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# Intelligent Knowledge Assessment Systems: Myth or Reality

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**Abstract.** The paper summarizes the experience obtained during more than a decade of research on intelligent tutoring systems (ITSs) and, in particular, on their integral part – the knowledge assessment systems. Special attention is paid to challenges and issues of automation of knowledge assessment. Possibilities of automation, a teacher's workload, objectivity of comparison with standard, and the assessed knowledge level in accordance with Bloom's taxonomy are chosen for selection of appropriate format for students' submitted answers and/or solutions. The focus of the paper is on motivation to use concept maps (CMs) as knowledge assessment tool. Advantages of CMs are discussed and the basic conceptions for the developed adaptive intelligent knowledge assessment system IKAS are presented. The short overview of IKAS highlights the novel theoretical solutions that are implemented in the system. Lessons learnt from the practical usage of IKAS in seventeen different study courses are used to define the unsolved challenging problems and open questions for future work.

**Keywords.** Intelligent tutoring systems, knowledge assessment, concept map, adaptive systems, feedback

## 1. Introduction

Nowadays when more and more countries in their stage of development have reached the level of information or knowledge society, the focus of teaching and learning once again has returned to individual, student-centered model. In contradiction to centuries ago when it was possible to enable one-to-one education mode (one teacher and one student), today it is impossible due to the fact that teachers frequently have a great number of students in one course. The use of computing technologies opened new facilities, but nowadays it is clear that even the most advanced e- and m-learning systems and tools can offer only one-to-many instructions. That is the reason why in the late 20th century more and more researchers started the creation of intelligent tutoring systems (ITS) for different students and different subject areas [1, 2]. Practically it was the beginning of modern ITSs that to the certain extent replace teachers. Nowadays a consensus among researchers has been reached that ITSs consist of four core modules whose functionality is supported by corresponding models. These modules are the following: the problem domain module, the student module, the

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tutoring (pedagogical) module (by the way, these modules often are called “the holy trinity”) and the communication (the user interface) module [1].

Today ITSs to the certain extent automate such pedagogical functions as problem (task) generation, problem (task) selection, offering, collection and assessment of student answers (solutions) and generation of feedback whose content and timing depends on achieved results (there may be immediate feedback on errors or summarized information about results of problem solving, detected lack of understanding and/or gaps of knowledge, as well as instructions how to acquire necessary knowledge). The development of more sophisticated ITSs requires the use of ideas from such areas of AI as natural language processing, machine learning, multi-agent systems, ontologies, semantic Web and emotional computing [1, 3]. These technologies are combined with other ones, such as modeling and simulation, multimedia and data processing, in attempts to move towards truly intelligent tutoring systems because the already developed ones have serious limitations concerning the provided feedback and hints, weak abilities of dialogue maintenance as well as difficulties to implement detection of different emotional states of learners. As a consequence, such systems have limited adaptation abilities. Besides, the experience of ITS development clearly manifests that these systems are expensive and commercially not feasible. Apparently the required expenses for research, development and implementation phases is the main reason why such important aspect of ITSs as knowledge assessment, which is the basis for effective and immediate feedback, remediation of knowledge gaps and construction of hint sequences, still is underdeveloped. The paper is focused on challenges and issues of knowledge assessment as an integral part of any truly intelligent tutoring system.

The paper is organized as follows. In the next section the issues of knowledge assessment automation and their relationship with provision of meaningful feedback is discussed. In Section 3 the motivation to use concept maps as knowledge assessment tool is presented. Experience amassed during the development and usage of IKAS as well as lessons learnt are discussed in Section 4. Finally, conclusions contain summary and suggestions for future work.

## 2. Automation of Knowledge Assessment: Issues and Their Relationship with Provision of Meaningful Feedback

The final goal of ITS development is automation of teaching process (simulation of teacher’s activities) as well as learning process (learners’ support) during knowledge acquisition. The teaching and learning process may be divided into two interrelated phases with three main activities in each of them, as it is shown in Figure 1.

Figure 1 represents a summative evaluation of student’s knowledge level that usually is provided in face-to-face as well as in technology-enhanced education. In this case the developer of system faces the common issue of any tutoring system – how to provide objective evaluation of each student’s knowledge level. As a rule, it is achieved by comparison of student’s submitted answer and/or given problem’s solution against some standard defined by the teacher. The degree of subjectivity depends on the format of submitted answers or solutions. At the one end of format scale there are Yes/No type tests, while at the other end – answers written as free-text essays. Between these endpoints one can find a plethora of other formats, such as multi-choice tests, adaptive tests, concept maps, etc., as well as combinations of several formats.

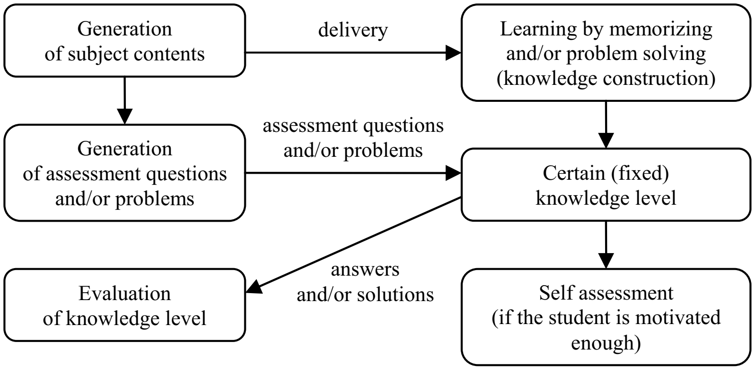



**Figure 1.** Two phases of teaching and learning process

The usability of each particular format may be evaluated according to at least four criteria: a teacher's workload, objectivity of comparison with the standard, possibilities of automation and the assessed knowledge level in accordance with Bloom's taxonomy. For instance, the workload of teachers who evaluate students' test results is the lowest comparing with all other formats. Yet more, automatic checking of test results is relatively easy to implement in computer-based systems, including ITSs. Objectivity of comparison is high because it is not influenced by subjective factors. That is the reason why tests are so popular, especially when large number of students must be assessed. At the same time even the most advanced tests allow the assessment of students' knowledge not higher than the third or the fourth level (application and analysis, respectively) of Bloom's taxonomy [4]. Contrary, free-text essays require the highest workload of teachers for students' knowledge assessment, and the latter to the large extent is subjective due to the fact that humans frequently interpret the same information worlds apart. It is also important that even the most advanced ITSs nowadays are not able precisely and unambiguously to process and compare free-text essays written in natural language. The unquestionable advantage of free-text essay format is that they allow assessing knowledge also at the two higher levels (evaluation and creation or synthesis) of Bloom's taxonomy [4].

From abovementioned it follows that criteria are contradictory. As a consequence, a reasonable compromise should be found in case of practical implementation and usage of ITSs (see Section 3). Another issue concerning knowledge assessment is mapping of evaluation results to defined scale of grades (this is shallowly touched in Section 4.1).

Now it is worth to point that solution of knowledge assessment issue is only one side of the coin, that is, a teacher can get the assessment of each individual student's knowledge level, but in summative evaluation a learner usually receives a summarized information (mapped to the final grade) without a message what he/she should do to improve his/her knowledge (how to eliminate knowledge gaps). The half a century experience of the author in teaching different subjects at different levels of studies allows remembering no more than a dozen cases when students wanted to know why they have this particular grade and what they need to do for improvement of their knowledge. It is obvious that a final assessment or grade cannot provide a meaningful feedback and in case of ITSs such a system lacks adaptability.

Thus issues of feedback implementation appear on the stage. Two qualitatively different cases should be distinguished because an ITS's developer faces various issues with different degree of complexity. First is related to the provision of feedback after a summative evaluation, while the second is related to immediate feedback during a problem solving.

The objective in the first case is provision of feedback information that in an effective way will support knowledge remediation if a knowledge gap is detected, giving suggestions which motivate and help a learner to achieve better results in future [5]. The content of feedback plays primary role, while timing of feedback is secondary. A crucial problem is how to relate assessment results and information from student's model, such as, learning style, preferences of feedback format, etc., with provided content because only in case if satisfactory solution is found, ITS will show capabilities to adapt to each individual learner.

The objective in the second case is provision of immediate feedback that guides a learner towards successful achievement of his/her learning goals. The system must detect deviations from correct solution of task and react in time. According to [6] the critical issues in this case are nature, targeting and timing of feedback. Implementation of such kind of feedback is connected with maintenance of effective dialogue [7], which is considered as one of serious limitations of modern ITSs because the latter should recognize learner's emotions, mood, body language and other attributes that can influence the learning process.

The rest of the paper is devoted to nearly two decades long experience obtained during research and development of an intelligent knowledge assessment system based on concept maps. Regardless of fact that it is only one possible alternative for the development of ITSs, the author believes that lessons learnt may be useful for ITS researchers because several of abovementioned issues of automation have been solved and approbated in practice. At the same time new open questions appeared and they may serve as stimuli for future work.

## 3. Motivation to Use Concept Maps as Knowledge Assessment Tool

Modern information and communication technologies (ICT) penetrating in education allow construction of computational environments that aim at facilitating teaching, learning and assessment, but at the same time the latter has become a constant concern [8]. The strong and weak sides of two widespread knowledge assessment methods (tests and free-text essays) are already outlined in the previous section. According to [9], built-in mechanisms for knowledge assessment based on various tests, such as tests with pre-defined answers, multiple choice questions, multiple response questions, text/numerical input questions, graphical hotspot questions, fill-in-the-blank and matching questions, are included in virtual learning environments and specialized assessment systems [10]. As it is already mentioned above, these systems have advantages, but their main drawback is the level of intelligent behavior that can be assessed in accordance with Bloom's taxonomy. Contrary, tasks such as essays or free-text responses allow assessing higher level knowledge and higher level skills but require more complex structure and functionality of ITS that, as a rule, is based on various artificial intelligence techniques, in particular, natural language processing (a hot topic of deep learning). Besides, the already developed examples of corresponding systems show that they are subject- and language-dependent [9].

The concept mapping approach offers a reasonable balance between possibilities to assess higher levels of knowledge and complexity of an assessment system [9]. Cognitive Theory that underlies concept mapping has its roots in Assimilation Theory [11] and Associationist Memory Theory [12]. Starting from the very beginning of development of concept maps (CM) as a pedagogical tool, done by Novak and Govin [13], the mainstream of research is aimed at the use of CMs for teaching and learning. Around three decades of history of concept mapping as a research field resulted in a variety of methods and tools as well as experimental work in various study fields and with different groups of learners. Nowadays one can notice researchers' interest in innovative ways of using CMs, for example, to organize instructions, to gather students' feedback, to study different groups of learners, to plan and design curricula, and to organize collaborative concept mapping. Meanwhile the problem of CM assessment and scoring is still an open problem. It is worth to add that a rich information source on recent trends and solutions in concept mapping may be found in proceedings of the biyearly held international conferences on concept mapping (see http://cmc.ihmc.us/).

The basic idea of concept mapping is that each CM represents a part of an individual's cognitive structure revealing his/her particular understanding of a specific knowledge area or, in other words, that representation of knowledge structure (concept interrelatedness) is the topmost quality of CMs. Mathematically CMs are graphs whose nodes and arcs represent concepts and relations between them, respectively (see Figure 2).

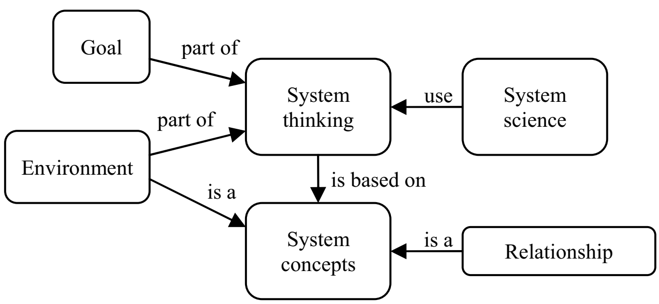



**Figure 2.** A fragment of CM of study course "Systems Theory"

Thus CMs may be processed, analyzed and evaluated using computers, thereby providing automated knowledge assessment. As a consequence, their processing satisfies the criteria of automation and objectivity. Moreover, as CMs represent an individual's knowledge structure, they promote system thinking, which is a critical point even for university students who have many study courses that may contain fragmentary knowledge without clear associations between knowledge units. Besides, the use of CMs supports process-oriented learning in which a teacher divides a course into several stages (topics). At the first stage a definite number of concepts are taught which are represented with a corresponding CM ($CM_1$ in Figure 3). At each of the following stages new concepts are learned and the corresponding CMs are extensions of a CM of a previous stage. The CM at the last stage displays all concepts and relations between them, representing complete knowledge structure of a given study course ($CM_N$ in Figure 3) [9].

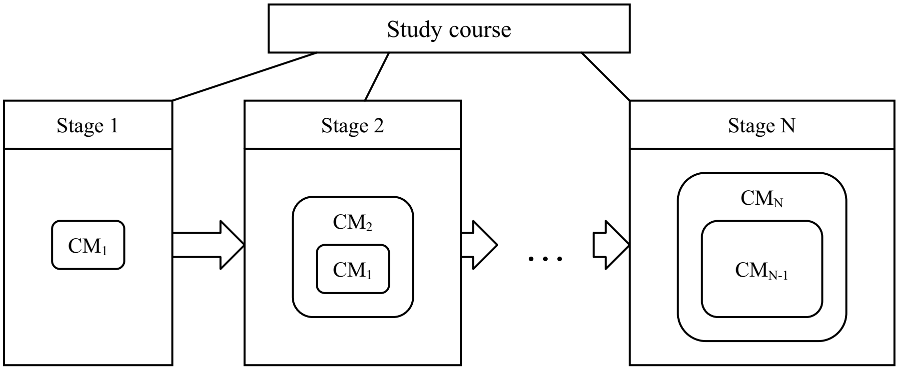



**Figure 3.** Schema of division of study course into assessment stages

One of unquestionable advantages of CMs is a wide variety of different tasks because CMs themselves are different (the corresponding graphs may be directed or undirected, arcs may have labels or so called linking phrases, arcs may have different weights, the structure of the corresponding graph may be hierarchical or with crosslinks and may contain cycles). CM building tasks range from high-directed (fill-in-the-map) to low-directed (construct-the-map) depending on information for students [14]. The structure of a CM may be given (some concepts may be filled in, too) or students may be asked to construct a CM. Lists of concepts and/or linking phrases may be given or students may be required to define them by themselves. There also may be tasks that contain misleading concepts and/or linking phrases [14]. Such wide variety of CM based tasks allows a conclusion that this tool is suitable for adaptive knowledge assessment [9]. It is also worth to point that the transformation of problem domain ontology into a CM may significantly reduce the workload of teacher [15]. So CMs to the large extent correspond to all four criteria listed in Section 2.

CMs are a viable, computable and theoretically sound solution to the problem of expressing and assessing students' learning results [8]. In addition to already mentioned advantages of CMs, it is worth to point that CMs enable students' support (knowledge self-assessment and reception of help and feedback) and teachers' support (statistics about typical mistakes, that is, differences between teacher's and students' CMs) as well as improvement of study courses. The final conclusion is that CM based intelligent knowledge assessment systems fill the gap between knowledge assessment systems based on various tests and those which are based on free-text response.

The advantages of CMs should inspire researchers to be more active in development of CM based knowledge assessment systems. In reality it happened only more than ten years after CM ideas were proposed. In [16] it already was declared that although the potential use of CMs to assess students' knowledge structures has been recognized, CMs still more frequently are used as instructional tools than as assessment tools. Ruiz-Primo and Shavelson [16] also proposed the first framework according to which an assessment is a combination of three components:

1. A task given to a student (usually it is either fill-in-the-map or construct-the-map task with predefined constraints such as, for example, a structure of CM is given, a list of concepts is given or synonyms are allowed to use, etc.).
2. A format for the student's response (paper and pencil or computer-generated).

3. A scoring system – a systematic method used for evaluation of students' CMs. Many scoring systems have been proposed that can be classified into three general scoring strategies [17] that are explained in Section 4.1.

Several scoring systems are proposed in [16] and other novel scoring systems are dispersed in numerous publications, but in practice, as a rule, simple CMs comparison methods are used. The overview of known scoring systems is out of the scope of this paper, but should be very helpful for the developers of intelligent knowledge assessment systems. At the end of this section it is needed to point that, in our knowledge, publications devoted to the issue of mapping scores to scales of final marks do not exist.

## 4. The IKAS Experience

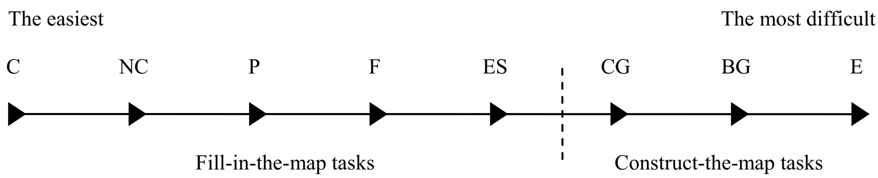
The development of concept map based intelligent knowledge assessment system (IKAS) started in 2003 and since that year five versions (the first prototype in 2005) of IKAS have been developed at the Department of Artificial Intelligence and Systems Engineering of Riga Technical University (RTU) [18]. The IKAS was tested (more than 300 students were involved) in thirteen study courses of computer science and information technology programmes at RTU and three courses of the same profile at Vidzeme University College, as well as in one pedagogical course at RTU.

The conception, architecture, development and approbation of IKAS has been presented in many publications [18, 19, 20, 21, 22, 23, 24, 25, 26, 27], and five doctoral theses directly or indirectly connected with the IKAS were defended. That is the reason why in the following, only novel ideas and solutions (comparing with other known knowledge assessment systems) implemented in the IKAS are discussed.

### *4.1. The Overview of Main Solutions*

The initial preliminary plan of the IKAS development was based on the problem's statement: how to individualize teaching and learning and how to reduce the workload of knowledge assessment for teachers in study courses with large number of students. The decision was made to develop an intelligent agent-based system that is adaptive, enables systems thinking and promotes systematic and computable knowledge assessment. The traditional four module architecture of ITS was chosen and conceptually the intelligent knowledge assessment agent as a multi-agent system (including the communication, knowledge evaluation and interaction registering agents as well as the agent-expert) was defined [9], but never implemented due to the lack of needed agent programming skills of available programmers. The targeted implementation of the IKAS lasted around eight years. The last three-tier version was implemented using the following technologies: Eclipse 3.2, Apache Tomcat 6.0, PostgreSQL DBMS 8.1.3, JDBC drivers, Hibernate, VLDocking, JGoodies and JGraph. To fulfill requirements for enabling systems thinking and promotion of systematic and computable knowledge assessment, the decision was made to develop the IKAS based on concept mapping. To meet the requirement of adaptability, it was planned that the IKAS will have the capacity for adaptation to each learner's current knowledge level. The latter is reached by implementation of two possibilities: 1) possibility to change the degree of task difficulty and 2) possibility to choose the form of feedback both in case of formative as well as in case of summative knowledge assessment.

All predefined CM based tasks are ordered in ascending order corresponding to increase of the degree of task difficulty, as it is shown in Figure 4.




C – a structure of CM is given, all linking phrases and some concepts are already put in correct places

NC – a structure of CM is given, linking phrases are already put in correct places

P – a structure of CM is given, a list of concepts is given, linking phrases are not required

F – a structure of CM is given, lists of concepts and linking phrases are given

ES – only an empty structure of CM is given (not used in the IKAS)

CG – a list of concepts is given, linking phrases are not required

BG – lists of concepts and linking phrases are given

E – learners must contruct a CM from scratch (not used in the IKAS)

**Figure 4.** The increase of the degree of task difficulty (source: [14])

The change of task difficulty may be initiated by a learner or by the IKAS. A learner may ask to reduce the degree of task difficulty, for example, asking the IKAS to insert one or more concepts from the list into the right places (of course, such actions must reduce the score received after finishing the task). A student can also reduce or increase the degree of task difficulty working in self-assessment mode. The IKAS automatically performs actions of increasing or decreasing of the degree of task difficulty after the analysis of student's CMs or during execution of given task, assisting the student in carrying out a task by finding a suitable degree of its difficulty. The second possibility is provided by implementation of three forms of explanation of concepts, namely, a student can choose between a definition, a short description or an example of concept if he/she faces difficulties during the task execution. In Figure 5 the abovementioned actions are denoted as "Help". Another way for student's support is feedback. The IKAS has some possibilities to inform a student about correctness of his/her actions and progress towards the completion of the task (see Figure 5).

The main content of feedback is given after a completion of task and it concerns a labeled student's CM (see Figure 6) and presented quantitative and qualitative data (see Figure 7).

The abovementioned adaptation operations or, to be more precise, selection of the degree of task difficulty of the first assessment stage and changing the degree of task difficulty at the next stage, setting initial priorities of types of concept explanations and changing of these priorities are supported by a student's model.

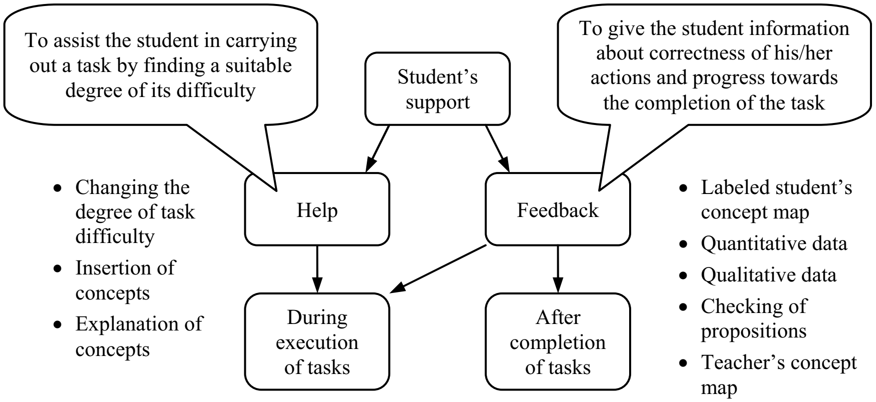
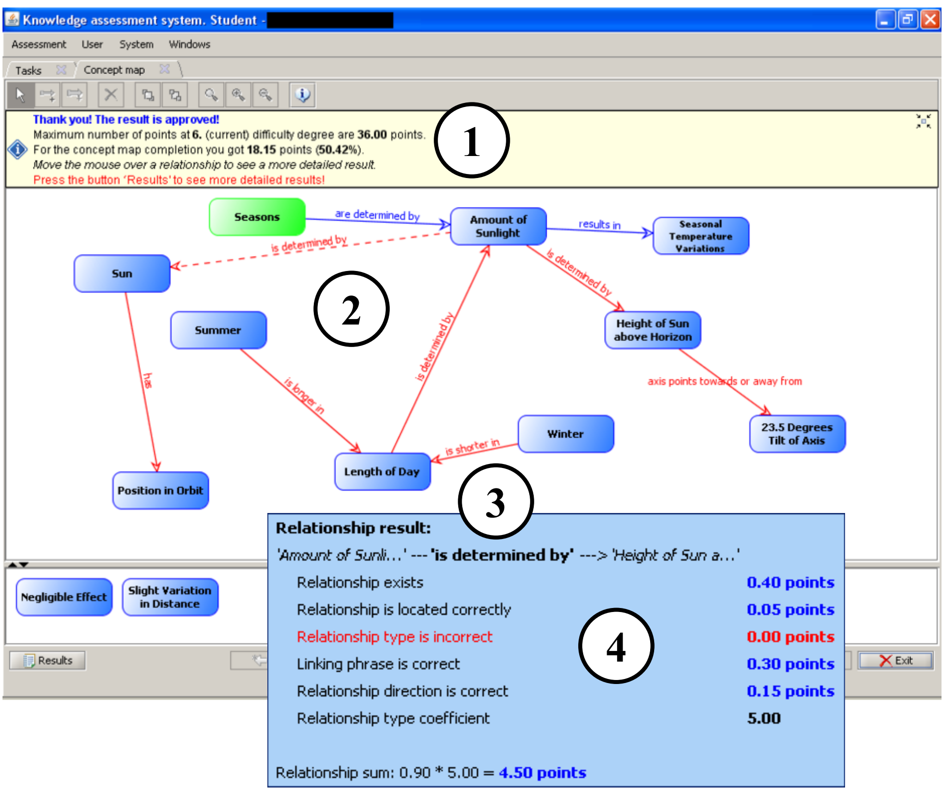
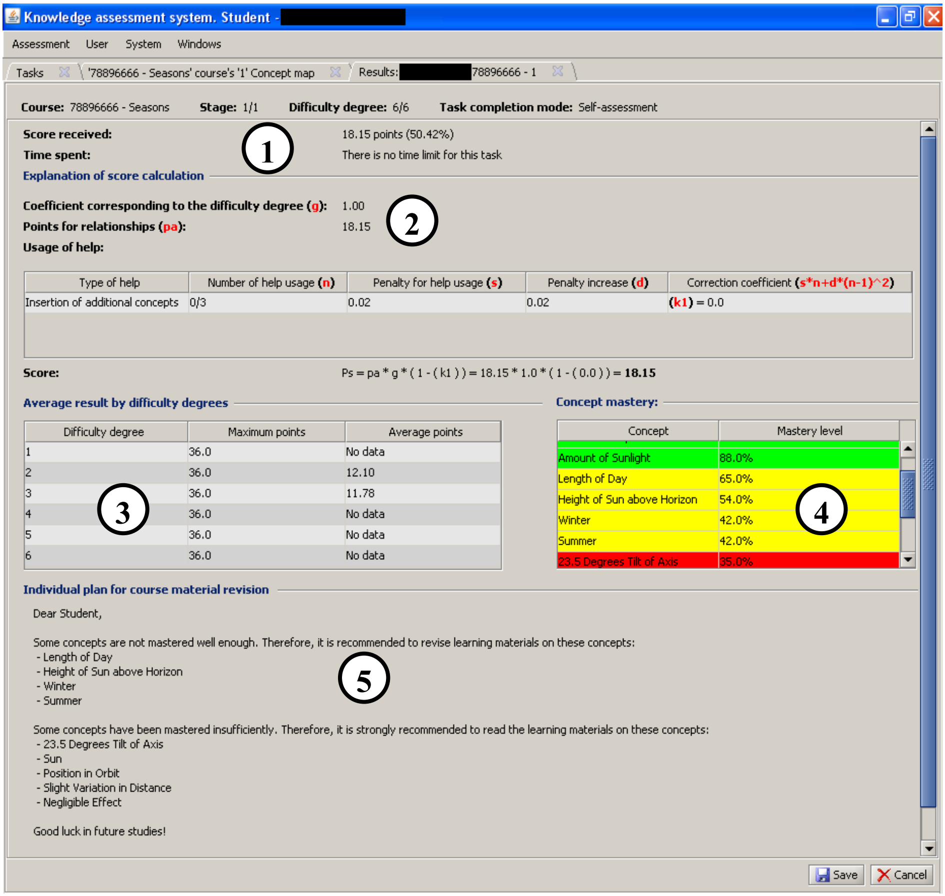



**Figure 5.** The schema of student's support




1 – Information about score received; 2 – Student's concept map with highlighted relationships; 3 – Relationship under consideration; 4 – Indication of the degree of relationship correctness and points for the relationship

**Figure 6.** A labeled student's map




1 – General information about assessment; 2 – Detailed explanation how the score was calculated; 3 – Table of average results; 4 – Table showing degrees of concept mastery; 5 – Individual study plan

**Figure 7.** Information about student's results (quantitative and qualitative data)

In the IKAS a student's model developed by Lukashenko [28] besides ordinarily used general data (first and last name, e-mail address, etc.) includes also the following characteristics: psychological characteristics, that is, a learning style (well-known Felder–Silverman model is implemented [29]), preferences (priorities of types of concept explanations and statistics on their use) and information on knowledge and mistakes (the initial knowledge level, constructed CMs, received scores, lists of incorrect relationships, concept mastering degrees, and individual study plan targeted towards knowledge remediation [5]). The initial knowledge level is the student's own evaluation of how well he/she masters a corresponding stage at a study course. The IKAS has a production rule (IF… THEN… rule) base that captures information about initial knowledge level and learning style of each individual learner. This knowledge base supports selection of the initial degree of task difficulty, changing the latter at the following assessment stages, as well as setting and changing of the priorities of types of concept explanation (a definition, a short description, or an example) included in the feedback. Priorities of concept explanation types may be changed also according to statistics collected by the IKAS during monitoring of student's task solving behavior, and if necessary the system automatically alters the priorities in such way realizing an adaptive approach.

Concerning a scoring system as a systematic method with which learners' CMs can be evaluated accurately and consistently, it is needed to stress that despite of existence of very many alternative scoring systems, no one is generally accepted. One general strategy of scoring a learner's CM components focuses on four components: 1) propositions (number and accuracy of linking phrases); 2) hierarchy levels (causal relationships between concepts); 3) crosslinks (meaningful connections between segments of the concept hierarchy) and 4) examples (valid instances). Another general strategy is based on comparison of a learner's CM with an expert's CM and scores the overlap between them, namely, counting the number of terms expressed as a proposition of terms in an expert's CM mentioned by a learner and the number of links expressed as a proposition of necessary accurate connections with respect to an expert's CM. It is also possible to use a combination of both general strategies, counting the number of linked concept pairs (points are deduced for incorrect links) and assigning different scores for mandatory, possible and forbidden links.

In the IKAS rather sophisticated scoring system has been implemented. It is based on a mathematical model [30]. The special algorithm performs the comparison of students' CMs with the teacher's CM taking into account the following aspects: the presence of relationship, its type (important or less important), correctness of linking phrases taking into account synonyms and troponyms, arrangement and coherence of concepts, types and directions of links, so called "hidden" relationships that "destroy" a strict hierarchy, the degree of task difficulty and frequency of usage of help function. A student's score $P_S$ is computed as follows:

$$P_S = \left(\sum_{i=1}^{n} p_i \cdot c_i\right) \cdot d - h$$

where

- $p_i$ – the maximal number of points according to the type of $i$-th relationship,
- $c_i$ – the degree of correctness of $i$-th relationship,
- $n$ – the number of relationships in a CM,
- $d$ – a coefficient representing the degree of task difficulty,
- $h$ – the number of penalty points spent on the usage of help.

It is important to point that the coefficient $d$ is aligned with the Latvian grading system (4 – the lowest possible mark, 10 – the highest). Thus in the IKAS an attempt is made to map a score for CM based task to the scale of final marks. The variable $h$ has three components: the number of penalty points spent on explanations of concepts, the number of penalty points spent on insertions of concepts, and the number of penalty points spent on checking the correctness of propositions (triples "concept–relationship–concept"). Initially the value of each component is equal to zero. More details of the implemented scoring system may be found in [30].

The abovementioned summarizes the current situation of IKAS, the further evolution of which is uncertain because the active period of enthusiastic work has ended.

### *4.2. Lessons Learnt*

Accumulated experience of the development and use of IKAS serves as the basis for evaluation of usefulness of CMs as knowledge assessment tool. The important point is that at the involved institutions of higher education, courses are not taught using CMs. So the developers of IKAS can get unbiased opinion from novice users of CM based approach. At the end of each study course when all CM tasks were solved using the IKAS, students handed in questionnaires. In brief, students pointed out that they liked using CMs for knowledge self-assessment because it helped them to systematize their knowledge and enabled logical, analytical and systems thinking. Besides, CMs as graphical objects were easy to perceive. At the same time rather many students answered that this approach required an unusual way of thinking and the ability to see “a whole picture”. Moreover, it was stated that CMs basically require understanding of relationships between concepts, but not their essence and possible applications. Thus it is only a superficial assessment and probability of making mistakes is high because the assessment and scoring system pushed them to construct their knowledge structure in a way that mimics the knowledge structure of a teacher. This serious drawback of CMs was also noticed in [8] where the authors mention that CM based approach ignores the fact that humans construct their knowledge in a number of different but correct ways.

Students also found that CM tasks are difficult regarding semantics of relationships. In this connection the construct-the-map task was used (201 students participated) to justify the necessity to include the correctness of linking phrases in the scoring system used by the IKAS. The results of experiment are processed at the moment.

From the teachers’ side interesting aspects appeared. Pretty large number of colleagues expressed their interest to use the IKAS in their courses, but it stops when they realize that they need to construct their own (teacher’s) CMs for their courses. In some cases fill-in-the-map tasks failed because in digital age students are so skillful using their phones that the correct version of CM was distributed in the auditorium very quickly. It is worth to point that unexpected results also were revealed. In average only less than 50% of students in all 17 study courses used the possibility to reduce the degree of task difficulty. Reasons were different – some of those who did not use this possibility answered that they were sure for their knowledge, while others did not want to lower their scores. Contrary to prediction the most popular explanation form of concepts was definition, while nobody used examples.

After all, experience with the IKAS puts forward open questions and challenges that to the large extent match those which are also discussed among CMs community. Among theoretical issues the following need to be examined empirically:

1. CM assessment techniques,
2. reliability of CM scores,
3. validating of CM inferences,
4. evaluation of CM complexity.

Regarding CM assessment techniques it is important to verify which CM tasks generated by combining task demands with task constraints are realistic and which are not. Besides criteria such as differences in the cognitive demands required by the task, appropriateness of a structural representation in content domain and practicality of technique must be explored.

Speaking about reliability of CM scores there is the psychometric issue – whether CMs can provide reliable scores and representations. There are also two open questions.

The first is: how large a sample of CM tasks should be to measure a learner's knowledge structure reliably? The second is: how stable are CM scores across time?

Validity of CM inferences is related to justification of proposed implementations of CMs as measures of a learner's knowledge structure in a given domain. For that evidence should be found whether or not CMs provide a sensible representation of knowledge in a domain, whether or not process oriented and student-centered studies converge on the same knowledge represented in a CM, whether or not different mapping techniques provide the same information on learner's knowledge structure, and whether or not different assessment techniques correlate differently with traditional multi-choice tests.

Evaluation of CM complexity is important at least from two points of view. First, it can help developing of more accurate estimation of the degree of task difficulty within one class of CM tasks, for example, NC or BG (see Figure 4). Second, it will allow comparison of students' submitted CMs and correction of a score taking into account complexity of really accomplished task or its part. The ongoing research is aimed towards the development of a formal method for evaluation of CM complexity from the systems viewpoint. The main idea is to find correlation of the degree of CM based task difficulty with the complexity of CM as a whole, namely, as a system [14]. The correspondence between four criteria of system complexity (the number of elements, the number of relationships, the attributes of specific elements and the organizational degree) and CM complexity has been found. For instance, the third criterion – systems attributes for CM corresponds to linking phrases, that is, their number and variety of categories and/or the number of synonyms of concepts. Application of this criterion allows to formulate two hypotheses:

- Hypothesis 1: In case of concepts the complexity of CM increases if the number of synonyms grows.
- Hypothesis 2: The complexity of CM increases if the variety of linking phrases increases.

More details are given in [14].

Experience with the IKAS also uncovers some practical issues. First, how to reduce the teachers' workload needed for construction of experts' CMs to raise their interest and readiness to use CMs as knowledge assessment tool? As it is already mentioned, the possible solution is to use algorithm for transformation of problem domain ontology (if it exists) to CM. Second, how effectively to use CMs as knowledge assessment tool in large scale audience taking into account learners' different facilities to use CMs (pedagogy students had significantly worse results than computer science and information technology students)? Third, whether the final examination may be based completely on the assessment of CMs (their scoring), that is, whether the knowledge assessment may be carried out totally automatically?

## 5. Conclusions

At the time being, intelligent knowledge assessment systems are neither a myth nor a reality. Finished researches and developed systems give evidence that such systems have potential and they step-by-step move towards at least partial replacement of teachers. At the same time a lot of work must be done till we shall have really intelligent tutoring and knowledge assessment systems. At present it seems that further advancement concerning technological aspects will depend from progress of modern methods and techniques of Artificial Intelligence, such as Deep Learning, Multiagent Systems and Emotional Computing. Another relevant aspect is pedagogical issues that for computer-enhanced teaching and learning rather frequently are neglected. One also should take into account the influence of financial aspects – expensive investments for research and implementation of such systems, that is, their commercial success nowadays seems to be problematic and it may slow down their progress. These statements are based on the author's expertise in Artificial Intelligence and experience regarding the IKAS.

Even taking into account that till now the IKAS is unfinished, not fully integrated system, it has several advantages among similar systems. The IKAS is a good example of combination of modern ICTs and advanced didactic methods. It provides automatic knowledge assessment using CMs and supports teachers who think about improving their courses, teaching methods and study materials. The IKAS can operate in the self-assessment mode, motivating a student to improve results because the system offers to assess his/her current knowledge level, to choose tasks according to his/her learning style, in case of difficulties to change the degree of task difficulty, to receive help (in case of formative assessment) and meaningful feedback (in case of summative assessment) thus motivating to learn more following the advised personalized learning path. The scoring system implemented in the IKAS is based on a mathematical model in which much more factors are taken into account in comparison with other known scoring systems. The student's model ensures adaptability by capturing information about initial knowledge level and learning style of each individual learner, as well as giving possibilities to change the selected degree of task difficulty and the priorities of types of concept explanation.

It is evident that in the IKAS only small part of relevant issues of knowledge assessment systems development has been solved. First, the IKAS is based on CMs – only one of possible approaches to knowledge assessment, while many issues are general ones and are characteristic also for others (various tests and essays or free-text responses). Unquestionable advantages of CMs are the following. Using CMs as a knowledge assessment tool urges educators to teach students more than simple facts and concepts, that is, to teach how different concepts relate to each other. Besides, concept mapping as knowledge assessment tool urges the individual learner to think on a deeper cognitive level comparing with tests. At the same time there are theoretical and practical challenges listed in the previous sections that require solutions of corresponding problems to reach the mature intelligent framework for CM based knowledge assessment. The author hopes that concurrently with his own ongoing research, namely, the development of formal method for evaluation of CM complexity from the systems viewpoint, the paper will inspire other researchers to investigate mentioned problems and to find answers on open questions. Even the CMs based approach is waiting for many young researchers and we must be ready that it is a long way until we reach the goal – truly intelligent knowledge assessment systems that will replace human teachers or significantly will reduce their workload.

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