Transfer Effects of Semantic Networks on Expert Systems: Mindtools at Work

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Abstract: Semantic networks and expert systems can support learning and critical thinking as Mindtools (knowledge representation formalisms for analyzing the world, accessing information, interpreting and organizing personal knowledge, and representing what learners know to others). Both are cognitive reflection and amplification tools that help learners to construct their own knowledge by designing their own knowledge bases. This study examined the effects of building semantic networks on the coherence and utility of expert systems subsequently constructed by undergraduates. The ambiguity of the task was problematic for many of the students, so more scaffolding of required actions would be appropriate. The kinds of thinking required to build semantic nets and expert systems were quite different, with no facilitative effect of one on the other. That kind of transfer would also have to be better scaffolded.

Introduction: Computers as Mindtools

Instructional technologies have traditionally been used as conveyors of information and tutors of students. In these traditional applications, information is stored in the computer. During the "instructional" process, learners perceive the messages stored in the computers and "interact" with the technology. In contrast, Derry and LaJoie (1993) argue that "the appropriate role for a computer system is not that of a teacher/expert, but rather, that of a mind-extension "cognitive tool" (p. 5). Cognitive tools are *un*intelligent tools, relying on the learner to provide the intelligence, not the computer. So, we believe that computers are more effectively used as Mindtools (Kommers, Jonassen, & Mayes, 1992). Mindtools enable knowledge construction and knowledge representation so that learners can learn *with* technology, not *from* it (Salomon, Perkins, and Globerson, 1989). Mindtools (Jonassen, 1996) include (but are not limited to) databases, spreadsheets, semantic networks, expert systems, multimedia/hypermedia construction, computer conferencing, microworlds and even programming. Mindtools are knowledge representation formalisms for analyzing the world, accessing information, interpreting and organizing their personal knowledge, and representing what they know to others. They are cognitive reflection and amplification tools that help learners to construct their own realities by designing their own knowledge bases.

A number of studies have demonstrated the effectiveness of Mindtools for engaging critical thinking in learners. However, none have examined the combinatorial effects or the effects of using one Mindtool for facilitating representation by another. Since each Mindtool provides a different formalism for representing content and personal knowledge, it is reasonable to expect that representing knowledge with one Mindtool might facilitate another.

Semantic Networks as Mindtools

Semantic networking tools are cognitive tools that provide a visual and verbal means for developing concept maps, otherwise known as cognitive maps. Cognitive maps are spatial representations of ideas and their interrelationships that are stored in memory, i.e. structural knowledge (Jonassen, Beissner, & Yacci, 1993). Programs such as SemNet (Fisher 1990,1992), Learning Tool (Kozma, 1987), and TextVision (Kommers, 1989) enable learners to interrelate the ideas that they are studying in multidimensional networks of concepts, to label the relationships between those concepts, and to describe the nature of the relationships between all of the ideas in the network.

The purpose of semantic networks is to represent the organization of ideas that someone knows or the underlying organization of ideas in a content domain. So, semantic networks require learners to analyze the structural relationships among the content being studied. They can also be used as evaluation tools for assessing knowledge acquisition.

Semantic networking aids learning by requiring learners to analyze the underlying structure of ideas they are studying. Constructing computer-based semantic nets engages learners in:

- the reorganization of knowledge,
- explicit description of concepts and their interrelationships,
- deep processing of knowledge, which promotes better remembering and retrieval and the ability to apply knowledge in new situations,
- relating new concepts to existing concepts and ideas, which improves understanding, and
- spatial learning through spatial representation of concepts in an area of study (Fisher, Faletti, Patterson, Lipson, Thornton, & Spring, 1990).

Constructing semantic networks and cognitive maps has been shown to be an accurate means for representing cognitive structure (Jonassen, 1987). Semantic networks also provide a useful evaluation tool for measuring the acquisition of knowledge In a geometry class, concept maps were used to evaluate teaching outcomes and to monitor student progress in the course (Mansfield & Happs, 1991).

The usefulness of semantic nets and concepts maps is perhaps best indicated by their relationships to other forms of higher order thinking. They have been significantly related to formal reasoning in chemistry (Schreiber & Abegg, 1991), and reasoning ability in biology (Briscoe & LeMaster, 1991; Mikulecky, 1987). Semantic nets have also been shown to be related to examination performance (Goldsmith, Johnson & Acton, 1991). Knowledge of subject content is more organized after using semantic nets as a study tool (Jonassen, 1994).

Expert Systems as Cognitive Tools

Expert systems have evolved from research in the field of artificial intelligence. An expert system is a computer program that simulates the way human experts solve problems — an artificial decision maker (Grabinger, Wilson, & Jonassen, 1990). For example, when we consult an expert (e.g., doctor, lawyer, teacher) about a problem, the expert asks for current information about our condition, searches his or her knowledge base (memory) for existing knowledge that relates to elements of the current situation, processes the information, arrives at a decision, and presents his or her solution. Like a human expert, an expert system is approached by an individual (novice) with a problem. The system queries the individual about the current status of the problem, searches its own knowledge base of IF–THEN rules for pertinent facts and rules that reflect an expert's knowledge previously stored in the expert system, processes the information, arrives at a decision, and reports the solution to the user.

Although, expert systems are primarily used in businesses as advisors that control processes, they also have many applications in education. A good deal of research has focused on developing expert system advisors to help teachers identify and classify learning disabled students or to assist students in selecting the correct statistical test (Karake, 1990; Saleem & Azad, 1992).

Expert systems can also function as cognitive tools. Trollip, Lippert, Starfield, & Smith (1992) believe that the development of expert systems results in deeper understanding because they provide an intellectual environment that:

- demands the refinement of domain knowledge,
- supports problem solving, and
- monitors the acquisition of knowledge.

Building expert systems requires the developer to explicitly model the knowledge of the expert in a causal manner. Expert systems is one of the only formalisms for depicting procedural knowledge (Gagne, 1987). As learners identify the IF-THEN structure of a domain, they are forced to articulate the nature of decision making tasks; this deeper understanding should make subsequent practice opportunities more meaningful. This is not to suggest that the mere development of an expert system necessarily leads learners to acquire the compiled procedural knowledge of a domain. Starfield and Lippert (1987) found that the analysis of subject matter required to develop expert systems is so deep and so incisive that learners develop a greater comprehension of their subject matter, because building expert system rule bases engages learners in analytical reasoning, elaboration strategies such as synthesis, and metacognition. Lai (1989) found that when nursing students developed medical expert systems, they developed enhanced reasoning skills and acquired a deeper understanding of the subject domain. Physics students who used an expert system to create questions, decisions, rules, and explanations pertaining to classical projectile motion developed more refined domain-specific knowledge due to greater degrees of elaboration during encoding and greater quantity of material processed in an explicit, coherent context, and therefore in greater semantic depth (Lippert & Finley, 1988). MBA students who developed knowledge bases on tax laws in an accounting course were consistently engaged in higher order thinking, such as classifying information, breaking down content, organizing information, and integrating and elaborating information (Knox-Quinn, 1992). All of the students who developed rule bases showed substantial gains in the quantity and quality of declarative and procedural knowledge and improved their problem solving strategies.

This study examined the effects of building semantic nets as a Mindtool on the construction of subsequent expert systems in the same knowledge domain. Semantic nets engage significant knowledge analysis efforts, and they have been used successfully as knowledge elicitation tools for building expert systems (Cook & McDonald, 1987). Further, prior research shows that some type of preliminary knowledge organization task is necessary for expert system generation (Knox-Quinn, 1988; Tamashiro & Bechtelheimer, 1991). Thus, we believed that the knowledge analysis engaged in building a semantic network of a knowledge domain would positively transfer to the sensitivity, elegance, and coherence of the expert system knowledge bases that were subsequently constructed by learners.

Method

Materials

Semantic network and expert system shell software were chosen for their ease of use, availability on a Macintosh platform, and cost. The semantic networking software used in the study was SemNet (Fisher, 1992). SemNet is a Macintosh based semantic networking software tool which allows for easy creation of semantic networks by defining concept—relationship—concept sets, called instances, that describe the relationships between concepts. For example, an instance about dogs might be, dog—has type—border collie.

The expert system shell EXSYS was chosen for creating expert systems. EXSYS was chosen predominantly for its easy, Macintosh–based user interface. EXSYS allows users to create expert systems with probably the least amount of computer science programming type skills. Users construct the if–then rules of the expert system (often considered the most complex portion of expert system construction) by clicking on buttons and selecting previously created factors and choices that EXSYS then uses to create if–then rules.

Procedure

Subjects were undergraduate education students in a large eastern university. Subjects were enrolled in a junior/senior education course on the use of technology in the classroom. Subjects were randomly assigned to either the group that created semantic networks in conjunction with expert systems (hereafter, the SemNet group), or the group that created only expert systems (hereafter, the non–SemNet group). Regardless of the group, all subjects created expert systems. There were three expert system topics for the study. General education majors created expert systems to advise teachers on classroom management and discipline issues; exercise science education majors created expert systems to help a user create a physical fitness program, and special education majors created expert systems to help teachers decide how to handle a potential special education referral.

Once subjects were assigned their topics, they completed one to two page preliminary essays that described their introductory knowledge of their topic. Students were instructed to concentrate on a discussion of the pertinent factors needed to make decisions in their domains plus the likely domain decisions and inter–relationships between these decisions and factors.

All subjects were trained to use the expert system software, EXSYS, as well as in general strategies for creating expert systems. Training was conducted on three separate occasions giving subjects a chance to absorb the content and try out EXSYS between training sessions. In addition, we were available throughout the semester to provide additional help to subjects on use of EXSYS and creating expert systems. Subjects had a total of eight weeks to complete their expert systems.

Those in the SemNet group received training on the SemNet software. This training was conducted separately from the non–SemNet group so there would be no contamination of groups. Additionally, only SemNet group members had access to the SemNet software. Non–SemNet group members completed an alternative assignment in graphics while SemNet group members completed semantic networks. Subjects turned in their semantic networks three weeks after they had been trained. This still left them three more weeks before they turned in their expert systems, thus giving them time to use their semantic network results in their expert systems.

Once subjects turned in their expert systems, they were then instructed to write an ending essay which reflected not only on their specific expert system and its content (i.e. the factors, choices and rules it used), but also their thought processes as they created the expert systems. As researchers, we wanted to know what caused students difficulties, what worked and what could be improved. This ending essay data was supplemented by activity logs that subjects filled out to record the amount of time spent working on the project, and the kinds of activities engaged in during the project.

Results

Of the 32 subjects that began the study, 26 provided all aspects of the data set. Attrition resulted from dropping the course, failure to complete the assignments, and accidental data loss.

Preliminary essays on topic areas were used to determine the subjects entry level knowledge of their topic area. Similarly, ending essays were expected to show subjects' ending level of knowledge as well as an explanation of their reasoning processes during the expert system creation process. The expert systems, themselves, were expected to show an indication of subjects' depth of reasoning in the topic area. Finally, half of the subjects created semantic networks; these networks were analyzed for relationships between the networks and the expert systems. Specific variables collected for each of these data types is described more completely below.

Preliminary Essays. Subjects completed preliminary essays at the beginning of the study in order to show their entry level knowledge of the topic area. A content analysis at the phrase level (Weber, 1990) analyzed this data for the number of factors mentioned as necessary for decision making in the topic area, the number of choices or decisions that this subject considered could be made in the topic area and finally the number of relationships mentioned either between choices and factors or simply amongst factors.

Ending Essays. Subjects were to complete ending essays that addressed the same areas as the preliminary essays (i.e. factors, choices and relationships). However, in spite of specific instructions from the professor, most ending essays did not address these aspects. Thus ending essays could not be analyzed in the same manner as the preliminary essays as originally planned. Instead, this data was analyzed for common categories that were mentioned in many ending essays, such as how learners synthesized in their content area during expert system creation.

Semantic Networks. The experimental group produced semantic networks as a "warm–up" activity for developing their expert systems. Quantitative descriptive data collected for the networks included the total number of relationships in the network, the number of concepts in the network (breadth), the number of concept–relation–concept instances in the network (extent), the number of concepts that participate in three or more instances (enmeshed concepts), a count of the top 25 percent most embedded concepts as defined by counting all possible paths to a concept from two nodes away (central), the number of singly connected concepts (fringe concepts), and the maximum concept embeddedness of the network (max. embeddedness) where embeddedness is defined as the count of all possible paths to a concept from two nodes away.

Expert Systems. The actual expert systems were the main source of data for the study. Quantitative descriptive data collected for the expert systems included the number of rules in the system, the number of qualifiers (or factors) considered while making decisions in the domain, the number of choices (or possible decisions) that the expert system could produce, and maximum and average depths of the rules in the system (i.e. in the rule "if FACTOR A and FACTOR B and FACTOR C, then recommend CHOICE D", three factors are considered thus this rule has a depth of three).

Table 1: MANOVA Results for Independent Variable Group and Dependent Variables Qualifier, Rules, Choices, Sensitivity and Depth

VARIABLE	SS	DF	MS	F	P
QUALIFIERS	14.017	1	14.017	0.235	0.632
ERROR	1492.650	25	59.706		
RULES	360.150	1	360.150	2.001	0.170
ERROR	4499.850	25	179.994		
CHOICES	2.963	1	2.963	0.044	0.835
ERROR	1665.333	25	66.613		
SENSITIVITY	5.202	1	5.202	2.372	0.136
ERROR	54.817	25	2.193		
RULE DEPTH	0.949	1	0.949	0.175	0.679
ERROR	135.329	25	5.413		

A MANOVA showed that preliminary essays between the two groups were not significantly different from on another in terms of their initial knowledge in their domains. A MANOVA analysis was performed on the expert system data to determine whether those who produced semantic networks in addition to expert systems, produced "better" expert systems than those who did not produce semantic networks. Note that "better" is defined by the data attributes, as described above, that were collected for the expert systems. The independent variable was semantic network or non–semantic networking group. The dependent variables were: number of qualifiers or factors, number of rules, number of choices, expert system sensitivity, and rule depth. As shown in Table 1, no significant differences were found between the groups for any of the expert system variables.

Correlations between the data gathered for semantic networks and the expert systems were also computed. This data may be helpful in determining which aspects of the semantic networks are the best predictors of certain attributes of the resulting expert systems. These correlations are shown in Table 2. The semantic network data attributes are listed in the top row and the expert system attributes in the first column. Significant positive correlations occurred between the depth data items from the expert systems and the total number of relations (Ttlrels) in the semantic networks.

Table 2: Semantic Network and Expert System Data Item Correlations

Expert System Variables	Semantic Network Variables						
	Breadth	Extent	Enmesh	Embed25	Ttlrels	Fringe	Mxembd
Qualifier	0.143	0.147	0.042	-0.247	-0.191	0.166	0.492 *
Rules	0.198	0.193	0.168	0.045	-0.100	0.220	0.137
Rule Types	-0.299	-0.278	-0.267	-0.258	-0.627 **	-0.325	0.033
Choices	-0.154	-0.136	-0.064	-0.194	-0.081	-0.126	-0.241
Sensitivity	0.067	0.051	0.072	-0.062	0.365	0.093	-0.120
Max Depth	0.379	0.400	0.405	0.339	0.715 **	0.404	0.305
Avg Depth	0.387	0.376	0.350	0.315	0.731 **	0.425	0.277

Legend:

Ttlrels (Total Relationships): total number of relationships or links used in the network
Breadth: number of concepts in the network
Extent: number of concept–relation–concept instances in the network
Enmeshed Concepts: number of concepts that participate in three or more instances
Mxembd (Maximum Embeddedness): maximum concept embeddedness of the network where embeddedness is defined as the count of all possible paths to a concept from two nodes away.
Embedded_25: count of the concepts that have 25% or more of paths the maximum embedded concept
Fringe Concepts: number of singly connected concepts

* $p < .10$
** $p < .05$

Finally, a content analysis of the ending essays produced the following categories and tallies. As mentioned, the ending essays could not be analyzed in a manner congruent with the beginning essays as subjects consistently did not follow directions to include information about the factors, choices and relationships used in their expert systems. Table 3 shows the categories and their tallies.

Discussion

Early analysis indicates that several factors account for the non–significance of the results. Many of these reasons were clearly and frequently mentioned in the subjects' ending essays (see Table 3). Subjects were clearly not comfortable with the intentionally ambiguous nature of the project. They wished for very specific guidance about how many rules and qualifiers should be in their expert systems. This discomfort with ambiguity indicates this project may have been an early, and perhaps only experience with an assignment whose boundaries are not clearly stated. This in turn could lead to subjects concentrate predominantly on determining when they are *done* with the project rather than on transforming their semantic network knowledge organizations into expert systems.

The study hypothesized that the semantic networking exercise would help learners do a preliminary organization of their content knowledge that would then aid in construction of their expert systems. The data, as shown in Table 1, does not support this hypothesis. The data in Table 3, however, indicates that several students from the semantic

Table 3: Category Counts from Ending Essays

Category	Total Count	SemNet	Non–SemNet
Increased Content Knowledge	14	9	5
Increased Complexity Understanding	4	4	0
no content knowledge increase"	4	1	3
Described Synthesis Process	17	8	9
Semnet to ES Difficult	2	2	NA
Semnet to ES Helpful	1	1	NA
Frustrated - system didn't represent their knowledge	4	2	2
Frustrated - hit 50 rule limit	2	1	1
Wanted more coaching	8	4	4
Specified how to improve ES	4	2	2
Not used to ambiguity	2	2	0
Increased awareness computers classrooms	5	3	2
Increased confidence with computers	7	2	5
Preferred SemNet	3	3	NA

networking group commented on the "difficulty" in moving from the kind of thinking they had to do for creating a semantic network to the kind of thinking necessary for creating an expert system. Perhaps semantic network creation more closely approximates a free flowing brain storming exercise. On the other hand, expert system creation requires that not only one know the factors pertinent in the expert system domain, but understand clearly how and when these factors are related. This is a step or two beyond what one gleans from creating a semantic network.

The obvious conclusion from the above, is that learners needed more scaffolding to move them effectively from the preliminary knowledge organization task they completed in creating their semantic networks to the more structured task of creating the rules for an expert system. Prior to conducting this study, the research considered providing such scaffolding for the semantic networking group. However, given that both groups received a grade on their expert systems, the research and the professor were concerned that such scaffolding for the semantic networking group would have given them an unfair grade advantage over the non–semantic networking group. This decision was made to maintain a sense of equity between the two groups, but may not have been the most sound decision for testing the proposed hypothesis.

While the study did not result in the hypothesized improved expert systems for those who created semantic networks, it did confirm that the subjects experienced substantial amounts of knowledge synthesis in their respective domains. This result is consistent with previous research (Jonassen, 1993; Knox–Quinn, 1988; Lippert, 1988) in this area. Subjects not only reported that they were forced to synthesize and organize their knowledge very completely in order to finish the project (which is a pre–cursor to being better problem solvers in their domains), but that they also preferred this project over that of writing a paper on a topic.

Given the above, a future iteration on this study might consider the following changes.

- Provide more scaffolding between semantic network and expert system creation. For instance, model how a completed semantic network can be turned in to an expert system, thus giving subjects more guidance on how to make the most of their knowledge organization processes used in their semantic networks.
- Or, create a single new expert system shell which uses a semantic networking interface to gather data for creating its rules, choices and factors. This allows subjects to concentrate completely on relationships within the domain without having to use finite cognitive energy to translate their semantic networks into expert systems.
- Collect data on subjects' tolerance for ambiguity. Examine data for a positive correlation between those subjects with a high tolerance for ambiguity and those that create the "best" expert systems.

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