Predicting task performance with elicitation of non-explicit knowledge

- Assessing non-explicit knowledge in complex problem solving with structural assessment -

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Abstract. *Based on the assumption that nonconscious access to structural knowledge is part of individual implicit knowledge, we present a computer-based test, the AST, capable of eliciting individual structural knowledge for a given knowledge domain. We try to predict complex problem solving (CPS) performance, which partly relies on implicit knowledge and which we see as an operationalization of real-world problems, with AST scores. Structural knowledge correlates with CPS performance but the overall increase of variance explanation compared to traditional predictors of CPS performance such as declarative knowledge and intelligence is small.*

1. Introduction

Knowledge management, “the process of continuously creating new knowledge, disseminating it widely through the organization, and embodying it quickly in new products/services, technologies and systems” [TNH04, p. ix], has become an important management concept in the change towards knowledge-based economies. In this view, knowledge forms the basis for innovation and economic success [Dru93]. In this paper, we introduce Meyer’s and Sugiyama’s attempt to sharpen the concept of non-declarative knowledge (implicit and tacit knowledge, [TNH04], with the help of a dimensional model of knowledge types. Based on their model, we elicit structural knowledge, which is supposed to play a mediating role between explicit and non-explicit knowledge. In an experiment, we try to predict participants’ task performance with structural knowledge scores.

2. Tacit, implicit and structural knowledge

In order to "link the concepts of individual implicit, explicit, and tacit knowledge with findings from memory, cognition and knowledge science" [MS06, p. 2], Meyer and Sugiyama reviewed findings from those fields and concluded that different types of knowledge can be described on the two dimensions 'codifiability' and 'consciousness of use'. In the area spanned by these two orthogonal dimensions, different types of knowledge can be placed (see figure 1).

The main point of this model is the assumption, that Structural knowledge, the "cognitive structure, the pattern of relationships among concepts in memory, also referred to as internal connectedness, integrative understanding or conceptual knowledge" [JBY93, pp. 4f], is a part of individual implicit knowledge. For further details and reference, see [MS06].

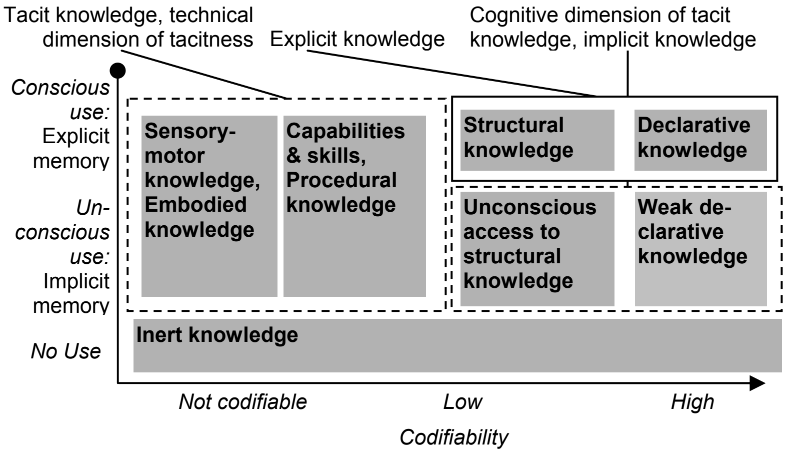

Figure 1: Dimensional model of knowledge types (adapted from [MS06, p. 12])

3. Elicitation of structural knowledge

The Association Structure Test AST [Me+06] is a computer-based test which produces a knowledge graph for each subject to which the Pathfinder algorithm is applied for measurement error adjustment. Individually, these techniques have proven to be valid and reliable [DCT03]. From the participant's perspective, there are two stages in the AST: Free term entry and a similarity rating task. During the first stage, the participants are asked to enter any term they can think of that they consider related to a given stimulus representing a knowledge domain. Free term entry (FTE), as this procedure is also called, mainly deals with the subjects' declarative knowledge.

The entered terms and the reflection times between two terms as well as the typing times are recorded and concept clusters are calculated from reflection times.

After FTE, the subjects perform similarity ratings for the terms that they entered during the first stage. These terms are presented as pairs and participants indicate the strength of the relationships between the paired terms with reference to their content on a scale from 0 to 4. A typical knowledge graph after an AST-test for a single participant is depicted in figure 2.

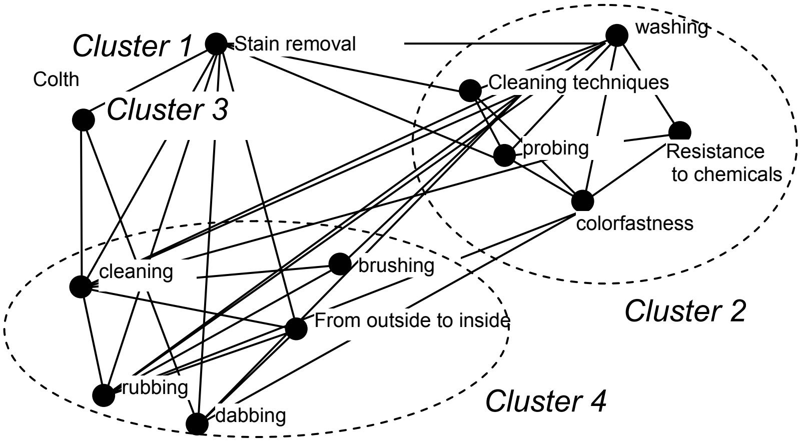

Figure 2: Knowledge graph elicited with the AST. This participant was a cleaner that completed the AST with the stimulus “carpet cleaning”.

First analyses of reliability and validity delivered promising results [Me+06], and the following graph-theoretic descriptors of individual knowledge graphs correlated with outside criteria: Size (number of nodes), Degree (number of edges), Density (number of present edges in comparison with the possible number of edges in a graph), Diameter (longest path in the network), and Number of Clusters. The size of the graph is considered to be linked to explicit knowledge, the degree has tight links to structural knowledge. The density measure is problematic as it is severely biased by the size of the graph. The relationship between clusters and outside criteria is still unclear.

4. Complex problem solving and non-declarative knowledge

According to [Dör95], difficult real-world problems have some typical characteristics: Intransparency (lack of clarity of the situation), polytely (multiple goals), complexity (large numbers of items, interrelations, and decisions), dynamism (time considerations). Recent studies have determined domain-specific declarative knowledge and intelligence, especially reasoning, as influencing CPS performance [Klo04]. However, the relatively small fraction of explained variance arose the question whether further undiscovered factors apart from intelligence and declarative knowledge influence CPS performance. It has been argued repeatedly that implicit knowledge is such a factor [BB95]. We believe that computer-simulated complex problem solving scenarios, such as the TAYLORSHOP simulation [SF90], are an adequate operationalization of everyday tasks that employees of knowledge intensive organizations face. We further assume that an interplay of explicit knowledge, non-explicit knowledge and intelligence is necessary for the successful performance in complex problem solving scenarios.

5. Hypotheses and Method

If one controls for intelligence and domain-specific declarative knowledge, measures of non-explicit knowledge should be able to predict complex scenario performance. We thus hypothesize:

H1…H5: The graph-theoretic features {Size | Degree | Density | Diameter | Number of Clusters} positively correlate with individual performance in complex problem solving.

H6: The correlating graph-theoretic features provide additional variance explanation with reference to the established determinants for complex problem solving, i.e. reasoning and domain-specific declarative knowledge.

In a laboratory experiment, participants completed the scale "reasoning" of the short version of the Berlin Structural Intelligence test BIS-K [JSB97] and acquired knowledge on successfully controlling the complex scenario TAYLORSHOP from texts. Half of the subjects were additionally able to learn scenario control from test runs through trial-and-error. After learning, the short version of the explicit knowledge test on TAYLORSHOP scenario control [Klo04] was performed, followed by the AST with the stimulus "Taylorshop". Finally, subjects worked on the scenario for 12 simulated months. The two variables "profit after twelve moths (profit)" and "number of months during which a profit was made in comparison to the previous month (trend)" operationalize performance in the Taylorshop simulation [Fun83]. In total, 104 participants (56 female & 43 female) took part in the study. Average age of the participants was 26,5 (SD = 6,4).

6. Results

Participants with trial-and-error experience and participants who only learned from texts did not differ in any way and are thus combined into one group. The dependent variables profit and trend correlate with the established predictors domain-specific declarative knowledge (WIS) and reasoning (BIS-4-K) as reported in literature [Ker99]. The trend measure correlates stronger with declarative knowledge and reasoning knowledge than profit (compare table 1).

	AST knowledge graph properties						
	Size	Degree	Density	Diameter	# of Clust.	WIS	BIS-4-K
Profit	.06	.20*	-.02	.20*	.07	.32**	.31**
Trend	.02	$.15^{+}$	.01	.05	.03	.45**	.45**
WIS	.17*	.08	-.06	.17*	.13	1	.54**
BIS	.10	.08	-.02	.06	.10	.54**	1

Table 1: Measurement variables correlation matrix. ** Indicates one-tailed significance on 1% - level, * on 5%-level and $^{+}$ marginal significance on 10% - level.

Two of the knowledge graph properties elicited with the AST correlate with at least one of the operationalizations of CPS: Degree (number of edges inside the graph) and diameter. Diameter correlates significantly with domain-specific declarative knowledge. Neither Diameter nor Degree correlates with reasoning. Size, i.e. the number of nodes in the graph, equal to the number of associated concepts in the free term entry section of the AST, does not correlate with complex problem solving performance refuting hypothesis 1; yet it exhibits a significant correlation with domain-specific declarative knowledge. Hypothesis two (degree and complex problem solving performance correlate positively) and hypothesis four (diameter and complex problem solving performance correlate positively) receive support for at least one of the operationalizations of complex problem solving performance, i.e. profit. Since degree and diameter correlate ($r = .25^{**}$) they are combined into one value by averaging their z-transformed values. This combined score of structural knowledge is inserted into a stepwise multiple regression on profit (compare table 2).

Two ß-coefficients reach significance: Declarative knowledge (WIS) in the first model and structural knowledge in the second. The inclusion of the combined measure for structural knowledge significantly increases variance explanation from 14 to 18 %. Thus, hypothesis 6 (correlating graph-theoretic features provide additional variance explanation with reference to the established determinants for complex problem solving) is supported.

Model and included variables	ß	T	p	R^2	p ΔR^2
Reasoning and declarative knowledge				.14	
Reasoning (BIS-4-K)	.20	1.839	.069		
Declarative knowledge (WIS)	.23	2.078	.040		
Reasoning, declarative knowledge and structural knowledge				.18	.030
Reasoning (BIS-4-K)	.20	1.855	.067		
Declarative knowledge (WIS)	.20	1.808	.074		
Structural knowledge	.20	2.198	.030		

Table 2: Stepwise linear multiple regression on the dependant variable profit.

7. Discussion

The fact that only one of AST's parameters assumed to operationalize structural knowledge by targeting concept interrelatedness (degree, density and diameter), i.e. diameter, correlates with measures of declarative knowledge and reasoning underlines the difference between reasoning, declarative knowledge and structural knowledge. The finding that the number of associated concepts significantly correlates with scores of declarative knowledge also hints at the validity of the AST, as this characteristic was thought to capture explicit knowledge. Of the two dependent variables profit and trend, only profit significantly correlates with some of the AST indicators. According to [RWH91], tasks relying on implicit memory processes correlate weaker (around .30) with explicit cognitive measures (such as IQ) than those relying on explicit memory processes. The fact that profit correlates with reasoning at .31 and declarative knowledge at .32 and the fact that trend correlates stronger with IQ and declarative knowledge (.45) suggests that it takes more implicit knowledge to achieve a high profit than it takes to achieve a positive trend value (in fact, a positive trend does not automatically lead to a profit as trend and profit correlate at .68, $p < 0.001$). If we take profit as the measure that relies more on implicit processes than trend, it is not surprising that profit correlates with structural knowledge, which we see as an indicator for implicit knowledge, and trend does not. The fact that the maximum variance explanation did not exceed 18% is somewhat disappointing, especially since the increase of explained variance achieved by the structural knowledge score is small (4%). This result can have three reasons: (1) Structural knowledge is related to implicit knowledge as applied in CPS but the AST is unable to measure structural knowledge sufficiently. (2) The AST is able to measure structural knowledge, but it has only a weak connection to implicit knowledge applied in CPS. (3) AST is able to measure structural knowledge and it is connected to implicit knowledge, but implicit knowledge has only very little application in computer simulated scenario performance. Our results and others [MCK+ 06] do not support the first assumption. The idea that structural knowledge is irrelevant to performance in the scenario is also not plausible because the Authors of the TAYLORSHOP simulation explicitly assumed an influence of structural knowledge on scenario performance [Süß96, p.67]. It is thus most likely that implicit knowledge in CPS performance becomes more important after many trials and a lot of practice. Our participants had only very little practical experience with the scenario before working on it und thus might have gained only little implicit knowledge. The fact that the participants who tried out the simulation prior to working on it did not score better than those who only learned from texts supports this assumption. The rather small correlations between structural knowledge and CPS performance and the poor variance explanation could thus be caused by two weak connections present at the same time: Between structural knowledge and implicit knowledge on the one hand, and between implicit knowledge and CPS performance on the other hand. Nevertheless, the fact that structural knowledge was the only significant coefficient in the second regression model underlines the importance of the concept.

8. Conclusion

One operationalization of complex problem solving performance, the overall profit in the complex simulated scenario TAYLORSHOP, could be predicted partly by structural knowledge scores. Since these scores show no correlation with established explicit measures of cognitive ability such as intelligence and domain-specific declarative knowledge, the data supports our notion that structural knowledge is interrelated with implicit knowledge and thus allows a psychometric approach to non-declarative forms of knowledge. However, correlations are small and the increase of variance explained is not satisfactory. Thus, structural knowledge and other tasks have to be explored in order to better capture non-explicit knowledge and its contribution to success.

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