Distinctive Ability of Concept Maps for Assessing Levels of Competence

Pilot study

Yulia Tyumeneva, Anastasiya Kapuza, Kseniya Vergeles

Yulia Tyumeneva
Candidate of Sciences in Psychology, Associate Professor, Institute of Education, National Research University Higher School of Economics. E-mail: jutu@yandex.ru

Anastasiya Kapuza
Postgraduate Student, National Research University Higher School of Economics. E-mail: a.v.kapuza@gmail.com

Kseniya Vergeles
Master Student, National Research University Higher School of Economics. E-mail: vergeles.k.soc@gmail.com

Address: 20 Myasnitskaya Str., 101000 Moscow, Russian Federation.

Abstract. Previous research has proved the concept mapping is an effective tool to evaluate knowledge structure, but usually the concept mapping served to foster and trace individual progress in specific field of knowledge. No attention was paid to identifying or verifying the formal indicators of concept maps or their sensitiveness to the level of competence in a specific field of knowledge. However it will make possible to use concept mapping as a standardized tool. In the current study some possible indicators are suggested based on concept maps of experts (n=4) and novices (n=9) in the field of data analysis. Experts and novices constructed their concept maps individually after receiving standardized instructions and brief training. Formal indicators were based on interpreting concept map as a graph. Specifically, indicators such as generality of concepts used, structure coherence, proportions of singular, complex concepts, etc. were expected to be discriminative for different levels of competence. We found that nearly all indicators actually discriminate between experts and novices. In addition, a few qualitative parameters of concept maps were identified (availability of key concepts, existence of erroneous relationships, procedural/conceptual nature of knowledge) which also differed across groups. As a result, concept mapping look potentially helpful for standardized evaluation of competence levels if we use the formal indicators. Although further research on extended and heterogeneous samples is required to test stability and generalizability of this formal approach to the concept mapping.

Keywords: cognitive development, concept mapping, knowledge structure, development of scientific concepts, expert, novice.

1. Restructuring knowledge as a result of education

In the two most important frameworks of new knowledge digestion, that is, the theory of cognitive development of J. Piaget and the cultural-historical theory of L. Vygotsky, the structural changes of the emerged system of knowledge are regarded as a base for intellectual growth and are used as a criterion of age periodization. For Piaget, changes in the cognitive structure are a result of interlinked processes of assimilation and accommodation: new information is understood by the existing structure to the extent of the ability of that structure to digest it, and at the same time new information modifies the existing structure [Piaget 2001]. Vygotsky regards education as the acquisition of new sign structures, which themselves gradually become the means for orientation in the activities following on from the next stages of education. The beginning of this process is considered to be the action of providing the child with a sign structure, which in the further process of education is reconstructed and assimilated, so that the knowledge obtained can be nimbly used in solving a whole class of exercises [Vygotsky 1982: 188–202, 244–267, 305; Vygotsky 1983: 78–85, 128, 147–151, 225, 292–316]. Some modern theories of education also directly indicate the importance of the structural reconstruction of the knowledge system during the course of education (for example, [Ausubel 2000; Novak 2002]).

From both fundamental and practical points of view it would be crucial to make certain that education does lead towards reorganization of the whole structure of knowledge, and not just to its quantitative growth. For the traditional means of marked evaluation (a control work or a test), through their configuration it is impossible to establish the changes in the structure of knowledge. They measure acquired skills, but not the way these new skills influence the existing ones, how the hierarchy within the system of new terms is built, what kind of virtue was given to certain elements of knowledge before learning something new and what is given afterwards, not to the changes on the structure of knowledge.

Lately, systems of educational result evaluation have emerged, which give priority to structural changes: for example, the SAM (School Achievements Monitoring) test, based on the theories of development and education of L. Vygotsky, V. Davydov and P. Galperin [Nezhnov, Kardanov, Elkonin 2011] or the method of concept maps created within the framework of the constructivist approach towards education [Novak, Cañas 2008; Lavigne 2005]. However, the developers of the SAM test do not presume a direct assessment of structural changes, but only admit that it is structural reconstruction of the knowledge system which lets pupils solve the tasks of more advanced levels. And as far as concept maps are concerned, today their effectiveness as a means of marked assessment is hard to estimate conclusively.

Figure 1. **The term of the concept map**

CONCEPT MAP

is

graph

having

*that provides
links between*

**knots
(peaks of
a graph)**

**linking lines
(connections)**

*explain
relations
between*

representing

contain

concepts

sentences
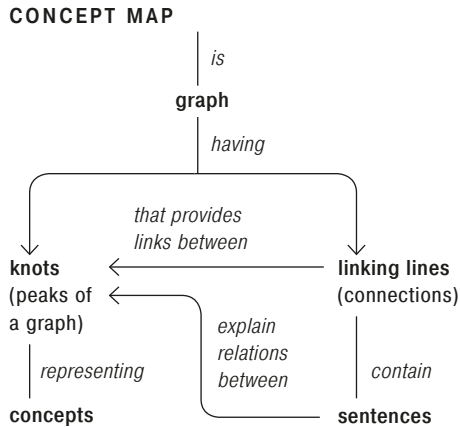
**2. Concept maps
as an instrument
for assessment of
knowledge systems**

A concept map (CM) is one of the instruments used for assessment of the changes in the knowledge structure alongside the problem sorting [Novak, Musonda 1991] and clinical interview of J. Piaget [Bringuier 2000]. A CM is considered to be a graphic representation of terms that refer to a certain topic or a field of knowledge. Usually the knots on the CM stand for the terms, while the ribs or the links between them reveal how these terms are connected to each other in the conception of the respondent (Fig. 1).

For us, it is crucial not only the fact that CMs turn out to be reliable and valid [McClure, Sonak, Suen 1999; Wallace, Mintzes 1990; Stoddart et al. 2000] and the most informative [Lavigne 2005] instrument among the other means to assess the knowledge structure, but also the fact that they have shown good susceptibility to the effects of education [Wallace, Mintzes 1990] and to the emergence, during the education period, of false generalizations and lacunes in the knowledge [Surber, Smith 1981; Lavigne 2005].

In this paper we examine how suitable a CM is for distinguishing the structures of knowledge of people who have different levels of competency in a certain discipline. It has been empirically established that a CM can reveal changes in an individual structure of knowledge that is linked to education (see, for example, [Novak, Musonda 1991; von der Heidt 2015]). However, firstly, the subject of assessment in these research works were individual changes in the knowledge structure of pupils in a certain discipline [Wallace, Mintzes 1990], and not common characteristics, that differentiate experienced people from unexperienced. It is quite possible that the instrument is sensitive to individual changes, but by being "deeply qualitative", it doesn't allow for generalization—which means that it leaves no space for the comparison of characteristics of the knowledge structure on various levels of competency development.

Secondly, in the available research papers on CM, the work of a pupil with these terms is analyzed, but only the ones that refer to a certain topic or a certain discipline [Lapp, Nyman, Berry 2010; Dauer, Long 2015]. The pupil's activity is assessed based on the criteria specified for a discipline examined; such assessment is important in relation to the diagnosis of the education path, but doesn't reveal the objective laws in the knowledge structure, common to various fields. For instance, it is demonstrated that a certain program of learning physics leads to the formation of two key concepts in pupils' minds, that is "atom" and "molecule", as well as their right linkage with the phenomena observed, with evaporation in particular [Novak, Musonda 1991]. However, this conclusion can't be transferred to another discipline, let us say, statistics, as for statistics it would be important to establish key terms that should be mastered, and with the "right" links of these terms with the phenomena observed. It means that a qualitative, substantial approach towards the analysis of CM doesn't allow one to judge on the applicability of this instrument for a diagnosis of the knowledge structure in various disciplines.

Thirdly, in previous research papers CMs were used rather as a means for education, than as an instrument of comparison assessment. For instance, some authors preferred closed CMs and offered them alongside with a framework of concepts, key for a certain topic or discipline [Wallace, Mintzes 1990; Lapp, Nyman, Berry 2010]. They intended to trace, how the connections between the key terms would change and how the new terms would be added to the map as the pupil learns. However, regarding the assessment, the prescribed framework of key concepts is a short hint for pupils who are beginners and an interrupting factor for those who are advanced in the topic. As the abilities to use such a framework are different in various pupils, its usage brings an uncontrolled possibility of possible error into the assessment, which lowers the reliability of CM as an instrument. In another research pupils were advised to fill in a CM with terms whose prepositional structure was already prepared [Ruiz-Primo et al. 2001]. Such tasks need well-developed relational thinking, which also is an interrupting factor.

Another variant of research design with applying concept maps is presented by their construction by the authors themselves based on clinical interviews with pupils [Novak, Musonda 1991]. The reliability of such a process of CMs remains in question, because it is not so clear what kind of effect any preliminary training of the authors of the research and their assistants has on the final shape of the maps. Besides, a clinical interview allows for specifying questions from interviewers, which could direct pupils towards certain answers and thus bring their share of accidental error in the final assessment.

The methodical diversity of the CM research available and the weak control of the effects of any given variations in the approaches to the work with CM do not allow for viewing on the results obtained

in such research as reliable. This is why the question as to whether a CM can perceive such features of the knowledge structure, which are typical for all individuals and differ depending on the level of competency, remains open.

3. Experts and beginners as contrasting groups

In order to verify the sensibility of CM to common features of the knowledge structure of more competent specialists, it is necessary to compare contrasting groups, that is people who must obviously differ based on objective characteristics in the level of competency in any given field of activities. Contrasting groups may be composed of people who have lengthy work experience and a higher formal qualification in a certain field of knowledge (the group of experts), plus those who have only begun to work or even have just commenced study this field (the group of beginners). A feature of such a—relative [Chi 2011]—approach towards the definition of experts lies in the fact that the term "expert" does not imply an "inherent" superiority of experts compared to beginners, but comes down to gaining experience in solving professional problems, and a formal attribute of experience is used in order to separate experts from beginners.

We are convinced that the knowledge structure of experts and beginners is different, and this judgment is based on the results of many empirical studies. Thus, one of the first important observations was made regarding the organization of expert knowledge: they are better structured and hierarchized [Chi, Glaser, Rees 1982; Kim 2013]. That is, when solving a problem, experts represent it in such a way that the representation itself already contains the basis for the subsequent decision [Jee et al. 2014; Chi, Glaser, Rees 1982]. Secondly, it was shown that experts distribute the time taken to solve a problem in favor of its good representation. They are satisfied with the result only when the representation of the task is brought to the executive level, that is, up to all intermediate actions and goals. Unlike the experts, beginners tend to try different ways of solving the problem, focusing on its individual signs [Lowe, Lowe 1996; Li, Kaiser 2011]. Thirdly, newcomers group tasks according to their external characteristics and proceed to their solution by procedures whose suitability is determined on the basis of these external characteristics [Chase, Simon 1973; Perkins, Salomon 2012]. For example, first-year physics students grouped and solved problems, focusing on their parameters such as the presence in the problem of an inclined plane or a falling body. Experts also grouped tasks on physical principles, such as energy conservation. On these more abstract parameters, they also built an approach to the solution [Van Lehn, Chi 2012]. Other studies also found a more abstract character of the information units allocated by experts in solving problems [Chi, Feltovich, Glaser 1981; Lowe, Lowe 1996; Bläsing, Tenenbaum, Schack 2009].

The described differences in solving problems between experts and novices persisted even when newcomers classified simple prob-

lems, and the type and principle of their solution were well known to them [Sloutsky, Yarlas 2000], and even if the instruction directly oriented them to classification by principle characteristics [Bilalić, Gobet 2009]. On the other hand, experts could classify tasks on the basis of their external similarity if they received the appropriate instruction, but when the instructions did not specify which principles should be classified, experts conducted it on key essential features of tasks, rather than on external similarities. Moreover, it turned out that expert task classifications are consistent among themselves [Ibid.], which may indicate the existence of some "ideal" structure of knowledge in a particular subject or discipline, to which all experts come to experience.

Distinctive features of CM experts were found in almost all fields of activity (sports, academic activities, meteorology, music, chess, etc.), in which the patterns of solving problems were compared by experts and novices (for a review, see [Vergeles 2017]). This means that a structurally complex, highly hierarchical and highly connected structure of expert knowledge can be the result of the development of knowledge as such, regardless of the specific content of the knowledge area, whereas the attention of the beginner to the methods of solving and single characteristics of problems can be a sign of a starting phase on the path to mastering knowledge.

4. Formal indicators of CM

We plan to show that the knowledge structure presented in the form of a CM has formal characteristics common to a certain level of competence development in a particular area of knowledge. By formal characteristics, we mean the structural characteristics of a CM, that is, their properties, which do not depend on the kind of specific concepts used. Formal characteristics of the map, thus, include only nodes and edges between them and do not include the names of concepts and edges. It is formal indicators that are central to our research, because, firstly, it is possible to make the CM evaluation objective and standardized (the same objective indicators are evaluated by the same procedure), and secondly, make such an assessment less dependent on the competence of evaluating and even accessible to non-specialists in the certain field of knowledge.

To analyze the formal characteristics of CMs, we relied on graph theory [Ore 1968], since a map consisting of a set of nodes (or vertices) and a set of links (or edges) is essentially a graph. Figure 2 schematically depicts a graph with its main characteristics.

We believe that CMs have formal characteristics that reflect the above-mentioned features of the knowledge structure. We refer to them as the following: the level of generalization of the concept, the uniformity of generalizations in the structure, complex concepts, single concepts, and the interconnectedness of the structure.

To operationalize the level of generalization of the concept, we simultaneously used two indicators: the volume of the concept and the number of hierarchies that lead the concept. In terms of a graph, the

Figure 2. **Graph and its main characters**

Summit (knot)

Rib:
incoming links;
emanating links

Dangling vertex
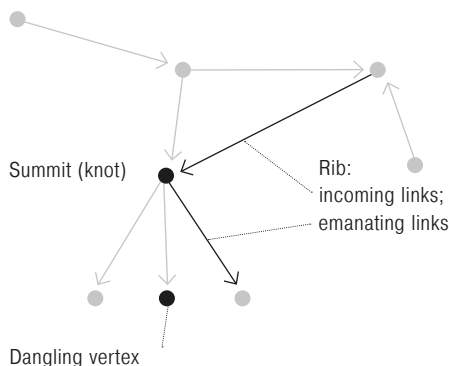
three-dimensionality of a concept can be measured by the number of outgoing edges, and the formation of a hierarchy by outgoing consecutive links to nodes. The volume in itself, that is, the number of outgoing edges may not reflect the level of generalization of the concept if all outgoing links lead to single concepts (without outgoing edges). On the other hand, the only hierarchical connection that emerges from the concept with many consistently subordinate concepts can, in terms of a graph, mean the stages of a process, for example, decision making, which again does not allow us to judge the level of generalization of the "upper" concept. Therefore, it is necessary to take into account both the volume and the presence of hierarchies. We calculated this indicator as the ratio of the volume of concepts (we took the average number of outgoing edges of the three most voluminous concepts in CM) to the level of the hierarchy of emanating concepts. We expected that the level of generalization (taking into account the hierarchy of connections to be understood) will be higher for experts than for beginners.

The uniformity of generalizations in the structure indicates a sequence in the transition from the most general to the individual concepts, the existence of intermediate links. Judging by the data available in the academic literature, with increasing competency of the learner, not only does hierarchy appear in the structure of his knowledge, but also becomes increasingly complex, detailed, representing all possible levels of generalization, the hierarchy of the concepts learned. So, we expected that the experts will be using concepts with intermediate levels of generalization, thereby revealing a more even structure of knowledge, while the beginners will be preferring extreme levels, i.e. to build direct ribs between very general and single concepts without using intermediate levels of generalization. This indicator we calculated as the average difference in the volume of the three most voluminous concepts.

Complex concepts are the result of the interaction of several other concepts. We expected that complex concepts will occur more often in the group of experts than beginners. The indicator was calculated by the number of adjacent ribs, that is, ribs having a common node.

Single concepts have no other connections, except one incoming. We expected that the beginners will have more single concepts than the experts. The indicator was calculated as the number of hanging nodes in the map.

The linkage of structure is an indicator of the density of connections between concepts. We expected that the experts will have a higher degree of connectedness of the map. The indicator was calculated as the ratio of the number of concepts to the number of ribs between them.

We expected that within the contrast groups the CMs will be similar in all the indicators indicated. The task of our work was, therefore, to show the distinctive ability of the CM in a theoretically expected direction in contrasting groups of specialists in terms of competence.

5. Quality indicators of CM

Another research task was to confirm that, in addition to formal characteristics, CMs have certain qualities, which, as already documented in the scientific literature, vary among the groups of beginners and experts. By qualitative indicators we mean the content of concepts and links on the CM, depending on the specific area of knowledge: what concepts are exactly used and what exactly the edges between them are called. Qualitative assessment can be carried out only by specialists in this field, and in this sense it depends on the characteristics of the appraisers themselves, that is, it is subjective. Nevertheless, it is also important because if we find the correspondence of qualitative CM indicators of our contrast groups in the data previously obtained, we will confirm the constructive divisibility of open (that is not containing a given list of concepts) CM as a tool for assessing the structure of knowledge of experts and beginners.

We analyze three qualitative indicators of the structure of knowledge. First, we expected to see a common set of key concepts in the group of experts. Numerous studies of problem solving problem by experts and beginners have shown that in any field the experts have a common understanding of what is the key (that is, structure-forming) information in their professional tasks, but the beginners do not yet have the key knowledge to solve professional problems. Accordingly, there should not be a common set of concepts common to all beginners—neither analogous to the expert, nor any other. Secondly, we expected that the experts will be predominantly using concepts related to so-called declarative knowledge (ideas, theories, concepts), and the beginners will be using concepts related to the methods of solving the problem, that is, with procedural knowledge, as shown in previous experiments [Chi, Feltovich, Glaser 1981; Sloutsky, Yarlas 2000; Stylianou 2002; Rittle-Johnson, Schneider 2014]. Thirdly, we

assumed that the beginners will make mistakes, linking concepts, and the experts won't. In all the studies known to us, without exception, errors of binding concepts in novices were fixed, although they did not use the open form of CM. Therefore, having discovered errors in the group of newcomers and not finding them in the group of experts, we also confirm the constructive validity of open CMs.

6. The design
6.1. Panel

The subject area in which we compared the CM of the experts and beginners was through methods of statistical data analysis. Thirteen respondents participated in the study. Nine of them, who made up the group of beginners, are students in their first year of a master's degree who have successfully completed a course on statistical analysis. All of them used quantitative data analysis while writing their term paper and had not performed more than one year of work related to the analysis of data. Some of the beginners had preliminary knowledge in statistical analysis, obtained during training in their Bachelor degree program.

A group of experts (four people) was made up of professors of data analysis methods, each with work experience of more than four years, and having at least six publications with statistical data analysis results in peer-reviewed journals. Such professional experience was demanded of each expert, quite conditionally. However, such characteristics are "appointed" expertly in all the other studies of beginners and experts carried out in the already noted relative approach. For us, the main criteria for selecting experts were the experience of teaching and the availability of publications that used data analysis as evidence at a certain level of expertise. The adopted criterion is rather conservative from the point of view of our goals: if there are differences between the CM of beginners and CM of experts at this level already, they can all the more be expected when compared with more qualified specialists.

6.2. Instruments and procedures

The study was conducted individually. First, the respondents became acquainted with the instructions for constructing concept maps. The instructions were given in written form and contained examples of maps on other subject areas. Once acquainted with the instructions, the respondents, if they had questions, could ask them to the experiment conductor, and then they made up a conceptual map on the topic of "Statistical Data Analysis". The task of constructing the map was presented in an open form: the instruction contained only a topic and did not contain a list of concepts. During the development of the map, no additional instructions, advice, or comments were received by the respondents. The time was not limited for the participants, while the terms of the assignment varied greatly from the respondent to the respondent: the minimum duration was 45 minutes, the maximum was about two hours. During the creation of the maps, one of the authors of this article was present in the same room as the respondent.

Table 1. **Mean values and deviations of formal indicators of conceptual maps for beginners and experts**

	Knots	Ribs	Connect-edness	Hanging knots	Adjointing ribs	Value (level)			Hierarchic level	The level of generality
						1st	2-nd	3-rd		
The beginners	20.6 (5.5)	17.0 (6.4)	1.4 (0.7)	12.0 (5.9)	2.8 (3.8)	6.7 (4.7)	2.2 (1.01)	1.6 (1.1)	6.6 (3.5)	0.8 (0.8)
The experts	14.3 (5.3)	17.8 (6.6)	0.8 (0.01)	2.5 (3)	11.0 (4)	3.5 (1.3)	2.3 (0.5)	2.0 (0.8)	9.8 (3.6)	0.3 (0.06)

Note: standard deviations are given in brackets.

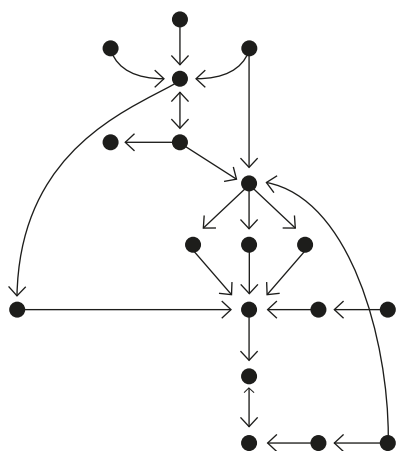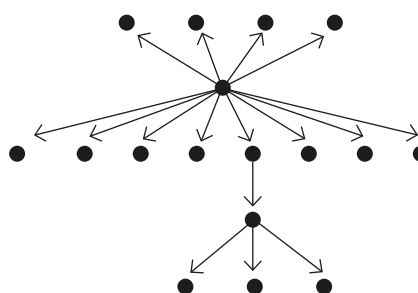Figure 3. **An example of an expert's map**

Figure 4. **An example of a beginner's map**

7. Results
7.1. The analysis of formal indicators of CM

We calculated the average values of formal CM indicators for contrast groups (Table 1). To assess the significance of differences in the indexes between contrast groups, a nonparametric Mann-Whitney test was used, suitable for cases where the nature of data distribution in a small sample is unknown.

The degree of generalization of the concepts used in the map was calculated as the ratio between the bulk of the largest concept (the number of edges coming from it) and the number of hierarchical knots, that is, the knots that have both inbound and outbound connections. It was found that contrast group contrasts significantly differed in level of generality ($U=0$, $p<0.01$)[1]. The examples of expert and beginners maps are shown in Fig. 3 and 4.

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[1] The Mann-Whitney criterion was used, since the necessary condition for the t-test is that the distribution is normal.

Another important indicator of the generalization of terms used in the CM is the average difference in the volume of the three most voluminous concepts, which also differs significantly in expert groups and newcomers ($U=0$, $p<0.01$). This indicator reflects the uniformity of generalizations in the structure of knowledge and the existence of transitional concepts on the level of generalization that connect the most common concept with individual ones. The experts of the generalization are more uniform, since the most voluminous concepts contain approximately the same number of links (3.5, 2.3 and 2.0), whereas newcomers use concepts that differ sharply in terms of generalization (6.7, 2.2; 1.6).

Although the groups of experts and beginners did not differ in the average number of knots in the CM, nor in the ribs ($U_{knots}=6.5$, $p>0.05$, $U_{ribs}=19.5$, $p>0.05$), the ratio of the number of knots and ribs to individual level by the Mann-Whitney criterion was statistically significant and varied in the two groups ($U=0$, $p<0.01$). As expected, the level of cohesion of CM among experts was higher than that of beginners.

The number of single concepts themselves, that is hanging knots, was significantly larger for the beginners than for the experts (12.0 and 2.5, respectively, $U=2.5$, $p<0.01$), whereas complex concepts, that is, knots with adjacent edges, were larger in the experts ($M_{experts}=11.0$, $SD=4.1$, $M_{beginners}=2.8$, $SD=3.2$).

7.2. Quality analysis of CM

As a result of the analysis of qualitative characteristics of knowledge structuring, we have revealed three distinctive features of beginners' maps: the absence of a unified set of concepts used; preferential use of procedural concepts; and erroneous connections between concepts.

The absence of a unified set of concepts used. A set of concepts common for a group of experts is treated as a key for this area of knowledge. In the literature, key concepts, as a rule, are considered to be found in more than half of the experts [Wallace, Mintzes 1990]. Our experts in this capacity were the following concepts: "hypothesis", "data", "analysis", "variables" and "results." They were used by all of the experts without exception. These concepts really reflect the basic elements of the statistical data analysis, since they determine the general approach to analysis, the choice of methods, the logic of all the procedures used and the interpretation. The beginners used only the terms "variables" and "data" from this list and in fact ignored the "hypothesis", "analysis" and "results." It was impossible to exclude the possibility that the beginners singled out some other concepts as the key ones. However, it turned out that their cards almost did not have the same concepts, which may indicate the absence of formed key concepts at the initial level of competence development.

The predominant use of procedural concepts. The available data on the specifics of problem solving by the experts and the beginners

give reason to expect the experts to preemptively use concepts related to the so-called declarative knowledge (ideas, theories, concepts), and for the beginners to use procedural concepts [Rittle-Johnson, Schneider 2014]. Indeed, in addition to general concepts that are key to the field ("hypothesis", "research question", "analysis", etc.), the CM of experts contained other theoretically loaded concepts, for instance, "sample", "connection", "differences" or "concepts," "models," "covariates," "interpretation of results," "research problems," and "method." The beginners preferred procedural concepts that describe actions for analyzing data. For example, they listed the types of regression analysis or the steps necessary to implement it.

Erroneous connections between concepts. Unlike the experts, the beginners often established erroneous connections between concepts. For example, it is erroneous to interpret "variables" as a form of describing "data," or "inference," which follows directly from the "constructed model," or an explanatory function of "statistics" in relation to "research," or a closed cyclical relationship between the concepts "data analysis", "variables" and "data".

8. Interpretation

The purpose of this study was twofold. Firstly, we wanted to theoretically define such formal CM indicators that would reflect certain features of the knowledge structure. Secondly, we wanted to make sure of the distinctive ability of these indicators by comparing two contrast groups—beginners and experts—in a certain area of knowledge. Both goals were achieved: indeed, it was empirically established that the theoretically distinguished characteristics of the CM differ between the group of experts and beginners in the field of statistical methods of data analysis. Such characteristics were presented by: the level of generalization of the concepts used, the presence of concepts of different levels of generalization, the connectedness of concepts with each other, and the share of complex and individual concepts. In other words, as a result of our work, the characteristics of the structure of knowledge, differing, judging by the data of previous studies, from experts and novices, received their indicator elements in the CM. These indicators, considered here as elements of the graph, are formally described as the ratios of the different types of nodes and edges presented in the map.

It is important to note that it was such a formal approach which made it possible to transform highly individualized CMs into a set of objective parameters that are independent of the professional level of the card evaluators themselves. Thus, CMs are derived from the range of tools of individualized assessment in the area of objective evaluation, are placed in line with other standardized methods of evaluation. Previous work has shown that CMs are sensitive to individual changes in the structure of knowledge as the level of competence rises. Our results testify that CMs are suitable for use in comparative studies.

The establishment of the discriminative capacity of a number of indicators is only the first step in confirming the diagnostic potential of the CM. But the formal approach proposed by us ensures the availability of CM for further checks: from the reliability of the indicators to the constructive validity. For example, from the point of view of reliability, it is certainly necessary to demonstrate the retest stability of all the declared indicators. To confirm the constructive existence it is important to obtain support for the proposed interpretation of our indicators. After all, the calculation of the various elements in the map does not automatically lead to their interpretation in terms of the structure of knowledge. Here we logically assumed that the elements and their relationship reflect certain characteristics of the structure of knowledge, for example, the ratio of the number of knots and links reflects the connectedness of concepts, and the hanging knots are concepts that the respondent regards as single. We showed that these indicators take different values in contrast groups, and these differences are exactly what we expected, but, of course, more fundamental support for our interpretation is required here.

We see the perspectives of this work in the logic of theoretical views of L. Vygotsky regarding the development of scientific concepts, since the formation of these concepts reflects a conceptual map. Vygotsky assumed that the course of development of scientific concepts is opposed to the ways of development of everyday concepts [Vygotsky 1982]. If everyday concepts develop from the recognition of individual phenomena or objects pointed at by the concept, to an understanding of the abstract meaning of the concept itself, then the scientific concept is immediately given as an abstract meaning, and its development proceeds in the direction of comprehending the object represented in it. Signs of the maturity of the concept (any: both everyday, and scientific) is what Vygotsky calls the possibility of linking it logically with other concepts, immersing him in the hierarchical system of other concepts of different levels of generalization.

Some of Vygotsky's theoretical assumptionswere reflected in the composition of the indicators we identified. So, for example, we used the indicator of the degree of generalization of the concept as a fraction of outgoing hierarchical relations among all outgoing from this notion of edges. The indicator, which we called "uniformity of generalization," was calculated as the average difference in the volume of the three most voluminous concepts in CM, suggesting that experts, unlike beginners, will use the concepts of all levels of generalization—in full accordance with the Vygotsky's idea of that the mature concept should function in a system of other concepts of different levels of generalization. Vygotsky seems to be very promising in terms of planning further work on CM analysis. On the other hand, it is possible that the concept map method can be used for empirical support of the theory itself.

A serious limitation of our research is that we checked the discriminative power of formal CM indicators on a single sample, and, moreover, the sample is homogeneous and small. Small numbers alone do not pose a great threat to pilot research. First, because its purpose is to approbate a new method of analysis rather than a rigorous assessment of the characteristics of the respondents. Secondly, research with conceptual maps as a deeply qualitative method is applied only individually, requires a lot of time and is usually used on small samples: for example, n = 19 [Jeong, Lee 2012], n = 3 [Lavigne 2005], n = 8 [Kandiko, Kinchin 2012], n = 11 [McNeil 2015]. However, together with the homogeneity of the selection, the small number of our groups of respondents prevents the dissemination of the findings to other areas of knowledge. And although the qualitative block of our work led to results that coincide with those obtained with the help of CM in other studies (for example, about erroneous connections between concepts or about the primary use of procedural concepts by beginners), it is absolutely necessary to study the CM patterns for the beginners and experts further. The first results, obtained with the help of the proposed quantitative method of analysis of conceptual maps, look encouraging.

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