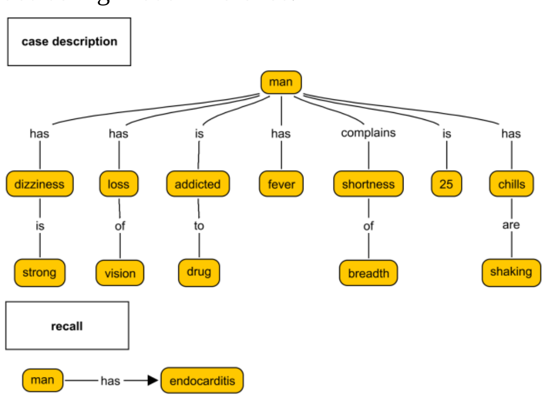

Figure 1: Example for the coding of high-level inferences

The second indicator, *encapsulated concepts*, was measured by the number of matching concepts between the participant's explanation and a reference model that included encapsulated concepts of the subject domain. For instance, the match between the graphs in figure two and three would have four matching encapsulated concepts. Thus, the participant would have used four encapsulated concepts.

For the knowledge integration, Rikers et al. used the number of mentioned *concepts* and *relations* in the explanations. For instance, the graph depicted in Figure 2 would have a detailedness index of four concepts and three relations.

Limitations of the classic indicators

Although the measure *high-level inferences* provides a fine-grained analysis on the level of inferences in the recall protocols, the analyses of the participants' explanations imply some shortcomings: The measurement of the use of encapsulated concepts and detailedness were solely based on the computation of frequencies of concepts and relations. However, structural dependencies, like inter-relations between concepts, were not investigated and thus lack validity. In order to properly measure knowledge encapsulation, what must be demonstrated is the reorganization of the knowledge structure, more precisely how participants subsume their knowledge of details under higher-level concepts (Boshuizen & Schmidt, 1992). In a similar vein, measuring knowledge integration requires both structural indicators for the connectedness and the fragmentation of the knowledge structures. Therefore, an in-depth analysis of structural properties is necessary for validly measuring knowledge integration and knowledge encapsulation.

A Graph-Oriented Approach for Measuring Knowledge Integration and Knowledge Encapsulation

The purpose of this paper was to improve existing measures in order to increase the reliability and validity of knowledge encapsulation and knowledge integration measures. Therefore, to capture key latent variables of knowledge encapsulation and knowledge integration, we developed four measures that were strictly based on graph theory (Sowa & Shapiro, 2006). The analysis of knowledge structures with graph-oriented measures has two main methodological advantages. First, they are capable of directly tracking structural differences, which heightens the validity of our methodology. More precisely, with graph-oriented measures, subsumption and integration processes can be captured in the graphical structure. Second, due to the mathematical formalization of knowledge encapsulation and knowledge integration, our graph-oriented measures could easily be automated, which increases objectivity and efficiency.

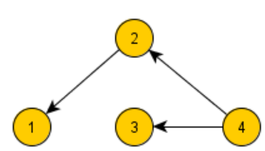

Figure 2: Example for a conceptual graph

Mathematically, an explanation segmented into single propositions can be interpreted as a directed simple graph (Sowa, 2006). A graph G is an abstract representation of a finite set of nodes V that are connected by edges E, mathematically as $G = (V, E)$. Nodes represent concepts, whereas edges represent relations between the concepts.

Knowledge Integration

For the analysis of knowledge integration, we used two different measures. C*onnectedness* was computed by the proportion of the sum of edges *e* and the sum of nodes *v*, formally as:

$$\frac{\sum_{i=1}^{n} e_i}{\sum_{i=1}^{n} v_i}$$

This expression describes the average relatedness of concept to concept and can take values between 0 and 1, where 0 represents a non-connected graph and 1 means that all concepts are directly related to each other. Figure 2 shows an example of a graph consisting of three relations and four concepts. The connectedness for the example graph would be .75.

The second indicator for integration is *fragmentation* of the knowledge structure. Fragmentation was computed as the number of isolated knowledge units. A knowledge unit is represented as a disconnected component in a graph, indicating a subgraph that is not connected to the rest of the graph. Formally, we define fragmentation as the number of components C_n which are subsets of the graph *G*, where each node $v \in V$ has no edge connection to the set of nodes *v* of the complement of $G \backslash C_n$ (Sowa & Shapiro, 2006). Our example graph would have a fragmentation index of 1, because there are no disconnected subcomponents in the graph.

Knowledge Encapsulation

For the analysis of the encapsulation of the knowledge structures, we used two different measures. The *omission of concepts* is an indicator of how many inferential steps a participant skips while explaining a phenomenon. The more encapsulated a knowledge structure is, the more concepts a participant omits. For the identification of the inferential steps, a reference model is needed. This reference model must include all causal relations to sufficiently understand the phenomenon under investigation. Thus, the reference model depicts an accurate causal representation of the phenomenon. The omission of concepts is computed as the number of concepts that are in the set of the reference model (*rm*), but not in the participant's model (*pm*), formally as:

$$rm \setminus pm = \{x \in rm \mid x \notin pm\}$$

The more omission a participant made the less accurate was her explanation. Figure 3 shows an example for a reference model. Located in the reference model are the concepts 5, 6 and 7 that do not appear in the participants' model in figure 2. In this case, we would have an omission of 3, because in this case the participant would have omitted three concepts in her explanation.

A second indicator concerning knowledge encapsulation is the length of the *inference path*. It describes the shortest path between the most distinct concepts and is an indicator for the average length of inferences in the experts' explanation (Dijkstra, 1959). It is computed as the shortest distance between the most distant nodes and can take values from 1 to *N*. A low index in the inference path indicates high encapsulation, whereas high *N* indicates a very detailed description of the phenomenon. In our example, the most distant nodes would be *Node 6* and *Node 7*, and the shortest path would include 4 edges; therefore the inference path would be 4.

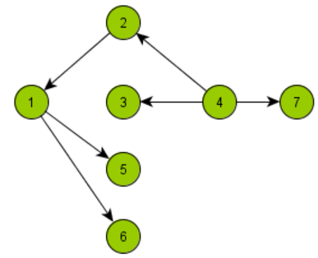

Figure 3: Example for a reference model

Research Questions and Hypotheses

The main purpose of the experiment was to test, if our graph-oriented measures were more sensitive when investigating expertise-related differences of knowledge encapsulation and knowledge integration compared to the classic measures (Boshuizen & Schmidt, 1992; Patel & Groen, 1986; Rikers, Schmidt, & Boshuizen, 2002). In more detail, we examined, if our graph-oriented measures were more capable to detect differences concerning knowledge encapsulation and knowledge integration compared to the classic measures. Furthermore, we validated our graph-oriented measures with the classic measures. For this purpose, we, analogically to previous experiments, asked cardiology experts and intermediate medical students to recall and explain the signs and symptoms of a clinical case description of a fictitious patient who had bacterial endocarditis, taken from Patel and Groen (1986).

Based on these theoretical considerations, we addressed the following research questions.

Predictions Regarding Structural Differences between Experts and Intermediates

For the classic indicators, in accordance with Rikers et al. (2002), we hypothesized that experts would make more *high-level inferences* and would use more *encapsulated concepts* compared to intermediates. For knowledge integration, analogically to Rikers et al., we assumed that experts' explanations would be less *detailed* (less concepts and less relations) compared to intermediates.

For the graph-oriented measures, we expected the following effects: Generally, we assumed that experts would subsume specific concepts under encapsulated concepts, which would result in *shorter inference paths* and more *omissions of concepts* in their explanations compared to intermediates. With regard to knowledge integration, we expected that experts' knowledge structures should be more *tightly connected* and less *fragmented* compared to intermediates (Chi et al., 1981).

Predictions Regarding the Validity of the Graph-Oriented Measures

In order to test concurrent validity of the graph-oriented measures, we examined whether the classic measures were correlated with the graph-oriented measures. More importantly, we tested whether our graph-oriented measures would be able to discriminate between experts' and intermediates' explanations. More specifically, we hypothesized that our graph-oriented measures would be more discriminatory with regard to differences related to expertise, because they would be better able to measure structural differences.

Method

Participants

Six experts and six intermediates participated in the experiment. Experts were recruited from a German cardiology hospital. All were medical specialists who had a mean work experience of 19.5 years and board certification in their specialty of cardiology. They were, on average, 49.75 years old (*SD* = 6.24). Intermediates were advanced medical students in the clinical block of their study program. They were on average 25.83 years old (*SD* = 1.72). Their average number of semesters in the medical program was 10.83 semesters (*SD* = 1.17) and they had attended at least one special course in cardiology.

Design

A quasi-experimental between subjects design was used, with expertise as the independent variable. Dependent variables encompassed measures of knowledge integration and knowledge encapsulation.

Materials

The materials were merged into one booklet, containing a demographic questionnaire about the participants' age, prior knowledge and experience in the area of cardiology. The main component was a clinical case description of a fictitious patient who had bacterial endocarditis (an inflammation of the inner layer of the heart). This description was used in several previous studies (Patel & Groen, 1986; Rikers et al., 2002). The clinical case description included context information, central findings of laboratory data, and descriptions of symptoms. Furthermore, we included two blank sheets for the recall task and the explanation.

Procedure

The entire experiment lasted approximately 40 minutes. First, the participants completed the demographic questionnaire (5 minutes). Second, they read the case description (5 minutes). Third, in the recall task, participants wrote down everything they could remember (5min). Fourth, the participants provided an explanation for the signs and symptoms of the case description, in full sentences (20 minutes). They were asked to write an intelligible and comprehensive explanation. Fifth, participants provided a diagnosis and suggested possible therapies (5 minutes).

Analysis of the Knowledge Structures

We used our graph-oriented measures, described above, to examine differences between experts and intermediates regarding their knowledge structures. For the cross-validation of our graph-oriented measures, we used the classic measures by Rikers et al. (2002) as well. To heighten reliability, we implemented a computer program which automatically calculated all mathematically formalized measures for knowledge integration and knowledge encapsulation, except for the number of high level inferences. Latter was coded by two independent raters that were blind to the experimental conditions. Interrater agreement as determined by Cohen's Kappa was very good ($\kappa = .77$) and differences were resolved by discussions.

Results

There were no significant differences between experts and intermediates regarding the number of propositions in the recall protocol, $F(1, 10) = 3.44$, $p = .09$, partial $\eta^2 = .26$, and the number of propositions in the explanations, $F(1, 10) = 3.01$, $p = .11$, partial $\eta^2 = .24$. Furthermore, as all of our participants were knowledgeable in the domain of cardiology, all participants correctly diagnosed that the patient had bacterial endocarditis, and proposed broad antibiotic mediation as first treatment. The means and standard deviations for all the dependent measures as well as for the propositions can be seen in table 1.

Predictions Regarding Structural Differences between Experts and Intermediates

Classic indicators

Concerning *knowledge integration*, our analyses showed that intermediates' explanations contained more *concepts*, $F(1, 10) = 6.23$, $p = .03$, partial $\eta^2 = .38$, but did not significantly differ with regard to the number of *relations*, $F(1, 10) = 3.04$, $p = .11$, partial $\eta^2 = .23$. Concerning *knowledge encapsulation*, there was no significant difference between experts and intermediates regarding the number of high-level inferences, $F(1, 10) = 2.43$, $p = .15$, partial $\eta^2 = .20$ and in the use of encapsulated concepts, $F(1, 10) = .06$, $p = .82$, partial $\eta^2 = .01$.

Graph-Oriented Measures

With regard to *knowledge integration*, intermediates' knowledge structures were significantly more fragmented than experts' knowledge structures, $F(1, 10) = 6.58$, $p = .03$, partial $\eta^2 = .40$. Concerning connectedness, there was no significant difference between experts and intermediates, $F(1, 10) = 2.83$, $p = .12$, partial $\eta^2 = .22$.

With regard to *knowledge encapsulation*, experts' inference paths were significantly shorter than those of intermediates, $F(1, 10) = 4.40$, $p = .05$, partial $\eta^2 = .33$. Furthermore, experts omitted more relevant concepts in their explanations compared to intermediates, $F(1, 10) = 7.50$, $p = .02$, partial $\eta^2 = .43$.

Table 1: Means, standard deviations and effect sizes for knowledge integration and encapsulation.

Variables	Intermediates	Experts	η^2
Propositions RC[a]	33.33 (5.99)	27.50 (4.85)	.26
Propositions EX[b]	44.67 (8.59)	34.50 (11.31)	.24
Classic measures of knowledge integration			
Concepts	50.83 (9.45)	35.83 (11.29)	**.38**
Relations	44.50 (8.46)	34.33 (11.52)	.23
Graph-oriented measures of knowledge integration			
Connectedness	.88 (.05)	.96 (.11)	.22
Fragmentation	6.5 (1.98)	3.5 (2.07)	**.40**
Classic measures of knowledge encapsulation			
High-level Inferences	1.17 (1.17)	5.33 (6.44)	.20
Encapsulated concepts	7.50 (1.87)	7.17 (2.93)	.01
Graph-oriented measures of knowledge encapsulation			
Inference path	10.83 (3.06)	7.17 (2.64)	**.33**
Omission of concepts	2 (1.10)	4 (1.41)	**.43**

Note. Differences with $p < .05$ are in boldface.
[a] mean number of propositions in the recall protocols.
[b] mean number of propositions in the explanations.

Predictions regarding the Validity of the Graph-Oriented Measures

Table 2 presents the correlations between the classic and the graph-oriented measures. With regard to *knowledge integration*, we found high correlations between the classic measure of detailedness and the graph-oriented measure of fragmentation.

For *knowledge encapsulation*, we found high correlations between the classic measure of high-level inferences and the graph-oriented measure of inference path. Correlations between high-level inferences and omission of concepts were not significant. As the effect sizes (table 1) indicated, the best indicator of knowledge integration was our fragmentation measure; for knowledge encapsulation, our omission of concepts measure.

To test if our graph-oriented measures discriminated better between experts and intermediates as compared to the classic measures, we conducted a discriminant analysis (step-wise). All variables both of the classic and the graph-oriented measures were entered into the analysis. The method of minimizing Wilks' lambda was used for inclusion of the variable, and the criterion F to enter was set to 4. The stepwise discriminant heuristic selected as relevant predictors *omission of concepts* and *fragmentation*, canonical $R^2 = .62$, which significantly discriminated all the cases into the expert's and intermediate's condition, $\Lambda = .39$, χ^2 (2) = 8.58, $p = .01$. The discriminant heuristic solely selected graph-oriented measures, but none of the classic measures was selected.

Table 2: Correlations of the dependent measures (N =12)

		1	2	3	4	5	6	7
Classic measures								
1	Concepts	-						
2	Relations	**.95**	-					
3	High-level Inferences	-.43	-.46	-				
4	Encapsulated Concepts	.24	.05	.25	-			
Graph-oriented measures								
5	Connectedness	-.35	-.04	-.20	**-.65**	-		
6	Fragmentation	**.64**	.41	-.06	.55	**-.78**	-	
7	Inference Path	**.68**	**.63**	**-.62**	.30	-.18	.45	-
8	Omission of concepts	-.54	-.49	.14	-.19	.24	-.34	-.26

Note. Correlations with $p < .05$ are in boldface.

Discussion

In this paper, we proposed four graph-oriented indicators for measuring knowledge integration and knowledge encapsulation. Based on graph theory, these indicators allow for an in-depth analysis of the structure of knowledge integration and encapsulation. The results from our study can be summarized as follows:

Overall, our results showed the validity of our graph-oriented measures with regard to knowledge encapsulation and knowledge integration by detecting structural differences between experts' and intermediates' knowledge structures.

For the classic measures by Rikers et al. (2002), the only statistically significant expertise-related difference occurred in regard to the number of concepts, indicating that experts' explanations were less detailed than intermediates' explanations. For the other classic knowledge encapsulation measures, that is, the number of high-level inferences and the number of encapsulated concepts, no significant differences between experts and intermediates were found. However, we concede that our sample of experts and intermediates was very small. Thus, given the considerable effect sizes for the classic measures, it can be assumed that with a larger sample size, those differences would have also reached statistical significance.

Our graph-oriented measures of encapsulation, namely the omission of concepts and the length of the inference path, significantly differed between experts and intermediates. Additionally, for knowledge integration, we found significant differences with regard to the fragmentation of the explanations, indicating that experts' explanations were less fragmented (i.e. more integrated) than intermediates' explanations. However, connectedness did not differ significantly between experts and intermediates. Generally, the largest effects in our study resulted for the graph-oriented indicators: analyses showed that the most discriminative indicator of knowledge integration was fragmentation. Similarly, regarding knowledge encapsulation, the omission of concepts was the most discriminative predictor. Hence, the graph-oriented indicators were more sensitive towards differences between experts and intermediates, that is, the graph-oriented indicators were better able to discriminate between experts and intermediates. Further evidence for the validity of our graph-oriented measures can be found in the high correlations between the classic measures by Rikers et al. (2002) and our graph-oriented measures. They seem to measure the construct of knowledge encapsulation and knowledge integration related to the classic measures, but due to the granularity of the graph-oriented measures in a more sensitive and discriminative way.

Despite the promising results of our experiment, there are also limitations and open questions that need to be addressed. One limitation refers to the small sample size in the experiment. Although we showed that the graph-oriented measures were more discriminative compared to the classic measures by Rikers et al., the small sample size limited test power and therefore results should be interpreted with caution. As our experts were cardiologists with around 20 years of work experience, it proved to be difficult to convince a large number of them to participate in our study. Additionally, in using only one task, namely to explain the reasons of bacterial endocarditis, the scope of our experiment was rather restricted. Therefore, additional tasks should be included to map a more integrated representation of the domain of cardiology. Apart from the scope, it should also be acknowledged that assessing participants' knowledge structures by analyzing written recall protocols and written explanations is a rather indirect measure of participants' knowledge structure. Therefore, it should be examined whether our results can also be replicated using a more direct elicitation technique, such as think-aloud protocols. Beside these methodological issues, there remains the question, if the graph-oriented indicators are able to model the development of expertise. Therefore, novices should be included in future studies.

In conclusion, we see our methodology as a promising starting point for future research. The results showed that our graph-oriented indicators are well suited to detect differences between different expertise levels concerning the encapsulation and integration of knowledge structures. Graph-oriented indicators proved to be more sensitive and therefore more valid measures of structural differences, compared to the classic measures that solely rely on frequencies of concepts and high-level inferences. Likewise, due to the formalization of the measures, they can be easily automated, which heightens objectivity and reliability and offers a more efficient way of measuring knowledge structures. It is up to further research to explore these possibilities.

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