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Validation of the Quantitative Approach to Assessing Conceptual Structure Using Network Analysis

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Table of contents

INFORMATION ABOUT THE APPLICANT AND DISSERTATION RESEARCH 3
INTRODUCTION 4
RESEARCH RELEVANCE 6
DEGREE OF DEVELOPMENT OF THE PROBLEM 7
Concept maps as a method for assessing conceptual structure 7
First component: problem statement for concept map construction 7
The second component: the response form 8
Pillar three: a system for evaluating concept maps 8
Network analysis as a system for evaluating concept maps 10
RESEARCH AIM AND OBJECTIVES 10
RESEARCH QUESTIONS 11
THEORETICAL FRAMEWORK OF THE STUDY 12
Theories of learning and cognitive development applicable to explain the development of conceptual structure 12
Network analysis for assessing conceptual structure 14
METHODOLOGY AND METHODS 16
MAIN RESULTS OF THE STUDY 19
Research Question 1: How are cognitive theories used to apply network analysis techniques to the measurement and interpretation of conceptual structure measurement results using concept maps to date? 20
Research Question 2: Are the indicators from network analysis valid for determining the level of complexity of conceptual structure using concept maps? 21
Research Question 3: How do concept maps of different types (with and without a given list of concepts) differ in terms of indicators from network analysis? 22
Research Question 4: What indicators for assessing conceptual structure based on network analysis can be developed so that they meet theoretical insights from the psychology of learning and cognitive development? 23
THEORETICAL AND PRACTICAL SIGNIFICANCE OF THE WORK 24
THESIS STATEMENTS 25
CONCLUSION 25
REFERENCES 26

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INTRODUCTION

Knowledge utilization is one of the most important concepts in cognitive psychology. In its most general form, knowledge generally refers to the storage, integration and organization of information in memory. Perceptions of how knowledge about a particular domain is organized in experts are a key aspect in understanding learning.

In cognitive psychology of the 20th century, much attention *has* been paid to how *knowledge is* organized and represented (*knowledge representation, representation of knowledge*). One of the basic theories of knowledge organization is the semantic network theory. Quinlan and Quillian developed this theory based on the idea that knowledge can be represented as a network, where nodes represent concepts of different levels of abstraction (e.g., canary; bird; animal), and links between nodes reflect relationships between concepts (Collins & Quillian, 1969). Each node stores information associated with that level (e.g., canary is yellow, bird has wings, animal breathes), and each subsequent node includes information about all previous nodes.

According to L. Barsalou, knowledge is not stored in the form of abstract symbols or language rules, but rather represents active mental models and, therefore, knowledge can be activated and changed depending on the context in which it is used (Barsalou, 1983). For example, the representation of the word apple may be different in the context of cooking and in the context of botany.

Further, the notion of storing and organizing acquired knowledge became more complex, as it was necessary to take into account the procedural side. Thus, in the 70s and 80s, propositional models began to be actively developed, which include nodes representing concepts and links between these nodes representing relations or connections between concepts, and each link can have different attributes such as link strength or direction (Anderson, 1996; Norman & Rumelhart, 1975).

In the 1990s, a model that summarizes and complements the previous ideas - ALCOVE (attention learning covering map) - also emerged (Kruschke, 1992). ALCOVE is a "connectivist" model that assumes that stimuli are represented as points in psychological stimulus space, and thus represent a vector. In doing so, it assumes that for each training stimulus there is exactly one radial-baseline node, that is, a node in the network that represents some pattern. In other words, such a node represents a template or "center" for a particular category or pattern. When a new stimulus arrives, it is compared to these centers, and the node whose center is closest to the input is activated, using a radial function to estimate similarity. Thus, this theory is applied to describe learning based on stimulus categorization. However, D. Kruschke himself (Kruschke, 1992) noted that the main limitation of this model is that it is applicable only to situations for which stimuli can be appropriately represented as points in a multidimensional psychological similarity space. In cognitive psychology, however, not all stimulus domains are fully amenable to spatial representation.

In general, a significant limitation of using such cognitive theories to develop procedures for measuring the structure of knowledge acquired in the process of education is that they describe to a greater extent the "natural", spontaneous acquisition of knowledge, which may include not only concepts, but also various sensorimotor experiences. As a consequence, the way knowledge is represented (as well as the way it is used) is different from what is required in formal education, especially in higher education, which focuses on students learning very abstract material.

At the same time, from the point of view of the organization of learning and teaching, the works in the field of developmental and learning psychology seem more important, since they are devoted to the "arbitrary", "designed" acquisition of concepts. Undoubtedly, the main works in this area are the theories of J. Piaget and L.S. Piaget. Piaget and L.S. Vygotsky. While differing in explaining the causes and consequences of development and learning, they converged in describing the basic mechanisms of development of conceptual structure in children. Vygotsky understood concepts as words and the meanings behind them (Vygotsky, 1999). At the same time, Vygotsky emphasized the development of scientific concepts in the learning process, contrasting them with spontaneous, everyday concepts, which were discussed to a greater extent by researchers from the field of cognitive psychology. He wrote: "A scientific concept, due to the fact that it is scientific by its very nature, presupposes some place in the system of concepts that determines its relation to other concepts" (Vygotsky, 1999, p. 208). The present work is devoted to the study of just such a conceptual structure arising in the process of learning, i.e. the relationship of the learner's ideas about objects or phenomena representing the content of the studied field of knowledge.

It is important to note that, as E.V. Ilyenkov noted, "...very often we confuse the development of the ability to think and the process of assimilation of knowledge provided by the programs. And these two processes do not coincide automatically, although one without the other is impossible" (Ilyenkov, 1964). (Ilyenkov, 1964). At the same time, the works of such outstanding Soviet and Russian scientists as V.V. Davydov, P.Y. Galperin, A.N. Leontiev, N.F. Talyzina and others were more focused on the study of how to build a school program that best meets the natural development of a child's ability to think and solve learning problems and tasks. This area of research is a separate large direction, but in this research we will focus on the **consideration of the possibility and method of measuring the result of concept assimilation in some area in** order to provide researchers of the most effective ways of assimilation of knowledge with a toolkit for making evidentiary decisions.

In the middle of the 20th century, within the framework of such a trend in education as constructivism, methods of assessing conceptual structure began to be developed. Traditional assessment methods, such as standardized tests, are unable to reflect the structure, relationships of concepts, and assess changes in conceptual structure, so J. Novak and colleagues, using clinical interviews, developed a method based on the graphical representation of such structure - *conceptual mapping* (Novak & Musonda, 1991). Conceptual maps differ from other assessment tools in that they allow to see the relationships between all concepts and come directly from the respondent.

Concept maps have come a long way in their development as a tool available for assessing the formation of conceptual structure during learning (Ruiz-Primo & Shavelson, 1996; Strautmane, 2012; Watson et al., 2016). However, methods for analyzing the constructed concept maps are still the subject of research, comparison, and validation.

Researchers and practitioners using concept maps to assess conceptual structure face two major difficulties. First, there are no objective, unified indicators of the degree of formation or development of such a structure, i.e., its change with increasing expertise of the learner in the chosen field of knowledge. Often the only indicator of the conceptual structure development is the number of used concepts and connections between them. However, the justification of what indicators and why should characterize the development of conceptual structure and how to interpret the values of this indicator is poorly developed. For example, should a developed conceptual structure be as broad as possible and include many concepts at different levels of abstraction, or should it include sufficiently abstract but strongly related key concepts in the domain?

Second, a weakness of using concept maps is their individualized use. The vast majority of findings regarding changes in conceptual structure represent individualized expert feedback for each observation (e.g., Conran et al., 2017; Cook, 2017). Of course, assessing individual progress and identifying misconceptions of individual students is an invaluable benefit of formative assessment in general and assessing changes in conceptual structure in particular. However, this approach does not allow researchers to focus on universal characteristics of concept maps that can be applied to assessing learning progress and monitoring conceptual structure development in general. In particular, this requires formal (objective, calculable) indicators that would allow differentiating between levels of competence in different domains without requiring expert interpretation.

Thus, the **problem of the** present study is the overdue need to unify and validate the way of assessing the conceptual structure formed in the learning process through concept maps.

RESEARCH RELEVANCE

The existing literature on the use of concept maps to assess conceptual structure emphasizes both the usefulness of this tool and the limitations of its application. First of all, it is worth noting the unsystematized variety of methods for interpreting the results of concept maps constructed by students. Thus, in general, we can distinguish two approaches to interpreting the results: qualitative and quantitative. The limitations of the qualitative approach are clear: indicators such as accuracy (Ruiz-Primo et al., 2001), quality of structure (Novak & Gowin, 1999), and so on, vary greatly from expert to expert (usually teachers and educators) (Watson et al., 2016). Furthermore, such criteria are usually applied in relation to a specific subject or even a specific topic, which greatly reduces the generalizability and comparability of results from different subject areas.

The quantitative approach seems to be more relevant for analyzing large data sets, as well as for comparative analysis of maps. It can be used to trace, for example, the development of conceptual structure, i.e. its changes with the increase of the learner's expertise in the chosen field of knowledge. However, it also has limitations, first of all, the weak justification for the use of certain indicators and the lack of an explicit understanding of how to interpret the results obtained.

More important than just the haphazardness and fragmentation of the methods used is the lack of a theoretical basis for selecting or developing the criteria by which the maps are analyzed. In many ways, it is the lack of psychological theories about the direction of conceptual structure development in the course of learning that has caused the noted methodological fragmentation. Even when speaking about objective criteria such as the number of concepts and connections between them, it is necessary to understand what this or that characteristic of a map (e.g., an increase in the number of concepts used by a student) means for learning and cognitive development in general. In particular, sometimes authors believe that the more concepts a learner uses in a concept map, the more developed the conceptual structure is. However, this claim is not entirely obvious: for example, a person may name many concepts that they have heard from computer science but have no idea how they relate. Can this be considered a good understanding of the subject area?

Analysis of the literature shows that in the absence of psychological theories, researchers are increasingly resorting to theories that were not originally designed to describe psychological reality, but rather used in the field of analyzing complex systems. First of all, graph theory and its more applied aspect, network analysis, which allow us to assess the relation of concepts to each other, draw attention. Since a conceptual map can also be represented as a network of interrelated concepts, graph theory, although technical in nature, has helped to advance the analysis of conceptual maps, in many ways laying the groundwork for psychological theory.

In general, network analysis has a wide range of tools for assessing various properties of systems with connected objects (M. Newman, 2018). One of the main challenges that network analysis addresses is the analysis of *complex systems*, i.e., systems whose behavior is difficult or impossible to deduce from knowledge about the behavior of their individual components (Estrada, 2016; Mata, 2020). For example, such systems could include the *World Wide Web* or the interaction of neurons in the brain. Among others, important problems for the study of *complex networks* are the identification of the most important nodes of the network and the connectivity of the network as a whole. And conceptual structure researchers have indeed recently often addressed these concepts(Cicuto & Correia, 2013; I. Koponen & Nousiainen, 2013; McLinden, 2013; Siew, 2018). But although network analysis offers a universal language with which to reason about network properties, for educational research it is necessary to interpret the results also in terms of learning theories, cognitive theories. At the moment, there is a weak synthesis of the analytical apparatus from network analysis and assumptions from theories describing the criteria of a developed, i.e. more advanced expert position of a learner in a certain field of knowledge, conceptual structure.

Thus, the **relevance of the** present study is that against the background of a fairly developed analytical tool that is suitable for investigating complex structures such as conceptual structure - network analysis - there is a lack of evidence for the validity of its use in terms of learning theories.

DEGREE OF DEVELOPMENT OF THE PROBLEM

As outlined above, the research problem is the unmet **need to unify and validate a quantitative approach to assessing conceptual structure using concept maps.** Network analysis provides a great opportunity for this. Let us review the existing research on the assessment of conceptual structure using concept maps and the use of network analysis for this purpose.

Concept maps as a method for assessing conceptual structure

A concept map is a graphical representation of the relationship between concepts and processes related to a subject area (mathematics, physics, biology). The map consists of nodes (concepts) and directed relations, or links, connecting these concepts (e.g., is, relates to, derives from, etc.) (Figure 1). Concept maps are considered a valid (Mcclure et al., 1999; Stoddart et al., 2000; Wallace & Mintzes, 1990) and informative (Lavigne, 2005) method for diagnosing conceptual structure.

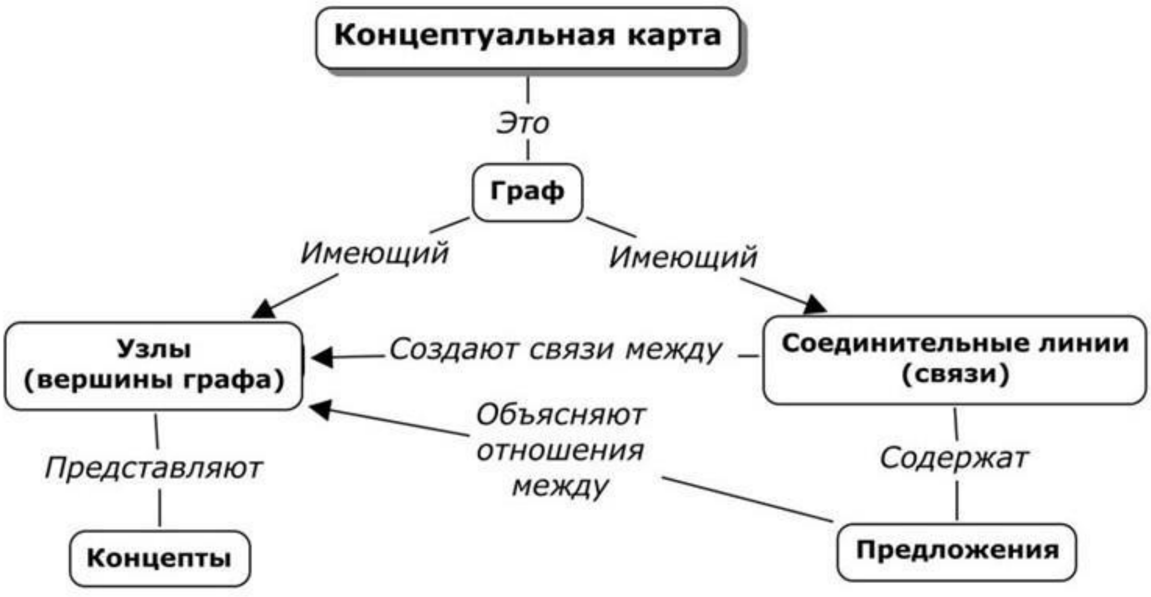

Figure 1. Example of a concept map

The procedure for dealing with concept maps includes three components: a task statement to elicit a map from the respondent, a response format, and a scoring system (Ruiz-Primo, 2004).

First component: problem statement for concept map construction

The first component is the problem statement for map construction. The construction of the map can be to varying degrees free, depending on the given map elements - concepts, structure or linking phrases (Ruiz-Primo, 2004). A task can thus vary in its type from fully open to fully closed (Figure 2) (Kinchin, 2014). Fully open contains only the knowledge domain relative to which the map has to be drawn. It has been shown that this type of task can provide the most information about how the learner understands the domain (Yin et al., 2005), although it requires more content knowledge (Ruiz-Primo et al., 2001). A fully closed task involves completing a map with a given structure and a given list of concepts. In addition, the amount of information given - the number of concepts or relationships - can also vary. Such closed, directed tasks are useful for activating students' knowledge (Gouli et al., 2003).

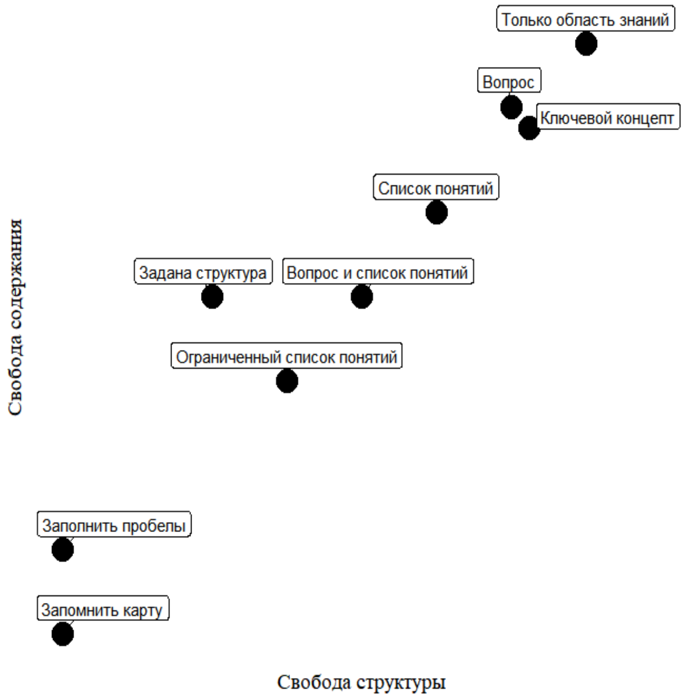

Figure 2. Degrees of freedom depending on the elements specified in the map construction task (Kinchin, 2014)

The second component: the response form

As for the second component, the student can make a map either on paper, drawing by hand, or with the help of computer programs or online services. The choice of specialized programs and services for building concept maps is quite large (Cmap, FreeMind, Xmind, etc.), and various services for graphical organization of information (e.g., Miro) can also be used. There has been no separate research on the differences between these forms. It is also possible to extract concept maps from texts - for example, from interviews or essays.

Pillar three: a system for evaluating concept maps

The evaluation system, in fact, allows to determine the degree of development of the conceptual structure, so it is a key element in the research. As mentioned above, we can distinguish two approaches to processing and interpreting the results of concept map construction - qualitative and quantitative. Further we will consider the specifics of using each of them.

The qualitative approach makes some expert judgments about the whole map at once or about individual elements of the map. For example, a number of studies use so-called holistic or holistic assessment. Several basic types of map structure have been identified: *spoke*, *chain* and *net, the* former being considered to reflect a less developed conceptual structure than the latter (Kinchin et al., 2000*)*. However, there may be difficulties in associating each map with a particular "net" type.

To make the quality assessment more in-depth, many authors have developed systems based on expert assessments of individual map elements. For example, Stoddart et al. used three criteria to analyze the relationships between concepts to assess map quality: *accuracy, depth of explanation,* and *complexity* (Stoddart et al., 2000). Each criterion was rated by experts according to a rubric, e.g., for the accuracy criterion, each student-reported connection between concepts was assigned to one of four rubrics: scientifically accurate ("*pressure rises at ocean depth"),* general knowledge ("*whales live in the ocean"),* erroneous ("*sharks are mammals"),* and emotional ("*dolphins are beautiful")*. However, even such complex systems are subject to subjectivity: in the cited study by Stoddart et al. expert agreement was acceptable, although not high (Cohen's Kappa ranged from 0.45 to 0.63 for different criteria) (Stoddart et al., 2000).

Some authors have aggregated qualitative characteristics into a quantitative score in order to make comparisons between maps possible. Novak and Gowin, the developers of the concept map method, proposed a protocol *for* assigning scores to four criteria: *propositions*, *hierarchy*, *crosslinks*, and *examples* (Novak & Gowin, 1999). For example, for the crosslinks criterion, assessors assigned 10 points for each valid and meaningful crosslink, and 2 points for valid but not illustrative crosslinks. Because the points were assigned during the peer review process, this methodology can also be categorized as qualitative.

Quantitative assessment, based on counting certain elements or characteristics of maps, has often been criticized for lacking information and depth. Nevertheless, this approach is often used because it is based on objective indicators and allows comparing different maps. For example, the number of concepts and relationships used, the number of hierarchy levels, etc. are often counted. (e.g. Novak, 1990; Wallace & Mintzes, 1990; Ruiz-Primo et al., 2001; Richmond et al., 2014). In this case, interpretation is usually ex post facto; there are no preliminary hypotheses about what a conceptual map corresponding to a more developed conceptual structure should look like. In other words, prior research has lacked a sufficiently firm theoretical grounding in what to expect from a more developed conceptual structure.

In his review, Ian Kinchin, who has authored numerous studies on the potential of using concept maps to assess conceptual structure in learning, wrote: "Most assessment techniques assume that bigger is better. However, with this approach, it can be mistakenly assumed that expert maps can be bigger than novice maps on the same subject" (Kinchin, 2014, p. 44). As an illustrative example, he cites a study (Johnstone & Otis, 2006) in which the number of concepts in the concept map of students who scored low and high on an exam was about the same (Figure 3). The authors concluded from these data that quantitative, formalized assessment of the quality of conceptual structure was not possible and qualitative, individualized assessment methods should be used. However, the development of computational theories and methods provides such quantitative indicators available for scoring.

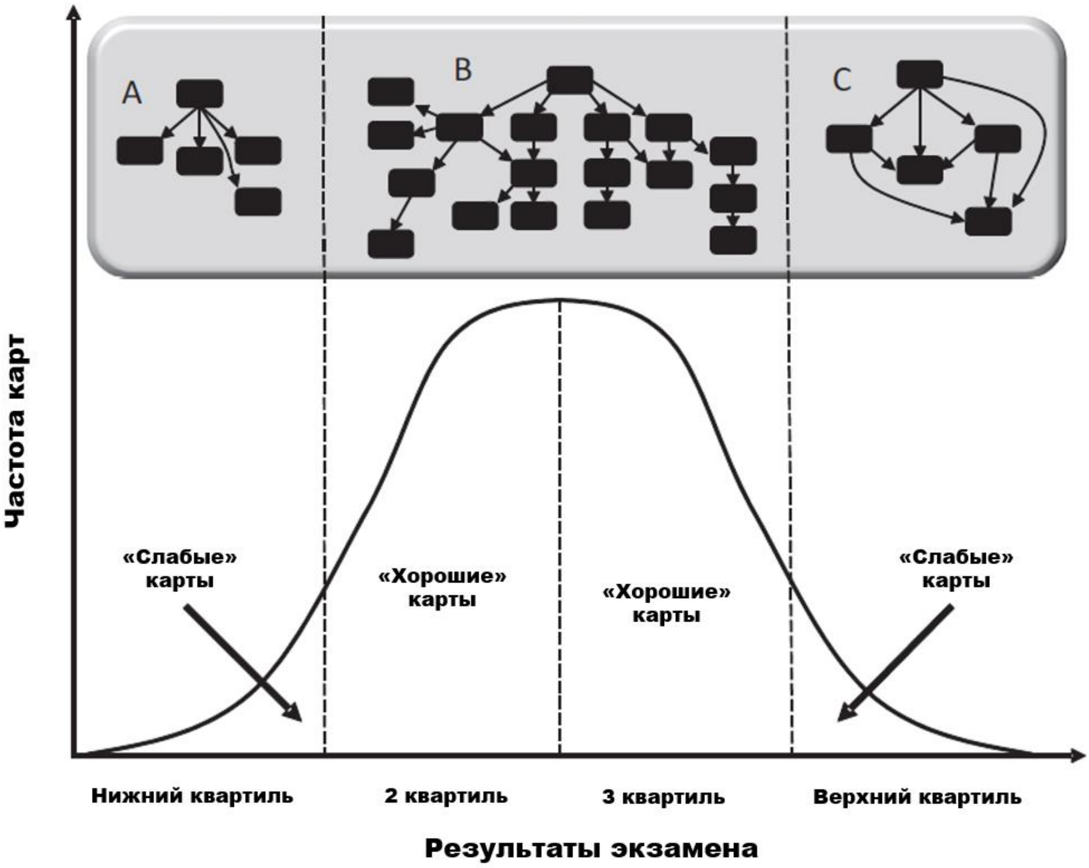

Figure 3. Relationship between exam results and map quality (by Kinchin, 2014)

Network analysis as a system for evaluating concept maps

During the last decade, researchers have quite often started to turn to graph theory (Ifenthaler, 2011; Jamieson, 2012; Stockwell et al., 2009; Zouaq et al., 2011) and its applied branch, network analysis (Frerichs et al., 2018; I. Koponen & Nousiainen, 2013; Siew, 2019; Thurn et al., 2020) to assess conceptual structure. One of the key advantages of network analysis is the set of computational methods that can measure the structural properties of a network. But beyond the methods, network analysis also brings a theoretically grounded approach to studying how the structure of a system affects the processes that occur within it. In other words, using the tools of network science, it is possible to compute network metrics that quantify parameters such as network connectivity. For example, authors have computed metrics such as network diameter (e.g., Siew, 2019) or different centrality indices (e.g., I. Koponen & Nousiainen, 2013), which will be discussed next. However, theoretical assumptions rooted in scientific understanding of human thinking have not been common in such works and have not been utilized in the interpretation of computational methods, which is supported by the findings of our study and will be further elaborated in the part describing the main results of the study.

Thus, at present, the problem of validating quantitative assessment of conceptual structure using concept maps has not been systematically described, nor has a common understanding been developed of what quantitative indicators tell us about the characteristics of conceptual structure.

RESEARCH AIM AND OBJECTIVES

The aim of the study was to unify and validate a quantitative approach to conceptual structure assessment based on network analysis. Thus, the present work contributes to the development of assessment tools for their further application in research on the developmental features of conceptual structure. Regarding validity, following Messick (1995), we believe that validation is a complex process with no single criterion, and to achieve validity requires multiple studies aimed at testing different hypotheses about the features of the tool.

The following objectives were accomplished to achieve the research objective:

1. Based on the analysis of theoretical approaches and empirical work, summarize and analyze existing methods for quantitative evaluation of concept maps and the potential of network analysis for such evaluation.
2. To test the validity of quantitative indicators from network analysis for assessing the complexity of conceptual structure using concept maps.
3. Using validated indicators, compare the functioning of concept maps of different types (with and without a given list of concepts).
4. Develop and validate comprehensive theoretically grounded quantitative indicators for assessing the complexity of conceptual structure using concept maps based on network analysis methods.

RESEARCH QUESTIONS

Several research questions need to be answered in order to achieve the objective of the research.

Research Question 1: How are cognitive theories used to apply network analysis techniques to the measurement and interpretation of conceptual structure measurement results using concept maps to date?

Answering this research question will systematize the field of existing literature regarding the potential of network analysis and cognitive theories to evaluate concept maps, and select network analysis indicators for further validation.

Results displayed in Kapuza, A. V., & Tyumeneva, Y. A. (2023). Making meaning: Psychological theories for interpreting concept maps. *World of Psychology*, 112(1), 132-143.

Author's contribution: problem formulation, data collection, analysis, interpretation

Research Question 2: Are the indicators from network analysis valid for determining the level of complexity of conceptual structure using concept maps?

The answer to this research question will provide evidence that the selected quantitative indicators are related to the level of knowledge development in an area.

The results are displayed in: Tyumeneva, Y. A., **Kapuza, A. V.,** Vergeles, K. P. (2017). Distinguishing ability of concept maps for assessing the level of competence. *Educational Issues*, (4), 150-170.

Author's contribution: problem statement, literature review, data collection, analysis, interpretation.

Research Question 3: How do the indicators from the network analysis distinguish between concept maps of different types (with and without a given list of concepts)?

The answer to this research question will provide insight into whether the type of instruction to construct concept maps should be considered when interpreting quantitative indicators from network analysis.

The results are displayed in: Kapuza, A. (2020). How concept maps with and without a list of concepts differ: The case of statistics. *Education Sciences*, 10(4), 91.

Research Question 4: Which indicators for assessing conceptual structure based on network analysis can be developed in ways that are consistent with theoretical insights from the psychology of learning and cognitive development?

Answering this research question involves correlating the analytical methods of network analysis tested in Tasks 2-3 with the theories of learning and cognitive development discussed in Tasks 1-2, and proposing more holistic and fundable indicators or methods for assessing conceptual structure.

The results are displayed in the publication: Kapuza, A., Koponen, I. T., Tyumeneva, Y. (2020). The network approach to assess the structure of knowledge: Storage, distribution and retrieval as three measures in analyzing concept maps. *British Journal of Educational Technology*, 51(6), 2574-2591.

Author contributions: problem statement, literature review, model development, data collection, analysis, interpretation.

THEORETICAL FRAMEWORK OF THE STUDY

In order to build a theoretical framework for the study, it is necessary to consider the cognitive theories describing the development of conceptual structure as well as the theoretical background of the use of different indicators in network analysis.

Theories of learning and cognitive development applicable to explain the development of conceptual structure

In the literature devoted to the measurement and evaluation of conceptual structure, authors quite often refer to *schema theory* (*schemata*), so let us start the review of theories with it. Schema theory in its modern form was developed by D. Rumelhart (Rumelhart). Rumelhart (Rumelhart, 1978) and R. Anderson (R. C. Anderson & Pearson, 1984). In its most general form, a schema is an abstract organized structure that consists of concepts related to each other through propositions and exists at a higher level of generality than direct experience (R. C. Anderson & Pearson, 1984). This idea is similar to the Gestalt psychologists' idea that humans perceive everything in "*chunks*" (J. R. Anderson, 2015). Theories of structural organization of concepts have also been developed in this logic, such as the double coding hypothesis of A. Paivio (Paivio, 1974) or the conceptual-propositional coding hypothesis of J. R. Anderson and G. Bower (J. R. Anderson & Bower, 1974). However, the main attention in them was paid to the classification of mental representations (verbal (semantic), figurative (iconic), etc.) and the explanation of the regularities of long-term information storage and its reproduction in principle.

When considering the issue of learning from the perspective of schema theory, it is important to note that an existing schema provides a context for interpreting new knowledge and is a structure for retaining it. Even before the active development of schema theory, the cognitive psychologist D. Ausubel developed the *meaningful learning* approach and emphasized that students learn new concepts more actively and efficiently with pre-existing cognitive structures (Ausubel et al., 1978). Teachers were advised to activate prior knowledge before starting a new topic and to place more emphasis on teaching higher-order comprehension processes. These suggestions were not new, but schema theory seemed to provide a theoretical and empirical basis for such practices.

D. Novak continued the idea of learning from students' existing schemas by applying the basic ideas of the theory of meaningful learning to classroom practice (Novak, 1977). In order to understand how new information is integrated into an already existing system, it was necessary to answer the question of how concepts are structured. At that time, however, there were no accepted research methods by which such integration could be investigated. Nevertheless, through clinical interviews, a team of researchers developed the concept map method [1](Novak, 1990).

Theoretical assumptions about how conceptual structure develops can be traced back to broader theories in the field of psychology. In cognitive psychology, several approaches can be identified to describe the organization of concepts and how it changes in relation to learning or the acquisition of new experiences (Capuza & Tyumenieva, 2023). Here, a group of theories about the formation of semantic schemas and networks (e.g., the theories of A. Collins and M. Quillian; E.

[1] From the English concept maps. The term concept maps is also used in Russian-language literature. A more accurate translation is concept maps or concept maps, but for comparison with the English-language literature we will stick to the term "concept maps".

Roche; P. Lindsay and D. Norman) appears to be the most useful. Concepts and hierarchies of concepts can be represented as semantic networks, in the nodes of which the concepts themselves are located, and the links between them are logical, associative, hierarchical and any other relations.

However, the question of changes in the structure of concepts during systematic learning has been beyond the scope of semantic network theories. Although it would seem that concepts themselves and the hierarchical relations between them are formed (at least purposefully) precisely in learning, the issue of concept formation is entirely in the field of interests of developmental and learning psychology. The English-language literature is primarily concerned with *conceptual change* (for a review, see Özdemir & Clark, 2007). - conceptual change is the reorganization of ideas in the process of learning. Conceptual change is described as occurring on several levels, although different authors use alternative terms to describe similar changes. Two types of conceptual change are most commonly referred to: weak knowledge restructuring, assimilation or conceptual absorption (conceptual accretion, capture, conceptual capture) and strong/radical knowledge restructuring or conceptual replacement (conceptual exchange, conceptual change) (for a review, see Harrison & Treagust, 2000).

This division is obviously inspired by Piaget's views on the development of thinking as a constant process of mutual adaptation of incoming information and existing cognitive schemes. Recall that Piaget distinguished the processes of assimilation and accommodation, where the former is associated with the construction of new information to fit it into an existing cognitive schema, and the latter with the restructuring of the schema itself to accommodate its assimilation to the new information (Piaget, 1964). These processes, according to Piaget, always work together to achieve a balanced, consistent interpretation of what is happening in the world around us.

Although the theoretical separation of these processes during the development of cognitive structures has proven extremely useful for understanding age-specific features of thinking, this theoretical foundation is still insufficient for understanding changes in conceptual structure in relation to learning. Vygotsky, sharing Piaget's position on the need to distinguish between spontaneous (everyday) and non-spontaneous (scientific) concepts, proposes an alternative method for investigating the genesis of scientific concepts that does not remove them from the system of connections with all other concepts (Vygotsky, 1999). Vygotsky sees the necessity of studying concepts in the system of other concepts in the fact that a scientific concept always exists as a certain generalization, and therefore can only be mastered in relation to other concepts: "...generalization, in turn, means nothing else but the formation of a higher concept, in the system of generalization of which the given concept as a special case is included. But if a higher concept emerges behind a given concept, it necessarily presupposes the existence of not one but a number of subordinate concepts to which the given concept stands in relations determined by the system of the higher concept - without this, the higher concept would not be higher in relation to the given one" (Vygotsky, 1999, p. 206).

Vygotsky's hypothesis is that the course of development of the structure of scientific concepts is opposite to everyday concepts. In this case, "worldliness" and "scientificity" are determined not by the content of concepts, but by the way of their assimilation. Worldly concepts arise as concrete, private, and develop to abstract generalized meanings. In contrast, scientific concepts, in the process of formal learning, are introduced as abstract meanings, and should gradually be realized as generalizations, subordinating specific objects and phenomena, and related to other scientific generalizations. For example, in the study of statistics, the concept of correlation may at first be introduced only as formal statistics, unrelated to other concepts and not ill equipped with examples of application. After one encounters various situations in which correlation is applied, this concept, firstly, forms a stable system of connections with other abstract concepts of statistics (regression, mean), and secondly, is concretized by the richly detailed content of the situations of its application (e.g., to predict weather or the spread of diseases).

Together with these theoretical generalizations, more specific expectations about learning-related changes in conceptual structure can be advanced. In particular, the features of cognitive processing that distinguish experts from novices are well known. For example, experts' knowledge in a domain is thought to be better structured and hierarchical; that is, when solving some problem, experts represent it in such a way that the representation itself already contains the basis for a subsequent solution (Chi et al., 1981; Kim, 2013). In addition, experts retrieve the necessary information from memory more easily than novices (Ericsson et al., 2000). Given that retrieval from memory indicates the presence of connections between different knowledge elements, we can assume that a well-developed conceptual structure has an extremely high density of connections between the elements of the structure (going back to Piaget - a high degree of accommodation).

The above suggests the idea that it is possible to combine the notion of network organization of concepts with theories of concept development, first of all, with Vygotsky's theory of the formation of conscious, scientific concepts, which offers a meaningful description of changes in the student's understanding of educational material as he or she learns it. Such a union could provide an entirely new approach to the dynamic assessment of learning processes and outcomes precisely from the perspective of the central transformation - conceptual development (Kapuza & Tyumenieva, 2023). So far, however, not much has been done in the direction of such a synthesis and the work, as was shown in the previous sections, is mostly empirical, descriptive in nature, but not interpretive.

Network analysis for assessing conceptual structure

Network analysis is a methodological approach that focuses on the study of interrelationships and interactions between different nodes in network structures. The main goal of this theory is to study the properties and dynamics of networks and to identify the general patterns that determine their functioning. One of the main tasks is to analyze the topology of networks - the structure and distribution of links between nodes.

Network analysis provides an important theoretical framework for the study of various networks due to mathematical models of graphs with well-described properties, and the availability of established statistical methods that allow formalizing and analyzing the structure of networks. For example, the work of M. Newman (M. Newman, 2018) provide an in-depth overview of network analysis theory, highlighting its theoretical nature and the key problems it addresses.

Network analysis is a powerful tool for studying the structure of complex systems, including the level of structuring of information in the network (M. Newman, 2018) For example, network analysis is widely used to analyze the breadth and interconnectedness of knowledge bases such as the *World Wide Web* or individual sites like *Wikipedia*. Such analysis allows us to determine the connectivity of the network, which is a key concept in this field, and the degree of importance of individual nodes in the graph. Network connectivity describes how closely connected the nodes in a network are and how easily information can propagate between them. There are various measures of connectivity that can be used to assess the connectivity of a network, such as clustering coefficient, centrality, etc. (Estrada, 2016; M. Newman, 2018). Centrality is a measure of the importance of nodes in a network, and it can be used to identify key nodes that play an important role in information transmission. Different centrality measures can take into account different aspects such as number of links, distance to other nodes, importance of links, etc.

Some of the most common measures of centrality include:

1. *Betweenness centrality* is a measure based on how often a node is used as an intermediate link on the shortest path between two other nodes in the network. Nodes with high mediation centrality can play an important role in transmitting information and controlling flows in the network.

2. *Degree centrality* is a measure based on the number of links a node has in the network. Nodes with high degree centrality are more connected and can play an important role in transmitting information and controlling flows in the network.

3. *Closeness centrality* is a measure based on the distance between a node and the other nodes in the network. Nodes with high closeness centrality are closest to the other nodes in the network and can quickly transmit information across the network.

4. *PageRank centrality* is a measure of centrality used in Google's algorithm to rank web pages. It is based on the idea that a web page is important if other important pages link to it. In other words, a web page is considered important if other important pages link to it. In this model, a random user starts from one page and navigates to another page via a link. The probability of going to each page depends on the number of links to the page and their importance. The more links to a page and the more important those links are, the higher the probability of going to that page.

The HITS algorithm is also developed to determine the importance of web pages based on their interconnectivity. HITS (Hyperlink-Induced Topic Search) is an algorithm used in network analysis to evaluate the importance of web pages and it is based on the concept of relationships between web pages.

The HITS algorithm uses two metrics to assess the importance of web pages: the *authority* statistic and the *hub statistic* (Fig.4). Authority is a metric that describes how important a given web page is to the specific topic being researched. Hub is a metric that describes how much a given web page links to other web pages related to a particular topic. The HITS algorithm is widely used in network analysis to evaluate the importance of web pages but can be used for other types of networks as well.

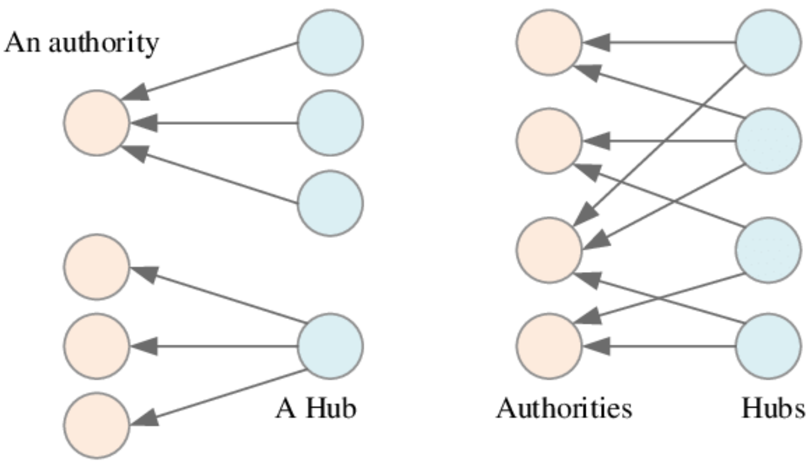

Figure 4. The visualization of hub and authority statistics[2]

In general, network analysis is a powerful tool for studying the structure and processes in networks, and can be used to measure the level of information structuring in a network. However, to achieve the best results, metrics and analysis methods need to be carefully chosen, and the context and goals of the study need to be taken into account. Being transferred to the field of cognitive psychology, such indicators require not only technical but also meaningful psychological interpretation (Kapuza & Tyumenieva, 2023).

[2] Source: https://www.researchgate.net/figure/The-basic-concept-of-the-HITS-model-used-in-our-method_fig1_334751984

METHODOLOGY AND METHODS

To answer the **first research question** ("How are cognitive theories used to apply network analysis techniques to the measurement and interpretation of conceptual structure measurement results using concept maps to date?"), a systematic literature review was conducted. Scopus, a bibliographic database that includes research literature in a variety of fields, was searched for abstracts of articles containing the phrase "concept map*" (whereby the second word could be any word beginning with map) and one of the following combinations: "network science", "graph theory", "network theory". A total of 88 articles were selected for further analysis.

The abstracts of all retrieved articles were screened for relevance to the research objective. For example, studies that used concept maps as a basis for intervention in experimental design (9 articles) and those that used concept maps as a method of organizing information in interviews or with experts (7 articles) were excluded. In addition, literature reviews on the use of concept maps and studies that did not analyze concept maps using network analysis methods were excluded. In cases where the abstract did not contain all relevant information, the full text was reviewed. A total of 10 articles were selected for substantive analysis.

Next, the full texts of the selected 10 articles were analyzed for the use of cognitive theories to interpret the results of the concept maps. The use of a theory was considered to be a description of the theory with reference to the indicators discussed below or an explanation of the results obtained within the framework of this theory. It was then assessed whether the theory used was related to cognitive psychology theories.

For **research questions 2-4**, concept map data were collected during 2016-2019 in the knowledge domain related to basic methods of data analysis in the social sciences. The sample included staff and students from the National Research University Higher School of Economics, more specifically the Institute of Education. In such a sample it is better to control the homogeneity of the environment in which this knowledge is acquired and applied and, in addition, this area of knowledge is familiar to all students.

A total of about 60 concept maps were collected and 55 were used for analysis. In the most general terms, to construct the maps, respondents were first introduced to a written instruction for constructing concept maps with visual examples, followed by a general instruction: "Using a white A4 sheet of paper, hand draw a concept map of the Statistical Data Analysis domain". The following will more specifically describe the data and methodology used to answer each research question.

To answer the **second research question** ("Are indicators from network analysis valid for determining the level of complexity of conceptual structure using concept maps?"), 13 open-ended maps were used (only the topic was given). The objective of the study was to identify and test the validity of formal indicators from computational theories for assessing the complexity of conceptualization using concept maps. For this purpose, the method of comparing concept maps of novices and experts was chosen. Comparison of such groups is used in many studies, including conceptual frameworks, as there are strong indications that expertise is characterized not so much by the accumulation of knowledge, but rather by the way it is ordered and the strategies for its application (Chi, 2011).

The study used data from the charts of nine "novices" (1st year master's students who successfully completed a course in statistical analysis) and four experts (teachers of data analysis methods with more than four years of experience, having at least six publications with statistical data analysis results in peer-reviewed journals). In the first step, the significance of differences between groups on formal indicators from network analysis such as:

- number of nodes;
- number of ribs;

- sparsity[3] (the ratio of the number of concepts to the number of edges between them);
- Dangling nodes (nodes that have only one link to other nodes, regardless of direction);
- adjacent edges (edges entering the same node);
- volume - level 1 (number of nodes with only one outgoing edge), level 2 (number of nodes with two outgoing edges), level 3 (number of nodes with three outgoing edges);
- hierarchical nodes (having both incoming and outgoing edges);
- degree of generalization (ratio of the average number of outgoing edges of the three largest concepts in the CC to the level of hierarchy of the outgoing concepts).

Experts were expected to have higher scores on adjacent edges, volume level 2, degree of generalization, and hierarchical nodes, and lower scores on number of dangling nodes and sparsity.

The second step involved a qualitative analysis of the content of the concepts and relationships in the maps, which concepts are used and what exactly the edges between them are called. Qualitative assessment is important because if the qualitative indicators of the maps of contrasting groups are found to be consistent with the previously obtained data, the construct validity of open (i.e., not containing a given list of concepts) concept maps as a tool for assessing the conceptual structure of experts and novices will be confirmed.

Three qualitative indicators of conceptual structure were analyzed. First, we expected to see some common set of key concepts in the group of experts. Numerous studies of task solving by experts and novices have shown that in any field experts have common ideas about what is the key (i.e., structure-forming) information in their professional tasks, while novices do not yet possess the knowledge key to solving professional tasks. Accordingly, there should be no common set of concepts for all novices, neither similar to the expert's nor any other.

Second, we expected that experts would predominantly use concepts related to so-called declarative knowledge (ideas, theories, concepts) and novices concepts related to ways of solving the task, i.e., procedural knowledge, as shown in previous experiments (Chi et al., 1981; Rittle-Johnson & Schneider, 2015; Sloutsky & Yarlas, 2000; Stylianou, 2002). Third, we hypothesized that novices would make errors linking concepts, whereas experts would not. Without exception, all of the studies we are aware of recorded concept linking errors in novices, even though they did not use an open-ended form of concept maps. Therefore, by finding errors in the novice group and not in the expert group, we will also confirm the construct validity of open concept maps.

To answer the **third research question** ("How do concept maps with different types of construction tasks (with and without a given list of concepts) differ in terms of indicators from network analysis?"), 22 maps drawn by 11 graduate students who had taken a course in basic data analysis techniques were used. Since the task was to test the functioning of the indicators identified in answering the previous research question in concept maps with different types of tasks, each student drew two maps. First, two months into the course, participants constructed open-ended concept maps (topic only). Then, after another three weeks, participants received the same instructions, but they were also asked to use a list of 25 concepts selected based on the course syllabus and previous research and using four expert concept maps from the previous study. Participants could add no more than two concepts to the list themselves. The design in which all participants did not use the list first and then all used it (i.e., there were no participants who first used the list and then did not use it) has both merits and limitations that must be kept in mind. Advantages include the fact that in free construction all participants were in the same position and could not rely on the list in any way because no one had seen it yet. The disadvantages include the impossibility to isolate the results from the effect of this particular construction direction (first without the list, then with the list). At the same time, because of the sample size, it was irrational

[3] Publications use the term "connectedness" following other publications that use this indicator in this form (the ratio of the number of concepts to the number of edges between them), but its interpretation is counterintuitive: the larger the value, the less connected it is. Therefore, in this research we use a term that is not generally accepted, but is more direct in interpretation - "discontinuity".

to construct the design by dividing participants into two groups (no-list - list and list - no-list) and comparing their results. In-group equalization, a standard procedure for this type of design, was not used by us because it would have introduced additional uncontrollable effects of prior experience with concept mapping.

The following hypotheses were put forward as part of the study:

(H1): the indicator values are the same for both types of instructions;

(H2): learners use more technical concepts at a low level of abstraction in instruction without a list than in instruction with a list;

(H3): students use fundamental concepts regardless of the type of instruction.

Indicators previously confirmed as having distinctiveness in a previous study (research question 2) were used as indicators to test hypothesis H1:

- number of nodes;
- number of ribs;
- node-to-rib ratio;
- number of hanging nodes (number of nodes with one edge);
- % of hanging nodes;
- number of nodes with three or more edges;
- % of nodes with three or more ribs.

And also two indicators from network analysis were added based on the literature review:

- network diameter;
- diameter fraction (ratio of diameter to total number of nodes).

The significance of differences in the mean values of all these indicators according to the type of instruction was tested using Student's t-criterion with Welch's correction for non-normality of distribution.

To test hypotheses H2 and H3, one overall map was constructed from respondents' maps for each type of instruction (without and with a list of concepts). Each concept was manually coded as technical (procedural knowledge - specific methods, software, or type of results) or other (more abstract). The number of edges between two nodes extracted from different maps was used as a weight. A weighted *closeness centrality* (*closeness centrality*) was then calculated for each concept. Closeness centrality indicates how central a given concept is with respect to the entire network. To test hypothesis H3, clusters (*communities) of* concepts were also identified using the Girvan-Newman algorithm (M. E. J. Newman & Girvan, 2004).

The following nine concepts were considered fundamental to the study: significance, sample, population, distribution, hypothesis, data, analysis, method, and research question. For H3 testing, one fundamental concept (significance) was removed from the list to see if students would add it to the list. The final list included both technical concepts (e.g., specific methods) (eight out of 25, 32%) reflecting procedural knowledge and more abstract concepts.

To answer the **fourth research question** ("What indicators for assessing conceptual structure based on network analysis can be developed in a way that is consistent with theoretical understandings of the psychology of learning and cognitive development?"), in addition to summarizing the findings of the previous two research questions, an empirical study was also conducted. The task of the empirical study was to develop and test a formalized approach to the evaluation of concept maps using network analysis. Ten first year undergraduate statistics students and 4 experts from research question #2 were recruited for this study. Each student constructed two maps while taking a course in Statistical Data Analysis. The first maps (beginner level) were created six weeks after the start of this course. The second maps (advanced level) were created at the end of the course, six months later, before the resulting course exam. Since the response to the second research question showed differences depending on the type of instruction, participants were randomly asked to construct either an open-ended map (topic only) or additionally using the list of concepts from research question #3.

Three new indicators based on network analysis and interpreted in terms of cognitive theories were then developed based on the literature review performed in answering the first research question (described in more detail in the Main Research Findings section).

To verify and validate the developed measures, we used Student's t-criterion with Welch's correction for non-normality of distribution to compare three groups (entry level, advanced level, experts - criterion) according to newly developed and already used in answering research questions 2 and 3 (number of nodes; number of edges; ratio of nodes to edges; average number of edges at a node) indicators, as well as indicators from network analysis used for development (components of the HITS algorithm - authoritative pages and hub-and-spoke pages).

It was expected that all the developed indicators, as well as the average degree of nodes and average values of hub page statistics would be higher in trained students, and especially in experts, compared to entry-level students. Conversely, the ratio of nodes to edges, mean values of authority page statistics and PageRank centrality would be lower in these groups because they are standardized.

MAIN RESULTS OF THE STUDY

The relevance of the research questions, objectives and publications that capture the main findings are presented in Table 2.

Table 2. Correspondence of publications, tasks and results of the thesis research

	Article 1 (Kapuza & Tyumenieva, 2023)	**Article 2** (Tyumenieva et al., 2017)	**Article 3** (Kapuza, 2020)	**Article 4** (Kapuza et al., 2020)
Research questions	IV 1	IV 2	IV 3	IV 1, IV 4
Objectives	**1:** summarize and analyze existing methods for quantitative evaluation of concept maps and the potential of network analysis for such evaluation	**2:** to test the validity of quantitative indicators from network analysis for assessing the complexity of conceptual structure using concept maps	**3:** compare the functioning of concept maps of different types (with and without a given list of concepts)	**1,** **4:** Develop and validate comprehensive theoretically based quantitative indicators based on network analysis methods
Sampling	88 abstracts of publications, 10 full texts	9 novices, 4 experts	11 participants, 2 waves	10 participants, 2 waves + 4 experts from article 2
Methodology	Analyzing texts for the use of cognitive theories to interpret network analysis metrics in concept maps	Open assignment, topic only 1. Comparison of groups by indicators from network analysis 2. Qualitative content analysis	Wave 1 is an open assignment, Wave 2 is a list assignment. 1. Comparison of waves by indicators from network analysis 2. Qualitative analysis of map content	Randomly open a task or list. 1. Development of theoretically relevant indicators 2. Comparison of groups according to indicators from network analysis

	Article 1 (Kapuza & Tyumenieva, 2023)	**Article 2** (Tyumenieva et al., 2017)	**Article 3** (Kapuza, 2020)	**Article 4** (Kapuza et al., 2020)
				and newly developed indicators
Main results	The potential of cognitive theories is not utilized in concept map research where network analysis is applied	The characteristics of the conceptual structure, which, judging from previous studies, differed between experts and novices, were given their indicative elements in the concept maps. These indicators are formally described as ratios of different types of nodes and edges of the network and answer the question about its connectivity.	Concept maps with a given list encourage learners to demonstrate higher coherence of conceptual structure, so the type of instruction should be considered in further analysis.	On the basis of network analysis, three indicators have been developed according to the theoretical notions of what a conceptual structure is: network capacity, concept distribution, and concept retrievability. They demonstrate their distinctiveness.

Research Question 1: How are cognitive theories used to apply network analysis techniques to the measurement and interpretation of conceptual structure measurement results using concept maps to date?

A total of 19 indicators related to network analysis were used in the publications under review. The most commonly used were the number of links (edges) and nodes, the degree of node centrality, which is the number of incoming and outgoing edges, and the clustering coefficient (tendency to form closed triangles). While the number of links and nodes tells primarily about the size of the drawn concept map, the other measures somehow reflect the degree of connectivity and closeness of the nodes (concepts) in the map. In addition, the indicators characterized in one way or another the location of the nodes in relation to each other. In general, measures of centrality are most often computed, not only for individual nodes, but also average values for the network as a whole. A wide range of such measures is used: *degree centrality*, *betweenness centrality*, PageRank, *closeness centrality*, *subgraph centrality*.

As expected, the theoretical frameworks used to interpret the results were mainly within the realm of data science - complex systems theory, complex or complex networks theory (Table 2). Complex systems theory studies the interactions and relationships between different elements in complex systems and helps to understand how such systems function, how they change and how their performance can be optimized. We were able to explicitly identify only one interpretive framework given by a substantive psychological theory - the theory of conceptual change. Also the theories of semantic networks can be partly referred to the theories of cognitive psychology. However, the concepts mentioned by the authors do not find application in the interpretation of the indicators used.

Table 2 - Theories used in the 10 articles under review

Theory	Number of articles	Articles
Complex systems theory (complexity science)	2	Gkevrou & Stamovlasis, 2022; Siew, 2019
Complex/complex networks (complex networks)	2	Koponen & Pehkonen, 2010; Koponen & Nousiainen, 2013
Semantic networks (semantic networks)	1	Koponen & Nousiainen, 2018
The theory of conceptual change (co-conceptual change theory)	1	Thurn et al, 2020
Not explicitly labeled	4	Goldman & Kane, 2014; Sun & Qu, 2015; Walker & King, 2003; Wilson, 1998

Thus, our attempt to trace how researchers utilize the potential of cognitive and cognitive developmental theories to understand and assess conceptual structure in learners revealed that overwhelmingly the potential of these theories is not utilized in concept map research where network analysis is applied.

Research Question 2: Are the indicators from network analysis valid for determining the level of complexity of conceptual structure using concept maps?

In terms of comparing the groups by indicators from the network analysis, the expected trends were confirmed: experts had a significantly higher degree of generality ($U = 0$; $p < 0.01$), the number of complex concepts, i.e., nodes with adjacent edges, was higher for experts ($M_{experts} =$ 11.0, SD = 4.1; $_{Novices} =$ 2.8, SD = 3.2), and the number of single concepts was significantly lower ($U = 2.5$; $p < 0.01$). Importantly, the mean difference in the volume of the three highest-volume concepts differed ($U = 0$, $p < 0.01$). This indicator reflects the uniformity of generalizations in the structure and the presence of transitional concepts by the level of generalization, linking the most general concept with single concepts. In experts, generalizations are more uniform. Although the expert and novice groups did not differ in the average number of nodes and edges in the concept maps ($U_{узлов} = 6.5$; $p > 0.05$; $U_{ребер} = 19.5$; $p > 0.05$), the ratio of the number of nodes and edges at the individual level by the Mann-Whitney criterion was statistically significantly different in the two groups ($U = 0$; $p = 0.01$). As expected, the level of connectivity of concept maps was higher in experts than in novices.

In terms of qualitative analysis of the content of novice and expert maps, three distinctive features of novice maps were confirmed: the absence of a single set of concepts used; the predominant use of procedural, technical concepts; and erroneous links between concepts. A common set of concepts for a group of experts is interpreted as the key one for a given field of knowledge. In our experts the following concepts acted as such: "hypothesis", "data", "analysis", "variables" and "results". They were used by all experts without exception. The newcomers from this list used only the terms "variables" and "data" and actually ignored "hypothesis", "analysis" and "results". We could not rule out the possibility that the novices emphasized some other concepts as key. However, it turned out that the same concepts were almost never found in their maps, which may indicate the absence of formed key concepts at the initial level of competence development.

The available data on the peculiarities of problem solving by experts and novices give reason to expect from experts the predominant use of concepts related to the so-called declarative knowledge (ideas, theories, concepts), and from novices the use of procedural concepts. Indeed, in addition to general, key concepts for the field ("hypothesis", "research question", "analysis", etc.), expert QCs necessarily contained other theoretically loaded concepts, such as "sample", "relationship", "differences" or "concepts", "models", "covariates", "interpretation of results", "research objectives", "method". Novices, on the other hand, favored procedural concepts that described the steps involved in analyzing data. For example, they listed the types of regression analysis or the steps needed to perform it.

Erroneous links between concepts. Unlike experts, novices often made erroneous connections between concepts. For example, the interpretation of "variables" as a form of description of "data", or a "conclusion" that follows directly from a "constructed model", or the explanatory function of "statistics" in relation to a "study", or a closed loop between the concepts of "data analysis", "variables" and "data" are erroneous.

The results made it possible, first, to theoretically define such formal indicators of concept maps that would reflect certain features of the concept map, and second, to verify the distinctiveness of these indicators by comparing two contrasting groups - novices and experts in a certain field of knowledge. Both goals were achieved. In other words, as a result of our work, the characteristics of the conceptual, which, judging from the data of previous studies, differed between experts and novices, received their indicative elements in the conceptual maps. These indicators, considered here as graph elements, are formally described as ratios of the different types of nodes and edges represented in the map. Importantly, it is this formal approach that has made it possible to turn highly individualized concept maps into a set of objective parameters independent of the professional level of the map assessors themselves.

Research Question 3: How do concept maps of different types (with and without a given list of concepts) differ in terms of indicators from network analysis?

The first hypothesis (H1) suggested that there were no differences in the indicator values of concept maps with and without a list of concepts. The results showed that connectivity, measured through the ratio of the number of concepts to the number of edges, was higher (which is characteristic of a more developed conceptual structure) for concept maps with a list of concepts. The increase in connectivity was due to a decrease in the number of concepts with only one connection, while the number of concepts with three or more connections remained stable. This means that it was easier for respondents to incorporate concepts into the structure, but they still could not see the connections between all concepts. The fact that significant differences were found even in such a small sample shows the importance of these differences.

The second hypothesis (H2) concerned how learners used technical concepts related to the reproduction of specific actions and procedures. Previous studies, including the results of the previous research question, indicate that the use of such concepts is associated with less developed structures and is characteristic of novices. The results showed that such concepts were used in the same way regardless of the type of instruction. The same groups of technical concepts ("regression" or "hypothesis testing") appeared in both cases, with and without a list. However, this trend did not appear for more abstract concepts. It is important to note that respondents did not use very abstract concepts (e.g., "science") if they had a list, and tended to add mid-level concepts about data analysis. This finding is supported by the literature and can be interpreted as an advantage of using concept maps with a list for standardized assessment.

The third hypothesis (H3) concerned students' ability to think critically about concepts and their place in the structure. To test it, one of the fundamental concepts was not included in the list and it was expected that students would still use it due to its fundamental nature. Without the list, students tended to use fundamental and technical concepts in the same way and remembered both. Using the list, they may have missed important concepts even though they had used them before. Providing a list may have caused students to doubt their concepts, which is useful when using concept maps as a comprehension exercise, but unhelpful and even harmful if there is no feedback on the results of the map construction.

Thus, on average for the selected indicators, concept maps with a list of concepts were more coherent, indicating a more developed conceptual structure. However, content analysis showed that using a list of concepts stimulates students to evaluate each concept and its role in the whole structure more thoroughly. At the same time, they pay less attention to concepts outside the list.

Research Question 4: What indicators for assessing conceptual structure based on network analysis can be developed so that they meet theoretical insights from the psychology of learning and cognitive development?

To begin with, the assumptions from cognitive theories were analyzed and based on their content, three main characteristics of a developed conceptual structure were put forward: such a structure has a high capacity, and the knowledge itself is better distributed and easier to retrieve. Using information indices that were originally developed to study knowledge retrieval and storage in large databases (HITS, PageRank, diameter), three comprehensive indicators were developed: network capacity, concept distribution, and concept retrievability.

Network *capacity* S, as defined in equation (1), is a normalized measure of the ratio of hub-page values (H) to authority page values (A) of nodes. Nodes with high values of authority page statistics "store" knowledge, high values of hub-page statistics mean that nodes link to other nodes with high values of authority statistics. Thus, the division operation can be viewed as a measure of the relative capacity of the knowledge repository:

$$S = \frac{H}{A}, \tag{1}$$

where H denotes the average of hub page statistics in the network, A denotes the average of authority statistics. The value of S can range from 0 to 1, where S=1 means balanced storage and S=0 means that, the most authoritative nodes are not referenced by hub nodes.

Concept distribution D describes how concepts are stored in the network. It is a metric that describes the global or local distribution of hub pages and the difference between the values of hub pages and authority pages. Thus, it is a comprehensive measure of the distribution and diversity of the role of nodes in the network. The distribution of concepts D is defined as a logarithmic measure given as follows:

$$D = log\,(T * H(1 - A))\,, \tag{2}$$

where T denotes the diameter of the network and is thus a measure of the average length of connections within the network. The value H denotes the average value of hub pages, A denotes the average value of authority pages. The value D << 0 means there is no diversity, all information in the network is stored locally and does not "circulate" through the network. The logarithmic form is chosen for practical reasons, to provide values that can be easily compared.

The retrievability of concepts R describes how easily concepts can be retrieved from the network by starting at any of the nodes in the network. Retrievability is affected by the capacity of the network and how easy it is to reach a given node. To describe this latter property, the PageRank statistic is a useful value. Hence, we define R as follows:

$$R = \sqrt{S * P}\,, \tag{3}$$

where S is the capacity of the network and P is the average value of PageRank statistics for all nodes.

The validation of these developed measures was then empirically investigated. For this purpose, three groups of indicators were tested. First, indicators traditional to concept maps that aim to assess the complexity and coherence of the structure, measured through the number of concepts and the links between them, were tested. In line with many other studies using concept maps, in this study the values of such indicators were higher for experts than for novices. Thus, it was shown that the expert and novice groups were indeed different groups and could be reliably used to test other indicators from network analysis.

The second group of indicators was taken from network analysis. The indicators used are related to outgoing and incoming links and their relations. The analysis of the experts' concept maps demonstrated that their conceptual structures were balanced in terms of this relationship, while the concepts in the novices' maps were more likely to receive information than to transmit it.

However, the most valuable findings concern the third group of indicators. The new composite measures (concept capacity, distributionality, and retrievability) revealed significant differences between experts and novices, with higher values for experts. All of these indicators are constructed to measure the whole structure and the role of individual concepts in spreading information across the structure. More specifically, they show how knowledge spreads and how easily it can be acquired. Even more importantly, it seems that these structural indicators were sensitive enough to show some progress for students.

Thus, comprehensive measures have been proposed that, on the one hand, meet the theoretical assumptions of cognitive theories about what can be considered a developed conceptual structure and, on the other hand, have good discriminative power. The approach developed in this study converts the theoretical model into empirical measurable indicators.

THEORETICAL AND PRACTICAL SIGNIFICANCE OF THE WORK

The theoretical significance of the research lies in its contribution to the development of a method for analyzing concept maps to assess conceptual structure. Since network analysis has a broad toolkit for assessing various properties of systems with related objects, the present study utilizes its capabilities to unlock the potential of cognitive theories for assessing concept maps. Such evaluation is highly relevant in the context of modern learning, especially in the vein of constructivism. In this way, concept maps are removed from the circle of individualized assessment tools and placed on a par with standardized methods.

In addition, a formalized approach to assessing conceptual structure based on network analysis and incorporating assumptions from learning and developmental theories is developed and introduced. The use of the three developed comprehensive measures (network capacity, concept distribution, concept retrievability) allows a more complete assessment of the conceptual structure and how it is represented in concept maps.

The developed approach has a high potential for generalizability to different knowledge domains. This is due to the fact that the model does not set thresholds and does not require expert judgment, which allows the approach to be used in different knowledge domains. Moreover, the developed approach does not require expert visual inspection of concept maps, which reduces the likelihood of subjective influence. However, despite the versatility of the approach, further research on its capabilities is needed. The present work is a starting point for further research in the area of conceptual structure assessment and will help to unlock the potential of this methodology. For example, the concept map toolkit can be used to analyze how key (or fundamental) subject or cross-curricular concepts develop over the course of learning; whether the size and properties of conceptual structure depend on the domain of knowledge; what nested structures can be seen within each domain; and many other questions that require a measurement approach to conceptual structure.

The practical significance of the work lies in the possibility of using the developed approach to study and evaluate the integrated mastery of learning material by students in different areas of knowledge, for example, in the field of mathematics, physics, biology, etc. It is possible to create automated tools that can be used by educational researchers or practitioners to monitor students' progress.

Although the results of the research have significant potential for the study and evaluation of integrated learning mastery, this topic needs further research and development. In particular, further research is needed to improve and automate the evaluation methodology and bring it to a higher level of accuracy. It is also necessary to take into account the different types and formats of the concept mapping task, as well as the differences in the application of the developed approach for summative (sammative) and formative assessment.

THESIS STATEMENTS

The following **statements** are put forward for defense:

1. The potential of cognitive theories and theories of cognitive development has not been exploited in studies of conceptual structure using concept maps, although the possibilities of network analysis make it possible.

2. There are valid quantitative indicators for assessing conceptual structure using concept maps based on elements of network analysis that demonstrate the distinctiveness of these indicators with respect to novices and experts in a particular domain of knowledge.

3. The task given to construct concept maps is an important factor in interpreting the results, as having a given list ща concepts encourages students to demonstrate a higher coherence of conceptual structure.

4. We developed and validated complex theoretically grounded quantitative indicators for assessing the complexity of conceptual structure using concept maps based on network analysis methods, namely: network capacity, concept distribution, and concept retrievability.

CONCLUSION

Thus, our examination of how researchers use the power of cognitive and cognitive developmental theories to understand and assess conceptual structure in learners has shown that, overwhelmingly, the potential of these theories is not utilized in concept map studies where network analysis is applied. Nevertheless, quantitative indicators from network analysis show their criterion validity in differentiating novice and expert concept maps.

In validating the quantitative approach to assessing conceptual structure, we made the following recommendations and suggestions for further research using concept maps:

1. The number of nodes in the network is not in itself a characteristic of the development of the conceptual structure, so it should not be used as an independent or the only parameter.
2. An important characteristic of the conceptual structure is the connectivity of the network, which should be the subject of evaluation. It can be assessed through the relation of concepts and links in the simplest variant, and through complex indicators developed by us: network capacity, distribution of concepts, and retrievability of concepts.
3. When using concept maps to assess conceptual structure, differences in types of instruction must be considered, as students tend to show higher coherence when using a list of concepts.

As mentioned earlier, the advantages of the holistic approach to assessing students' concept mapping performance lie in its ability to assess the quality of the structure as a whole, whereas the quantitative approach allows for a more objective assessment. The recommendations developed in this study bridge the gap between these two approaches. It is worth noting that we selected and developed our measures based on theoretical insights into conceptual structure development and some previous experimental results. This rationale makes our measures more interpretable from a psychological perspective.

L.S. Vygotsky's theory seems promising for planning further work on analyzing concept maps. L.S. Vygotsky assumed that the development of scientific concepts goes in the direction of realizing the subject, in contrast to the development of everyday concepts, which develop from realizing individual phenomena to understanding the abstract meaning of the concept. The maturity of a concept, as L.S. Vygotsky notes, is manifested in its logical connection with other concepts and its inclusion in the hierarchical system of other concepts of different levels of generality. Perhaps, the method of concept maps can also be used for empirical support of the theory itself.

We note the **limitations of** this study. First, the sample was homogeneous and relatively small in number. As in many psychological studies, the sample was students from the same university. Although the design minimized the effects of this homogeneity as much as possible (compared to each other; experts were from the same environment; first-year master's students with different undergraduate experiences), it is necessary to test the methods on other, larger samples. Nevertheless, a fair number of deep, immersive studies of concept maps have been conducted on small samples, e.g., n=19 (Frerichs et al., 2018), n=3 (Lavigne, 2005). Second, a very specific domain of knowledge was utilized, which may also bias the results and their interpretation in certain ways. In particular, this domain involves the use of mathematical methods and tools, which may generate in students a fixation on concepts related to procedural knowledge (e.g., varieties of t-test or data manipulation software) during the mastery process. At the same time, this tendency may not be observed for, for example, basic ideas in philosophy of education.

Thus, verifying the external validity of the findings and methods developed is a necessary area for future research. In addition to working with other samples, it is important to test their functioning in different fields of science and for different age categories. Also of interest is the establishment of thresholds for developed and other standardized measures, as well as the unification and development of software for automated scoring.

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