Using Students' Performance to Improve Ontologies for Intelligent E-Learning System

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Abstract

Ontologies have often been recommended for E-learning systems, but few efforts have successfully incorporated student data to represent knowledge conceptualizations. Defining key concepts and their relations between each other establishes the backbone of our E-learning system. The system guides an individual student through his/her course by evaluating their progress and suggesting instructional material to review based upon their answers. Three main tasks are performed within this framework: building ontologies for the course, measuring a student's understanding level for the concepts, and making personal suggestions to create an individualized learning environment. This paper presents: the integration of ontologies, assisted with student data, together with an intelligent Recommendation Module for the development of an E-learning system; the comparison and correction adaption of ontology from students' mind maps; and the assessment of students' actual weaknesses in comparison to what Recommendation Module suggests. The sample of 127 students, five classrooms, was conveniently selected among seventh grade students of a demographically average school in a major city in Turkey. The students' achievement was assessed and the scores for different questions were investigated for associations with concepts made in the students' minds. The results provided significant correlations among scores, and a fit model for the concepts represented by questions. The student suggested model slightly differed from the ontology map from the experts. Based on the data-supported model, the Recommendation Module more accurately determined the students' learning deficiencies and suggested concepts to be reviewed.

Keywords: Ontology • Graph Database • Concept Map • E-Learning • Intelligent Learning Systems • Structural Equation Modeling

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The most important goal of Artificial Intelligence (AI) is to improve computer understanding and make it as close to human intelligence as possible. One of the most significant areas of application for artificial intelligence is within the E-learning system. Most of the E-learning systems lack AI tools and merely present the content materials without evaluating the students' prior learning. However, using ontologies together with semantics for various intelligent systems have showed promising results in various fields such as real estate (Yuan, Lee, Kim, & Kim, 2013), geospatial problem-solving environment (Jung, Te Sun, & Yuan, 2013), and collaborative learning (Isotani et al., 2013). In addition, some intelligent have already been commercialized (Fensel, Van Harmelen, Horrocks, McGuinness, & Patel-Schneider, 2001). It has been showed that when ontology-based methods used the essential building block of AI, semantics and ontology can drive the E-learning systems to the next phase (Bittencourt, Costa, Silva, & Soares, 2009; Gaeta, Loia, Orciuoli, & Ritrovato, 2015; Gaeta, Orciuoli, & Ritrovato, 2009; C.-C. Hsu & Ho, 2012; Kontopoulos, Vrakas, Kokkoras, Bassiliades, & Vlahavas, 2008; Leony, Parada Gélvez, Mũnoz-Merino, Pardo, & Kloos, 2013; Muñoz Merino & Kloos, 2008).

The intelligent learning systems are basically systems that make decisions on student learning as oppose to other e-learning systems where a teacher makes all the instructional decisions (Isotani et al., 2013). The system evaluates the student's prior learning, decides what to learn next, analyzes the achievement, determines their competency level, and then directs the student to the next learning objective. One of the advantages of intelligent learning systems is that it provides students with a learning course that is specifically tailored for their individual learning style. Adaptive learning implementations include learning environments that change according the students' individual learning needs, and consequently, increase meaningful learning and student achievement (Özyurt, Özyurt, & Baki, 2013). Besides assessing the student's prior knowledge, an intelligent system needs to track the student's comprehension during the learning process. This can be achieved by collecting test scores and attendance from the learning activities.

Ontology houses a semantic map of pieces of information collected in order to represent knowledge. Ontology is an explicit way to conceptualize and represent knowledge (Gruber, 1993). In its simplest form, it consists of a set of concepts, a body of labels describing how the concepts are related, and a set of information about relationship features of the connected concepts. In the context of education, an ontology would cover all the concepts and relationships about the subject to be taught (Gultepe & Memis, 2014). A novel approach of using ontology in E-learning systems is to use technology to make instructional decisions on "what to learn next" based on semantically connected pathways very similar to learner's cognitive structure. For learners to construct their own knowledge, the content should be presented in a meaningful, unique way. Knowledge background and cognitive profiles vary from student to student and require personalization in all educational settings, including E-learning systems. A personalized E-learning system should: measure the student's knowledge on a subject, determine the concepts that need to be learned or reviewed, and provide essential content to the student. Supporting personalization in E-learning systems is one of the major benefits of using ontologies (Gaeta et al., 2009; Nganji, Brayshaw, & Tompsett, 2011; Ongenae et al., 2013; Yalcinalp & Gulbahar, 2010). There are adaptive systems designed to make personal recommendations by acquiring user's knowledge. In these systems, short-term and long-term log of user actions were kept in layers of ontologies (Aroyo, Denaux, Dimitrova, & Pye, 2006; Aroyo, Dicheva, & Cristea, 2002). Using the information about content or user traces can be useful to make automated decisions on instruction, but this point of view misses a critical detail. Namely, that learning occurs in learner's mind with meaningful connections and repeated review of concepts and processes represented by neurons. Organizing knowledge about the content is helpful in deciding on what is the next logical topic. A more useful intelligent learning system, that is, one that incorporates the individualized process of student learning, should accurately identify what is still needed to learn. There are E-learning systems that use ontologies and are designed to identify gaps during the assessment process and provide feedback to students (Kazi, Haddawy, & Suebnukarn, 2010; Litherland, Carmichael, & Martínez-García, 2013; Sánchez-Vera, Fernández-Breis, Castellanos-Nieves, Frutos-Morales, & Prendes-Espinosa, 2012).

The E-learning model used in this study is designed to organize learning objects in a semantically oriented way that uses ontological practices in order to find relevant learning content. However, ontologies used for the E-learning systems should be tested in the field to determine whether the ontology actually represents the student's conceptual scheme. Since the students' conceptual scheme changes

and evolves, ontologies should adapt to the way a student connects concepts. By using our approach, ontologies heavily absorb users' conceptual maps to give a unique experience to each learner.

Various systems (Abel et al., 2004) use ontology built by experts, which represent experts' own conceptual scheme of the subjects. For example, an article by Knight , Gašević, and Richards (2006) described a framework to connect learning design to learning objects based on various features of the subject, learning content, and metadata on the learning objects. A novel effort by Hsu (2012) proposed a model based on an ontology that enables learning content to be easily found. Another model was proposed by (Serçe, Alpaslan, & Jain, 2008) which incorporated students' learning styles to help make instructional decisions. In a different approach, students were required to build their own concept maps which the E-learning system then compared these concept maps with the ontology created by an expert (Kumaran & Sankar, 2013).

Within the current literature there are models that implement ontology in E-learning environments in order to make better instructional decisions or meet student needs (Anohina-Naumeca, Grundspenkis, & Strautmane, 2011). Aroyo et al. (2006, p. 573) discussed the need to "…focus on the development of a good classification of user's mismatches and patterns for clarification dialog based on systematic studies of empirical and computational approaches for ontology aligning and reconciliation." Researchers strongly recommend future research on using ontology in E-learning systems and evaluating it with student input (Aroyo et al., 2006; Kholief, Nada, & Khedr, 2012; Kumaran & Sankar, 2013; Yalcinalp & Gulbahar, 2010). There are, however,

no studies that have directly focused on addressing student achievement or competency by using actual data collected from end-users. This study not only suggests a model for an ontology-driven intelligent learning management system, but also proposes how the system is supported by student input.

Firstly, we will briefly introduce our system and ontology editor together with the ranking module. Secondly, we present a case study of 127 students in seventh grade taking a Science course whose data was collected to better explain the Recommendation Module (Module 3). Thirdly, we describe the structural equation model based on student data and compare it with the concept map. Finally, we propose a novel approach for building ontologies and designing recommendation systems for personalized E-learning system and discuss the feasibility of implementation.

Overview of the Intelligent E-Learning System

The main modules of Intelligent E-Learning system are illustrated in Figure 1. Experts prepare concept maps and load to database using the ontology editor, which is explained in more detail in the following section. All the content materials such as videos, audio files, animations, texts, pictures, simulations, and other features are labeled with at least one main concept and are loaded onto the system database by content reviewers. Modified SCORM standards are preferred for labeling content materials. The concept map is the backbone of the system and heavily used by every other module. After loading concepts and contents, the system is ready to interact with users. Module 2, the Teaching/Test/ Rank Module, communicates with the database and presents content to the users. A user can navigate
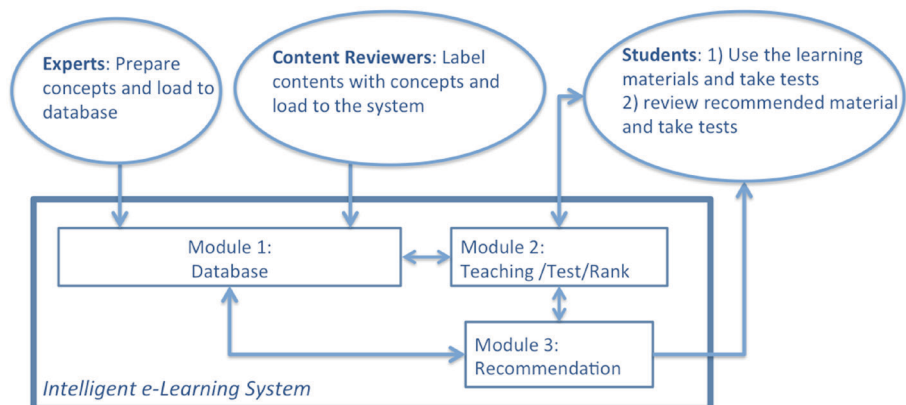

Figure 1: System diagram of the intelligent E-learning.

the limited content that are classified according to grade levels or log-in to the system in order to benefit from the Recommendation Module. The Recommendation Module is able to record student activity and test results, and uses this information for making personalized suggestions.

Ontology Editor and Ranking Module

Ontology editors have an important role on building, saving, and handling concept maps. Protégé is an open source ontology editor developed by Stanford University and widely used. Protégé software is able to define classes and relationships between classes. The latest version of Protégé supports XML, RDF, and OWL formats. Although Protégé is available to the public, some researchers prefer developing their own ontology editors like OntoEdit (Maedche & Staab, 2001). OntoEdit program offered more tools to edit ontologies than Protégé version at that time and then it was later commercialized. Ontology editors allow the assignment of relation types to connect concepts. In our study, we first practiced in Protégé to create ontologies for various courses and later developed our editor, which will be explained in more detail in the next sections. Some complex ontologies are built by integrating

multiple ontologies engineered by different users. In this case ontologies should be combined without losing any concepts (Doan, Madhavan, Domingos, & Halevy, 2002). In order to maintain consistency and to prevent any conflicts, the concepts were predetermined from the curriculum. In order to do this, area experts were included in the process to determine all the concepts which were then loaded onto a database (Icoz, Cakar, Yigit, & Egi, 2014).

The cooperation of Teaching/Test/Ranking and Recommendation Modules are connected to concept maps. Concepts include the terms or procedures mentioned during the lesson, which are included in the learning objectives or in the learning goals of the unit. The concepts are first determined by teachers and area experts and then uploaded to a database, which allows for later additions. The main role of the person who creates the ontology is to build concept maps by picking content from the database and connecting them with a suitable type of relation. By defining five relation types (subgroup, feature, composition, function, or cause) and three strengths (high, medium, or low), we have eight parameters to control for a recommendation module. As mentioned above, all content material uploaded to the E-learning system is associated with at least one concept so that the concept maps can guide the
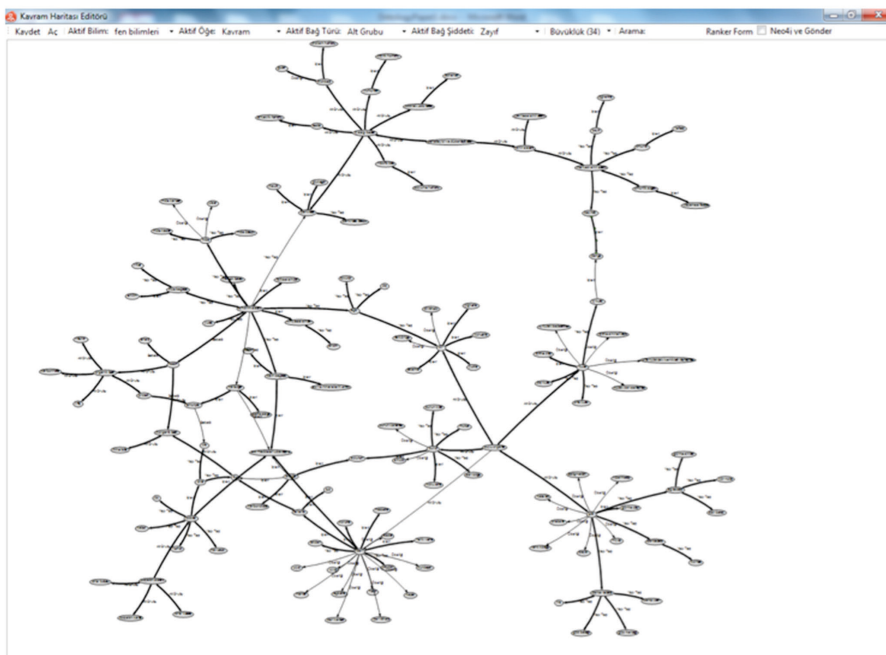

Figure 2: Screenshot of the ontology editor and a concept map built for the case study (concept map is presented just to show the "big picture," the links between the concepts, and the hierarchical structure).

artificial intelligence in making recommendations and offering related learning material based on student learning needs. Details of the ontology editor were briefly explained in the work done by Icoz and colleagues (2014); Neo4j (graph database and Cypher-query language) was selected to practice recursive queries and to implement mathematical equations. In addition to usual tasks such as adding, connecting, and saving concepts, the editor enabled the assignment of one of five different relation types along with one of three strength values (low, medium and high) to a connection between two concepts. The editor included a ranker feature, which used the weights of relation types and strengths to perform calculations for the Recommendation Module related concepts. The thickness of the arrow reflected the strength as high, medium, or low relationship strength. By defining five relation types (subgroup, feature, composition, function, or cause) and three strengths (high, medium, or low), we have eight parameters to control for a recommendation module. Figure 2 shows a complete concept map created for seventh grade science course. The values of eight parameters are initially assigned based on the experience and recommendations of area experts and teachers. The initial weights of relation types, ranked from very related to less related, are suggested to be subgroup, feature, composition, function, and cause. For a chosen concept, $c(i)$, the ranking module first grouped the concepts according to distance from $c(i)$. The first group was called *length 1* which included concepts directly connected to $c(i)$. Among the first group, the ranker module calculated the scores by multiplying the weights of relation types and strengths. The second group is called *length 2* and included concepts that directly connected to other concepts in first group, *length 1*. The implementation of complex mathematical formulas was not within the focus of this study but will be a part of our future research and improvements.

Method

Basic semantic connections within a unit of science course were investigated in this study. Relational research model was used to compare the experts' conceptual relationships with students' mind maps on "Our Body and Systems" unit in seventh grade physical science course. Each question in the achievement test is associated with at least one concept. The concept map was created by area experts with the guidance of teacher judgment and the use of an editor program, explained earlier in this paper.

Instrument

A regular in-class paper and pencil exam was used to collect data from the seventh grade students. The questions were determined by the experts with teacher's guidance to maintain content validity. Then each question was thoroughly examined by the research group to assign pre-determined concepts related to the questions. Concepts were added to the list when needed. Then using the mentioned procedure, a concept map was created and saved onto the server. The exam had four sections, including 35 main questions; Section A (true or false, 10 questions), Section B (fill in the blanks, 10 questions), Section C (figure and table filling, 5 questions with subsections), Section D (multiple choice, 10 questions).

Including subsections, there were a total of 74 questions in the test which covered all the topics in the unit. The highest number of correct answers was 69 and lowest number of correct answers was 8 (Figure 3). Following the regular school curriculum, the instructor assigned 1 or 2 points to each question. Among the five different sections of students (randomly assigned from five classes with the same instructor), none had significantly different mean scores ($F_{(4,122)}$ = .614; $p \le .653$). The scores from the test questions were investigated for their item difficulty and item discrimination indices. Eight questions were removed from model evaluations due to their inappropriate difficulty index and item discrimination index, and so 68 questions were used in the final analysis. The average difficulty index was found to be .579, which is considered to be proper difficulty value for tests. The item discrimination index was calculated for each question and it is found to be in the range from .24 and 1. Even if the lower end seems to be low, the discrimination indices are acceptable for a correlational study.
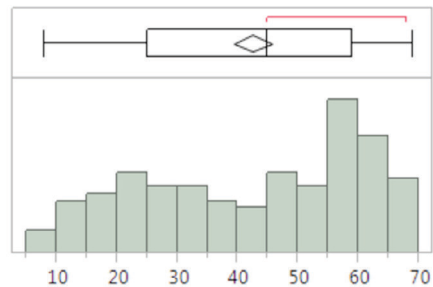

Figure 3: Distribution of correct answers given by 127 students, highest number of correct answers is 69, lowest number of correct answers is 8.

Participants

An average-sized state school located in an average income neighborhood was conveniently selected in a large city of a developing country (Altındağ, Ankara, Turkey). Of all seventh grade students in this school, five sections of a science course were selected (all having the same science teacher) and 127 students are included for this sample. Data was collected from 127 students with a 2% attrition rate. Out of 127 students, 63 were female and 64 were male.

Data Collection

The course subject chosen for this study was the unit "Our body and systems" of a science course taught to five sections by the same teacher. Achievement tests were administered on a regular school day after the end of the unit. The students were fully informed about the study and their consent was obtained to use their scores in this study. Four concurrent sessions were arranged for the test, which lasted for 45 minutes.

Data Analysis

Reliability and validity was maintained by analyzing internal consistency in the achievement test scores. Female students are more successful ($t_{(122)} = 3.41$; $p \leq .05$). The mean of correct answers was found to be 42.5, with a standard deviation of 18.05. In order to determine the coherence of the computationally designed concept map with students' mind map, confirmatory factor analysis techniques were used to analyze data. Since the tests were used to measure students' learning about a concept, each question was considered as an observed, or manifest, variable while each concept was considered a latent variable. In some cases, questions represented more than one concept within the ontology. Several models have been proposed, including the one displayed in Figure 4. Structural equation modeling was then administered to analyze the data and determine which model explained the most variance among the observed variables (the test questions, in this case). All possible models were examined during the analysis, and the most suitable model supported by data was considered to be the closest to students' mind map. Data analyses were conducted using SPSS and Amos.

Recommendation Module

Figure 4 shows the portion of a concept map built for the nervous system subject, including the main concepts determined by the area experts and teachers as relevant to the topic. Note that these concepts are for seventh graders, and the questions need to be more complex for higher grades. This portion of the map has a hierarchical tree structure,
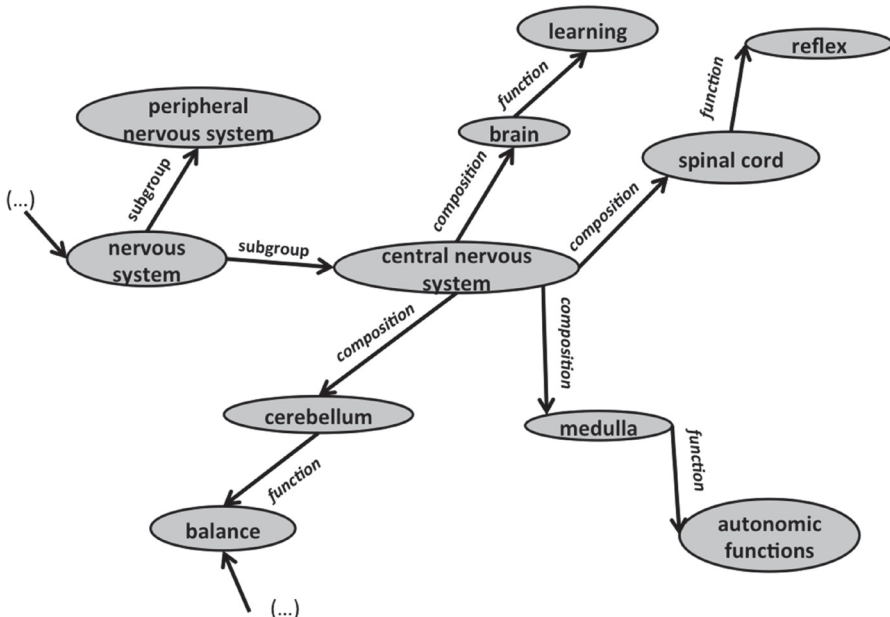

Figure 4: Portion of the concept map built for the science course (sketched for reader, the overall concept map is presented in Figure 2).

as this is how the area experts and teachers built this concept map. It is possible to implement various calculations, however for the sake of simplicity we preferred to use one that multiplied the weight of relation type with the strength and also considered the distance from the starting concept, or initial node. Based on this concept map, if a student did not understand the "brain," ranker form in the ontology editor calculated scores for 10 nodes starting from the node "brain." The initial weights entered into the ranker form: subgroup = 5, feature = 4, composition = 3, function = 2, cause = 1 and high = 3, medium = 2, low = 1.

The Recommendation Module considered length and ranking score calculated as explained above together with the contents related to the "brain" and "central nervous system" presented first to student. Afterwards, "learning," "nervous system" and other topics were presented (Table 1). Within the same length, the concept having the highest score was recommended next to the student.

Table 1
Ranking Results

Length	Score	Node Name
1	9	brain->central nervous system
1	6	brain->learning
2	12	brain->central nervous system->nervous system
2	9	brain->central nervous system->cerebellum
2	9	brain->central nervous system->spinal cord
2	9	brain->central nervous system->medulla
3	13	brain->central nervous system->nervous system->regulatory systems
3	13	brain->central nervous system->nervous system->peripheral n. system
3	8	brain->central nervous system->cerebellum ->balance
3	8	brain->central nervous system->spinal cord ->reflex

Initially, the weights of the relation types and strengths were determined by area experts and teachers. These values were fine-tuned after collecting actual data from the students.

Structural Equation Modeling (SEM)

In order to compare and validate the student data with respect to the area expert and teacher ontology, student exam results were transferred to Amos for structural equation modeling (SEM) and path analysis. The main motivation of this comparison was to investigate the amount of

agreement between students' conceptual scheme and the map of area experts and teachers.

Table 2
Model Fit Parameters

Criteria	Results	Standard (IBM SPSS Amos, 2012)
RMSEA	0.056	< 0.05 close fit < 0.08 acceptable
CMIN/DF	1.395	~1 good fit [1–2] acceptable
CFI (Comparative Fit Index)	0.934	> 0.9 good > 0.95 very good
IFI (Incremental Fit Index)	0.938	> 0.9
NFI (Normed Fit Index)	0.810	≥ 0.9
TLI (Tucker-Lewis Index)	0.909	≥ 0.9–0.95

For the portion of the concept map depicted in Figure 4, model fit parameters are presented above in Table 2. RMSEA of .056 and CFI of .934 indicates that this model fits the data very well. In the light of this model, we can also conclude that spinal cord and brain have high correlation (.83), which was not projected in the concept map due to its hierarchical structure. In other words, data suggest that rather than a tree structure, cross-links between concepts are also possible and suggest a more web-like structure (Figure 5).

We also compared other portions of the concept map in Figure 2 with the SEM results and found that the combination of the model with student data can modify and validate the general structure of the initial concept map by comparing the map and the model. For example, the original concept map had two concepts, the "digestive system" and the "liver," which had a "composition" relation type and medium strength level. The correlation between these two concepts in SEM was found to be .56, confirming the predicted strength level. Another example of the content map verification was the high strength level between the "nervous system" and the "endocrine system," reflected in SEM as having a correlation of .74.

SEM results revealed that the initial ontology built by experts were not a complete match with the students' conceptual schemes. The students' conceptual scheme, when compared to map built by experts, is more complex and has more links between the concepts. This important detail has an impact on personalized recommendations for individual students. For instance, the link between the "spinal cord" and "brain" suggest that a student who does not understand brain should also be presented with content related to the spinal cord by
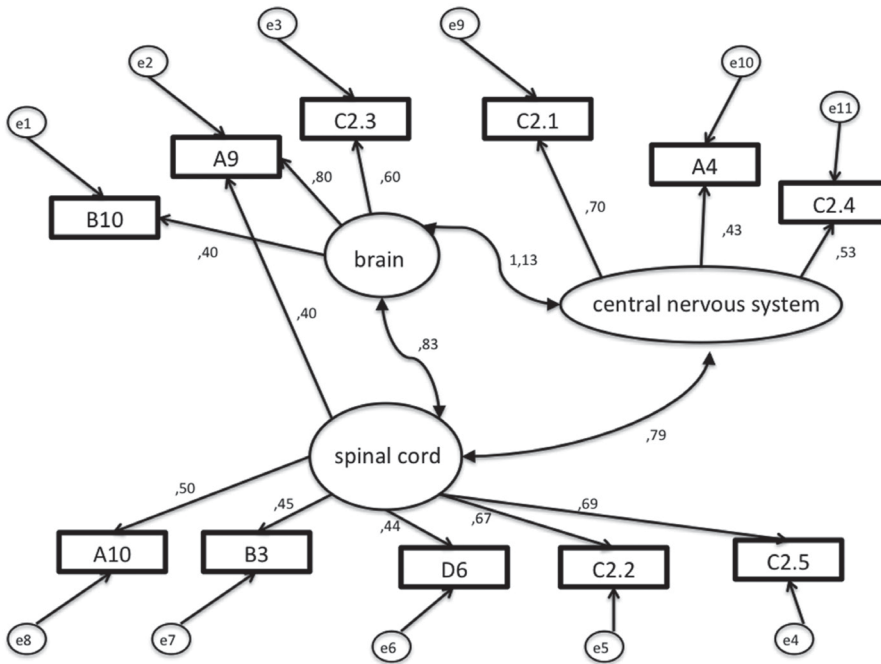
Figure 5: Amos SEM results showing standardized estimates. A10, B3, D6, C2.2, C2.5, and A9 are exam questions related to the "spinal cord" concept; B10, A9, and C2.3 are related to the "brain"; C2.1, A4, and C2.4 are related to the "central nervous system." e1–e11 are error terms.

the recommendation system. The reasons for this link can be attributed to different factors such as the learning environment or the quality of teaching the material, but these would be subject of another study.

Post-Hoc Procedures

In order to test the effectiveness of the Recommendation Module, we worked with 18 students to determine the concepts that were not well understood based on the results of the first exam. Each student then received a recommendation for the concepts that needed to be studied. Students were asked to review the same course materials (related portions of the textbook and class notes). For this part, no additional content material such as videos, animations, or illustrations were offered to students. Students verbally confirmed that they had studied the available material again based on the recommendations from the system. Another set of questions (the second exam) related to the concepts of interest, were then presented to the students. In one case, 12 students were recommended to review the "spinal cord" and answered two new questions about this concept with a success rate of 83.3% on the second exam. In another case, five students who did not

understand the "growth hormone" concept were recommended to read the related text and answered a new question with a success rate of 60% on the second exam. In a third case, five students who did not understand "urine" answered a question with a success rate of 100% after the recommendation. Note that this test is not a complete analysis of system performance because students are only advised to review the concepts, but the system did not introduce new content material and the content that was studied was not tracked. Tracking student responses to the recommendations could also have a prominent impact on these results. This could be because some students may not have followed the recommendation. That being said, this simple test indicated that recommendations individualized for each student did help him or her to increase their knowledge and guide them through their learning process. Similar to patient-prescription-healing relation, the designed system offer student-personal recommendation-learning model (Kumaran & Sankar, 2013; Nganji et al., 2011).

Discussion and Conclusion

There were three main purposes outlined in this study. First we proposed building an ontology,

which served as the backbone for a learning management system. Second, we verified the inter-correlations of the concept map by using student data and comparing the original relationships with the ones in the student' conceptual scheme and fine-tuned the relations in the original ontology. Lastly, we tested our recommendation system, which uses the modified ontology to investigate whether the students filled the learning gaps of the concepts that our recommendation system suggested.

The construction of the concept map was a very time efficient process and can be completed within a very short timeframe with the assistance of area experts. Incorporating teacher's guidance, knowledge, and perspective with student data enabled the verification of concept maps and adding new connections between concepts for accurate representation and organization of knowledge. However, it is a difficult task to cover all the concepts that are related to the units as well as the ones that were learned earlier. Once the list was crosschecked against exam questions for content validity, new concepts can be added as necessary. Building ontologies for educational purposes can be based on concept maps which are already used widely in educational settings (Yalcinalp & Gulbahar, 2010). Although the use of an expert may be sufficient to build concept maps for educational purposes, ontology efficiency can be improved further by using student input.

The second step was to investigate the gaps between the concept map that was prepared by area experts and the teacher with the one drawn by the student exam results, which represented the students' mind map. Findings suggested the students' mind maps were not quite the same as experts' conceptualization of knowledge. The actual concept map created by students was found not to always be hierarchical, as was predicted. In fact, it can be unexpected and chaotic. This has already been showed in previous research (Williams, 1998) where the concept maps created by two student groups and expert groups were compared. The concept maps of experts have general homogeneity compared to concept maps of students. Previous research on E-learning systems showed that offering the same content to every user without considering their background can cause inefficient results for various courses (Carr, 2000; Rovai & Barnum, 2003). There are two possible explanations for this: courses are not prepared with same quality or every student has a different knowledge level and so personalization is required. This is where intelligent systems can play an important role. Relying only on experts' conceptual schemes can inadvertently disregard some connections between the concepts. In addition, offering the same content map to every student provides no opportunity for personalization.

The results of this study suggest that the organization of knowledge in learners' minds is not the same as it is represented in experts' minds or in the textbooks. As explained by Yalcinalp and Gulbahar (2010), the need for personalization in E-learning by using ontologies is emerging and gaining widespread applications. In this study we showed that more accurate learning paths can be recommended by creating an ontological map for each individual, developed in part by student data. Additional efforts should be spent on improving the recommendation and test modules in order to better assist students by conducting more research studies with larger samples and on wider subject areas. By monitoring various factors, for example the amount of time spent on different content information, student's own unique learning style can be determined in more detail. Not only test scores but also user actions and interests can be used to recommendations about the content that should be reviewed. It was shown that learning management systems (software applications) used to administer learning activities and supervise learning as online educational applications should be evaluated for their effectiveness (Ozkan & Koseler, 2009).

Future work includes expanding this system so that more audio and visual content materials are available to larger populations of students. Success rates can be improved by introducing rich contents such as videos or other animations because it is possible that some students have improved learning from visually stimulating sources. In doing so, more data can be collected and the system can be further evaluated for efficiency. In addition, it is also planned to explore meaningful ways of faster processing of student data and easier modified ontologies from experts. The overall goal of the project is to develop a complete intelligent E-learning system that helps make instructional decisions based on student characteristics and individualized ontologies.

Acknowledgments

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