

# **The Influence of Cognitive Mapping, Learning Styles and Performance Expectations on Learning Effectiveness**

## **Introduction**

Learning complex concepts is difficult and often a lengthy trial and error process. Businesses have long been concerned with how best to develop skills and abilities of the workforce (Stevens and Campion, 2004). Knowledge that is hard to substitute or imitate is considered to be a key component of competitive advantage (Kogut and Zander, 1992). Knowledge that is difficult to replicate is generally complex in nature; therefore, requiring a means to represent it in an easier and meaningful form for learning. Developments in computer software for cognitive mapping, provide a platform for learning and integrating complex information in an editable and multimedia format. The use of this software encourages interaction with the course material which sets the stage for meaningful learning. The purpose of this research is to look beyond just the efficacy of the cognitive mapping software for learning and to also understand the factors that may influence performance expectations to use the software, the quality of the maps produced and what role individual learning styles may play.

## **Literature Review**

Cognitive mapping is described as a method used to create a graphical representation of knowledge (Novak and Canas, 2006) and has been used for decades as a means to help those learning do so faster and with better retention (Ruiz-Primo and Shavelson, 1996). Previously cognitive maps drawn with paper and pencil have had positive results (Mavers, et al., 2002; Pinheiro, 1998). Recently software systems have been developed for cognitive mapping that facilitates editing and incorporate the ability to dynamically link concepts between map nodes and external include links to other media.

One potential advantage of cognitive mapping is the promotion of meaningful learning over rote learning. Meaningful learning has been defined as a process in which “symbolically expressed ideas are related in a non arbitrary fashion to what the learner already knows”. There is support in the literature that principles, applications and generalizations are remembered over longer periods of time than factual data (Ausubel, 1968). This integration may facilitate further learning or expose faulty logic (Novak and Canas, 2006). In contrast, rote learning is relatable to cognitive structures in an arbitrary and verbatim manner which may be attributed to a steep drop off in memory (Ausubel, 1968; Novak and Canas, 2006). Despite the arguments for meaningful learning, students may continue to employ rote learning as a response to stress or previous pedagogical experiences (Ausubel, 1968). These predispositions are expected to have a bearing on acceptance of not only new learning strategies, but also the technology to support them.

The basic requirements for meaningful learning have been defined as follows:

1. The material must be presented in a way that is integrateable to the student’s prior knowledge.
2. The student must possess relevant prior knowledge.
3. The student must choose to learn meaningfully (Novak and Canas, 2006)

Cognitive mapping is expected to address the first requirement by providing a flexible framework for concept integration as well as the ability to connect concepts with prior knowledge either by explicit inclusion as nodes within the map or via external links to other media. Active participation required to construct the map also creates the opportunity for “discovery” and “reception” learning. The former being concerned with discerning patterns and regularities in concepts while the latter involves clarification between old and new concepts (Novak and Canas, 2006).

There is some evidence that the second requirement of prior knowledge has been seen when novice mappers build maps around well known concepts whereas experienced mappers create maps around foundation concepts (Stoyanov, 1997). The third requirement involves acceptance of the learning method and will be discussed under technology acceptance.

## Mapping Elements – structure, links and symbols

Cognitive mapping software supports networks made up of concept nodes linked by arrows to produce propositions. The use of clearly defined structures is also indicated in associationist theory which supports unambiguous representation of cognitive elements or groupings between sets of concepts (Deese, 1965). The creation of a cognitive map along with the process of determining hierarchical placement and coherent conceptual groupings is hypothesized to promote meaningful learning through deliberate organization of concepts from the general to the specific.

Integration and relationships between concepts through visual representations are expected to increase over time as the learner gains deeper understanding of the interrelations between concepts. Cognitive mapping software gives the learners the opportunity to assign their own chosen symbology (icons, colors, fonts, clouds, etc.) to visual representations. This is expected to be an aid to retention by maintaining the availability of a replica of acquired new meanings (Ausubel, 1968). The use of chosen symbols may have more personal relevance to students and their pre-existing cognitive structures (See Figure 1).

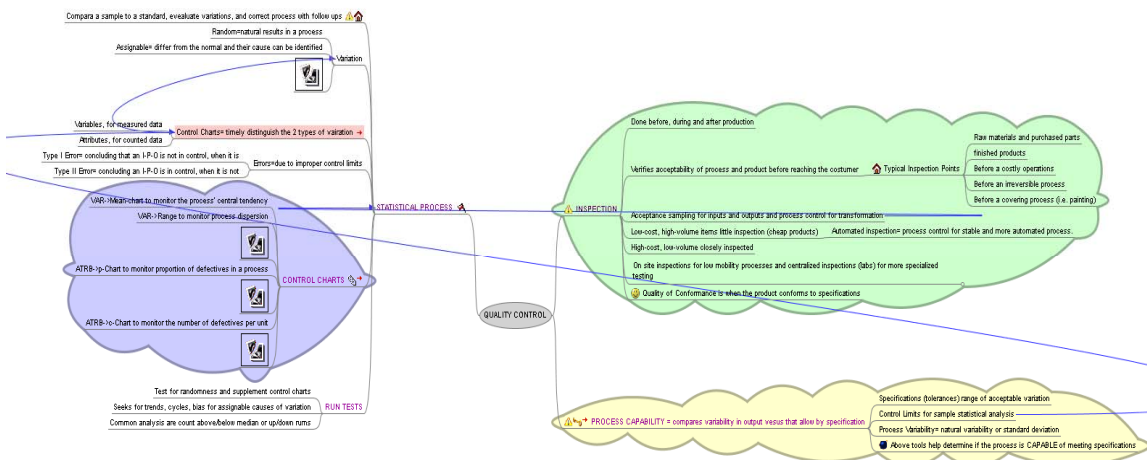


Figure 1: Sample Cognitive map created with FreeMind mapping software

## Learning Styles

Learning styles are preferences for information types (concrete vs. abstract), presentation styles (visual vs. verbal, written) and learning actions such as hands on versus planning and reflecting about a concept (Felder and Spurlin, 2005). Previous studies examined learning styles with hypertext and web-based media (Brown, et al., 2006; Redmond, et al., 2003; Stash, et al., 2004). A difference between this study and the preceding literature is that the former examined learning where the student is not the creator of the interactive materials being used.

In order to assess student learning preferences (styles), the Index of Learning Styles (Felder and Solomon, 1996) was used in which learning preferences are categorized over 44 questions by four dimensions:

1. Active vs. Reflective: active learners learn best if they are doing something with the information – discussing, testing or explaining. Reflective learners prefer time to process the information and think about it.
2. Sensing vs. Intuitive: sensing learners tend to enjoy facts and details; they may appreciate rote learning more. The intuitive learner will be more interested in the relationships of concepts and abstractions and may appreciate a course with more conceptual content.
3. Visual vs. Verbal: Visual learners prefer materials that show relationships of information via graphs, charts, pictures and cognitive maps. Verbal learners prefer written or spoken explanations.
4. Global vs. Sequential: Global learners look for the big picture first and then leap toward a synthesis of how it fits together. Sequential learners prefer information presented in a step-by-step process.

These classifications are consistent with other learning styles assessment tools such as the Kolb Learning Style Inventory (KLSI) (Bostrom, et al., 1990), field-dependence/independence (Witkin, et al., 1977) and the Honey & Mumford Learning Style Questionnaire (LSQ)(Duff and Duffy, 2002; Van Zwanenberg, 2000). The ILS was chosen for this study because it was constructed specifically for the target population – college students engaged in studies with a quantitative emphasis. Several validation studies of the ILS have been conducted and include (Litzinger, et al., 2005; Zywno, 2003) and (Felder and Spurlin, 2005).

## **Technology Acceptance – Performance expectations**

Learning styles alone may not be sufficient predictors of success using cognitive mapping. Technology acceptance has been hypothesized to be a driving factor (Bostrom, et al., 1990) and is therefore included in the current hypothetical model. There is a wealth of literature on IT acceptance containing fairly mature theoretical models such as technology acceptance (TAM) (Davis, 1989) and The Unified Theory of Acceptance and Use of Technology (UTAUT)(Venkatesh, et al., 2003). Since the effective use of cognitive maps in learning requires the learner to work with a new IT artifact, performance expectation (a sub-construct of UTAUT) is expected to affect performance in creating the map and subsequent use of the map.

The UTAUT questionnaire developed and validated by Venkatesh et al. (2003) was used to capture behavioral intent to use the mapping software. It is composed of 31 questions that load on eight factors:

1. Performance Expectancy (PerfEff): Does the student perceive the software will benefit their learning and success on exams?
2. Effort expectancy (EffExp): Will the student perceive the software as easy to use as well as having a degree of usefulness?
3. Attitude toward technology (AttTech): Does the student think the system will be fun and interesting to work with?
4. Social influence (SocInf): Is the student influenced by the opinions of others who support the use of the system?
5. Facilitating conditions (FacFactors): Is the training and support adequate for the student to feel they will be able to competently use the system?

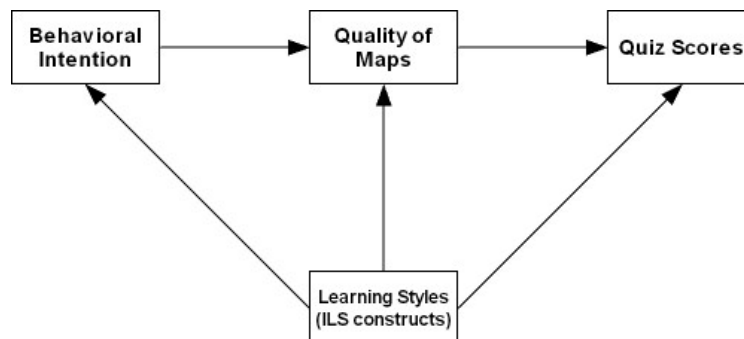
6. Self-efficacy (SelfEff): Is the student confident that they will be able to complete the assignment?
7. Anxiety (Anxiety): IS the student concerned about the system complexity and do they find it intimidating?
8. Behavioral intention to use the system (BehInt): What is the student's intent to use the system past the initial assignment?

## Learning Effectiveness and Cognitive Maps

Cognitive maps have been investigated for their use not only as a learning tool but also as a means to evaluate knowledge. The primary rationale behind the latter is that "the essence of knowledge is structure" (Anderson, 1984) and that interrelatedness is an essential property of knowledge (Ruiz-Primo and Shavelson, 1996). The map presents an externalization of the student's cognitive structure for viewing by both the student and teacher (Ruiz-Primo and Shavelson, 1996).

Based on the literature review, grading systems for maps fell into three categories: grade the map components, compare the map to an expert map, or a combination of the two methods. There did not appear to be a great deal of consensus in the literature on generating an appropriate expert map, therefore the decision was made to grade the map components based on the method developed by (Novak and Gowin, 1984). This method and its variations appeared to be the most widely used in the literature and therefore make it more feasible to compare the results of this study with others.

In summary, this study seeks to investigate potential relationships between learning styles, technology acceptance and possible effects on academic performance (See Figure 2).



**Figure 2: Model for construct relationships and propositions**

**Proposition 1:** There will be statistical differences in the mean quiz scores for students who use cognitive mapping than those who did not.

**Proposition 2:** A given learning style will be positively related to performance expectations.

**Proposition 3:** A given learning style will be positively related to the quality of the cognitive map.

**Proposition 4:** The level of performance expectations will be positively associated with the quality of the cognitive maps.

**Proposition 5:** The quality of the cognitive maps will be positively associated with the learning assessment.

## Methodology

### *Setting and Participants*

The participants were upper division business students enrolled in a single introductory course in Operations Management at a California State University. There were 163 students enrolled. The following describes the quantitative data collection sequence that is summarized in table 1. Data was collected using 4 tools: 1) questionnaire on learning styles (Felder and Solomon, 1996), 2) questionnaire to capture the intent to use cognitive mapping software (Venkatesh, et al., 2003), 3) graded cognitive maps, and 4) graded quiz. Qualitative data was also collected through interviews with students at the end of the study.

**Table 1. Data Collection Schedule Summary**

<b>Activity</b>	<b>Time (Weeks)</b>
Cognitive Mapping Software Training	T <sub>0</sub>
Complete questionnaire on technology acceptance	T <sub>0</sub>
Turn in Cognitive Maps	T <sub>3</sub>
Take Quiz for Cognitive mapping subject material	T <sub>4</sub>
Complete online Learning Style Assessment	T <sub>5</sub>

The students were given a 20-minute introduction and training session on the use of cognitive mapping software. At the completion of the training, the students were asked to complete a questionnaire on intent to use the software (UTAUT) adapted from Venkatesh et al. (2003). All questions, with the exception of the last three questions, were measured on a 7-point scale. The last three questions, on behavior intent, were measured with a 3-point scale.

The cognitive mapping software program used was FreeMind, which is open source and easily downloaded from a Wikipedia page. The students were assigned the task to create cognitive maps, one for each of two textbook chapters: 1) Management of Quality and 2) Quality Control. The chapter on the management of quality is a high-level view of the concepts and philosophies of quality. It addresses subjects such as Total Quality Management and Six Sigma. The Quality Control chapter is tool-focused and addresses several forms of Statistical Process Control Charts. Its goal is to instruct students in the tools to monitor and improve quality. Thus the two chapters were different in nature: the first being conceptual and the second fact-based.

### **Grading System for Cognitive Maps**

The maps were graded on the following variables (See Table 2):

**Table 2: Grading Rubric for Cognitive Maps**

<b>Item</b>	<b>Definition</b>	<b>Score</b>
Concept Nodes	Conceptual item present	1 point
Hierarchy (Novak and Gowin, 1984)	Subordinate concept (child) follows from parent node	1 point per child node
Notes	Explanatory note field	1 point
Cross-links (Novak and Gowin, 1984)	Show connections between concepts	2-points
External links	Hyperlinks to other media	4 points
Visual Aids	Consistent use of icons, etc.	5 points - subjective

A pure count, without quality judgment, of each category was made. After completing the cognitive maps, the students completed a 20-question quiz on the subject material. The quiz material was equally divided between the two chapters and had been used with previous classes. Two weeks after the quiz, the students

were requested to complete the learning styles questionnaire (ILS) online. Not all students completed all four assessments. Only students who completed the relevant sections involved in a regression were included for that regression.

## Results

A two-sample t-test (assuming unequal variances to be conservative) was used to evaluate the null hypothesis that the students who used the cognitive mapping software did no better on quizzes than those who did not. The results of the t-test showed that the null hypothesis was rejected with a  $p < .001$ . There were significant mean differences in test scores for students who created cognitive maps on an identical 20-question quiz than those who did not create cognitive maps; therefore, proposition 1 was supported (See Table 3).

**Table 3. Test of effectiveness of cognitive mapping in improving quiz scores.**

Test Population	# Of students in sample	Average Quiz Score	Standard Deviation	t-Stat	P(T<=t) one-tail
No cognitive mapping	64	18.69	2.62	5.51	< .001
With cognitive mapping	155	20.92	2.92		

The correlations shown in tables 5 and 6 also highlight some interesting relationships. In both chapters cross linking between concepts in a student's map held significant positive correlations with the actions of creating hyperlinks, visual aids and notes. Notes and hyperlinks serve as a means to add information and access to information deemed relevant to the map by the student. The cross links serve the purpose of tying information together, so it would be reasonable to expect that those students who built large amounts of information into their maps would also link that complexity in ways that helped them visualize relationships in that complexity. Another interesting point is that even though these chapters vary greatly in conceptual versus factual information, the students appeared to create them in similar ways: the correlations appear significant in the same grading categories for both chapters.

**Table 5: Pearson correlation coefficient for cognitive map on quality management**

	Primary Nodes	Child Nodes	Cross links	Hyperlinks	Visual Aids	Notes
Primary Nodes	1	-.028	.005	-.051	.007	-.053
Child Nodes	-.028	1	.204*	.157	.089	.100
Cross links	.005	.204*	1	.356**	.369**	.336**
Hyperlinks	-.051	.157	.356**	1	.214*	.268**
Visual Aids	.007	.089	.369**	.214*	1	.147
Notes	-.053	.100	.336**	.147	1	1
* Correlation is significant at the 0.05 level (2-tailed)						
** Correlation is significant at the 0.01 level (2-tailed)						

**Table 6. Pearson correlation coefficient for cognitive map of chapter on quality control**

	Primary Nodes	Child Nodes	Cross links	Hyperlinks	Visual Aids	Notes
Primary Nodes	1	-.036	.001	-.116	-.010	-.071
Child Nodes	-.036	1	.162	.004	.122	-.087
Cross links	.001	.162	1	.282**	.249**	.251**
Hyperlinks	-.116	.004	.282**	1	.232**	.337**
Visual Aids	-.010	.122	.249**	.232**	1	.272**
Notes	-.071	-.087	.251**	.337**	.272**	1
* Correlation is significant at the 0.05 level (2-tailed)						
** Correlation is significant at the 0.01 level (2-tailed)						

The next analysis is on the behavioral intention to use questionnaire (UTAUT). The one factor that stood out was associated with self-efficacy (SelfEff), with a mean of 5.10 and a standard deviation of (.97). This was interpreted to mean the students had great self-confidence they would be able to effectively use the software to complete their assignment. Their attitude towards the cognitive mapping software, susceptibility to social influence and their level of anxiety were just above neutral. This may suggest a wait and see attitude since this questionnaire was provided prior to their actual use of the software.

The correlation matrix in table 8 shows significant correlations among many of the factors. However, Behavioral Intention (BehInt) shows only one significant correlation with any other factor: Performance Expectations (PerfExp).

**Table 8. Pearson correlation coefficients among factors in Behavioral Intention Questionnaire**  
(Venkatesh, et al., 2003)

	PerfExp	EffExp	AttTech	SocInf	FacFactors	SelfEff	Anxiety	BehvInt
PerfExp	1	.524**	.696**	.556**	.460**	.443**	-.136	.264*
EffExp	.524**	1	.641**	.279*	.500**	.505**	-.401**	.069
AttTech	.696**	.641**	1	.663**	.339**	.390**	-.167	.152
SocInf	.556**	.279*	.663**	1	.255*	.292*	.104	.059
FacFactors	.460**	.500**	.339**	.255*	1	.382**	-.172	-.029
SelfEff	.443**	.505**	.390**	.292*	.382**	1	-.264*	.125
Anxiety	-.136	-.401**	-.167	.104	-.172	-.264*	1	-.077
BehvInt	.264*	.069	.152	.059	-.029	.125	-.077	1
**Correlation is significant at the 0.01 level								
* Correlation is significant at the 0.05 level								

These results differed from the initial study by Venkatesh et al. (2003) which was implemented in the workplace. Perhaps employees have a greater expectation of continued software use than students who may have perceived the software as being a one-time event for this particular course. Performance expectations seem to be correlated with all the other factors except Anxiety. This may be due to students' desire to perform well in the immediate class as opposed to long term performance.

The last part of the analysis is associated with learning styles. It is apparent from the learning styles means that students tend to on the average be in the middle of each of the four scales (zero being neutral on the scale which can range from -11 to 11). The structure of the scale is such that a positive means indicates the left-hand side of the scale. Thus although all four scales are relatively neutral, the students tend to be on average, Active, Sensing, Visual, and Sequential indicating a preference for course material and learning environments where facts are visually presented in a logical sequence and with opportunity to work with and discuss the material. Visual appeared to be most important overall scale with a mean score of 3 which is reasonable since cognitive mapping is visual in nature. Also of note are the large standard deviations among the students on all four scales indicating a wide variation among the students in learning styles. (See

table 9) This was also consistent with the variation in the design of the cognitive maps suggesting the students visualized the information in a multitude of ways.

**Table 9. Descriptive statistics for learning style scales (ILS)**  
Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
ACTREF	32	-7	9	2.38	3.916
SYSINT	32	-9	11	1.63	5.598
VISVR2	32	-5	11	3.00	4.458
SEQGLO	32	-8	8	1.25	4.181
Valid N (listwise)	32				

The Pearson correlations for Learning Styles (ILS) identified only one significant correlation between sequential/global (SEQGLO) and sensing/intuitive (SYSINT) of .599,  $p < .01$ , 2-tailed. Comparing the means for the scales with the correlation; it appears that the average student likes fact-based material presented in a sequential fashion.

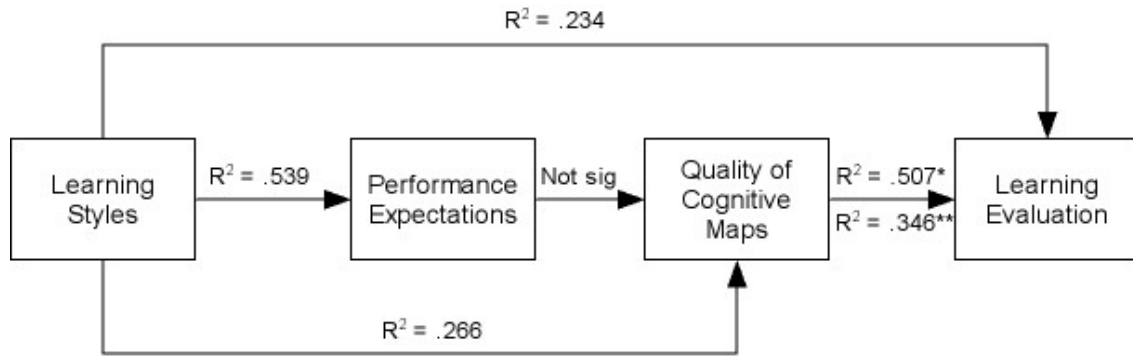
## The Model

SPSS was used to execute stepwise regressions to evaluate the proposed hypotheses and model. The stepwise regressions were all run with the limit of  $P \leq .05$  for variables to enter the equation and a  $P > .10$  to cause removal of the variable. Tolerances for all entered variables were monitored to ensure they were above .30 to protect against multicollinearity. Table 10 provides a summary of the 6 regressions performed and figure 3 shows the proposed theoretical relationships among the model components.

**Table 10: Regression results for propositions and model**

Regression	R <sup>2</sup>	F-Sig.	Dependent Variable	Independent Variables	Beta	t-Sig.
1) Learning style on Performance Expectations	.539	.002	Performance Expectations	SYSINT ACTREF	.638 .551	.002 .006
2) Performance Expectations on map quality			Total points for Cognitive maps	No Significant variables loaded		
3a) Cognitive map quality on Quiz score	.507	< .001	Quiz Score	Total ch10 Hyperlinks ch10	.738 -.541	< .001 .001
3b) Cognitive map quality on Quiz score	.346	.003	Quiz Score	Notes ch9 Hyperlinks ch9	.511 -.472	.003 .006
4) Learning style on map quality	.266	.003	Map Quality	SEQGLO	.516	.003
5) Learning style on quiz score	.234	.005	Quiz Score	SEQGLO	.484	.005

Learning style had a predictive influence on each component of the model and in particular a strong R<sup>2</sup> of .539 to account for the variation existing in performance expectations. The model indicates that performance expectation does not seem to significantly explain any of the variation found in the quality of the cognitive maps produced. Table 10 indicates the unexpected finding that the number of hyperlinks included in a cognitive map has a negative influence on quiz score. The hyperlinks are inserted by the students to support concepts in the learning process and should therefore support retention and conceptual understanding. Future studies may shed theoretical light on this assumption or indicate this was an artifact of the sample size and the students selected.



\* R<sup>2</sup> for Quality Control chapter  
 \*\* R<sup>2</sup> for Management of Quality chapter

**Figure 3: Model for regression results**

## Discussion

The study proposed to answer the questions of how learning style, performance expectations, and cognitive maps interact to influence learning. The results show that the learning scales most important in predicting performance expectations were Sensing/Intuitive and Active/Reflective. The descriptive statistics suggested the average student would learn best when the material is fact-based and they can actively discuss or work with the information. Thus it is reasonable to expect a student would perceive the cognitive mapping software would affect their performance in a positive manner. This was supported with a  $R^2 = .539$ .

A student's learning style is expected to influence the map quality. The students who like to learn by actively working with the information could be expected to find usefulness in creating the cognitive maps and put more effort and time developing them. The regressions show the learning style most associated with cognitive map quality ( $R^2 = .266$ ) as well as quiz scores ( $R^2 = .234$ ) was Sequential/Global. The descriptive statistics for this scale shows only a very weak support of a sequential focus over that of global. This scale is an interesting one in that it addresses the student's preference to learn information in either a sequential presentation or a high level conceptual one. Cognitive maps seem to serve both learning styles: sequential, by allowing the student to build out each concept in detail, one concept at a time; or globally by allowing the student to build by locating all the concepts of the domain at a high level, and then to build in the detail information in support of those concepts.

The data significantly supported the hypothesis that cognitive mapping improved quiz performance (t-test significant at  $p \leq .001$ ). The interviews with the students supported this. They expressed the maps helped them prepare for the quiz. The regressions associated with each of the two chapters showed some light on which components of the map had the greatest influence on the quiz score. The chapter on Quality Management was conceptual in nature. The components of a cognitive map that might prove most effective in learning conceptual material could be visual structure, links among the concepts, notes about the concepts and hyperlinks to WWW pages clarifying some of the concepts. What was found by the regression ( $R^2 = .346$ ) was that the number of notes used was the strongest variable followed by the number of hyperlinks. However, it is curious that the beta for the hyperlinks was negative indicating that the more hyperlinks were used, the poorer the student did on the exam. An evaluation of potential outliers showed this was not the cause. Further analysis with larger samples across multiple classes may shed light.

The chapter that was primarily based on facts and tools, Quality Control, produced a stronger  $R^2$  (.507) between the quality of the cognitive maps and learning evaluation. In this regression, the scale representing

all the components measured on a cognitive map was strongest. This can best be explained that the totality of the all the cognitive map components proves valuable in learning the material.

## **Limitations**

This study was exploratory in nature. More extensive data collection among multiple classes would hopefully uncover the inclusion of other significant variables and provide for a higher level of internal validity. Some of the limitations in this study are:

1. Use of students rather than the workforce: The technology acceptance tool used in the study was validated for work personnel and not students and may explained why performance expectations did not play a role in affecting the quality of the cognitive maps produced.
2. Only one class of students (N = 163) was evaluated: This raises concerns of internal validity and generalizability.
3. Small sample containing all components of study: There were four measures used in the study and students participated in some and not others. The sample size, which included measures for all measurements, was significantly reduced.

## **Future Study**

One of the more powerful aspects of cognitive mapping is the ability to convey relationships between concepts. Future study should include assessment between use of hierarchies, cross-links and academic performance on integrative test questions. Since cognitive maps can be used to build personal knowledge repositories showing relationships between concepts, the use of mapping should be tested in problem solving scenarios as well. The scope of this study was limited to a few constructs. More extensive analysis should be performed using structured equation modeling to generate a more integrative picture of cognitive mapping and cognitive learning constructs. Interviews with students and their learning style results, suggest a possible role for design research in improving the cognitive mapping tool to account for learning styles and improvement of visual display. Students who were interviewed also indicated they started visualizing material in other courses in the same fashion as the cognitive maps – links between topics and hierarchical representations. It may be useful to do a focused study on the effects of cognitive mapping and potential changes in learning styles.

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