A factor analysis of Statics Concept Inventory data from practicing civil engineers

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***Abstract*— This study reports the factor analysis of Statics Concept Inventory (SCI) data collected from 95 practicing civil engineers in the Pacific Northwest. In comparison to students' responses reported from previous studies, the analysis of the engineers' data yielded a different number of underlying latent traits and different loading patterns of the SCI items on each trait. The study revealed that engineers' responses to the SCI might reflect the conceptual coherence associated with knowledge of engineering practice. The engineers' combination of discreet concepts into broader and meaningful concepts in this study might provide the evidence about experts' characteristics in processing, organizing, and storing knowledge in chunks. Understanding the experts' knowledge structure would help inform the development of curricular materials and assessment instruments for undergraduate engineering education.**

Keywords*— *statics concept inventory, factor analysis, novice to expert, engineering education

I. INTRODUCTION

The Statics Concept Inventory (SCI) is a set of 27 multiple-choice questions developed for "identifying the fundamental concepts and typical student errors in statics" [1]. There is a consistent consensus among researchers and instructors that the development of fundamental engineering concepts is viewed as a necessary condition for the acquisition of knowledge in the senior years and the development of engineering expertise [1, 2, 3]. This study examines that consensus by examining conceptual knowledge of practicing engineers.

This study used factor analysis to provide evidence for the existence of underlying unobserved latent traits (or factors) that engineers may have while answering the SCI questions. In previous research, factor analysis was used to detect the conceptual change learners made after a certain period of learning [6]. As experts are believed to recognize underlying principles and be able to store and access information in larger cognitive "chunks" than novices can [7], factor analysis can be used to detect such conceptual changes. The loading patterns of concepts onto the factors from the engineers' data were then compared to the consistent loading patterns of concepts onto the Statics factors from the students' data and the difference would indicate conceptual differences between students and engineers.

II. METHODOLOGY

Engineers were recruited in the study via snowball sampling. Of the 116 engineers participating in the study by taking the SCI in an electronic format through survey monkey, only 95 test scores were valid for analysis. Most of participating engineers are male (70.5%), have an undergraduate engineering education (64.2%), and currently employed in medium sized companies (87.4%, N = 95) with over 100 employees. Their engineering experience varies from one month to forty five years and the average year of experience is 10.74 (SD = 10.43, N = 95). Engineers' data was analyzed for underlying, unobserved latent traits and then compared to the students' traits reported from a previous study [8] that collected test scores from over 1,300 students at 20 institutions during the 2006-2007 academic years. All factor analyses were conducted using the statistics software package SPSS 23 with a cut-off value of 0.3.

III. PROCEDURE AND RESULTS

A. Removing unreliable items from data set

Steif and Dantzler [1] and Jorion et al.[8] analyzed the students' responses on the SCI and extracted 9 factors from the student data set (Table I). This is also the number of areas of Statics concepts that were [1] conceived during the development and implementation of the SCI. This study takes nine Statics factors as an initial guideline in determining the number of factors to be extracted from the engineers' data set. Jorion et al. [8] proved that Question Q26 in the original SCI had the least reliability in assessing students' knowledge. Its difficulty and discrimination indexes (0.16 and 0.18 respectively) were out of the recommended ranges for them (0.20 to 0.80 for difficulty and greater than 0.20 for discrimination) and therefore was removed from the student data set. In the current study, Question Q26 of the engineer data set also had discrimination and difficulty indexes (0.08 and 0.06 respectively) out of the recommended ranges and was removed before factor analysis was conducted.

B. Constructing the tetrachoric correlation matrix

The initial step in the exploratory factor analysis is the construction of a correlation matrix with SCI questions. Pearson correlation makes the assumption that the data consist of continuous and normally distributed random variables and therefore is not appropriate for categorical and binary data [9].

TABLE I. AREAS OF STATICS CONCEPT AND THEIR QUESTIONS IN THE SCI

Areas of Concept/ Factors	Questions
Free Body Diagram	Q1 + Q2 + Q3
Newton's Third Law	Q4 + Q5 + Q6
Static equivalent	Q7 + Q8 + Q9
Roller	Q10 + Q11 + Q12
Slot	Q13 + Q14 + Q15
Negligible friction	Q16 + Q17 + Q18
Representation	Q19 + Q20 + Q21
Friction	Q22 + Q23 + Q24
Equilibrium	Q25 + Q26 + Q27

The engineers' responses of the SCI questions were measured either correct or incorrect so their data is basically classified as dichotomous. Tetrachoric correlation is a suitable measure of association for this type of variables [9, 10]. As the SPSS 23 package does not have any function to evaluate tetrachoric correlation, an alternative SPSS syntax program called Tetra-Com offered by [10] was used to produce a tetrachoric correlation matrix for engineers' data set. The initial tetrachoric correlation matrix was identified as non positive definite because there were negative eigenvalues in the matrix therefore a smoothing procedure was implemented inside the Tetra-Com program based on a technique called nonlinear transformation of the matrix's elements by Devlin, Gnanadesikan, and Kettenring (as cited in [10]). The final tetrachoric correlation matrix then was used to feed to another SPSS syntax program for factor analysis. All SPSS syntax programs can be downloaded from Springer Link's website with reference to [10]'s work.

C. Deternmining the number of extracted factors

The factor analysis was done using Principle Axis Factoring estimator on tetrachoric correlation matrix with both Varimax and Promax rotations. The orthogonal rotation (Varimax) assumes there is no correlation among factors, and the oblique rotation (Promax) assumes factors have correlations with others. The attempts to extract 9, and subsequently 8, factors were terminated early as the communality of a variable exceeded 1 regardless the number of iterations input during the extraction. The scree plot of eigenvalues from the analysis suggests that four factors should be extracted instead of nine because there is a substantial drop in the eigenvalues after Factor 4 (Fig. 1). This number is also far below the ten factors inferred from the same scree plot using the eigenvalue-greater-than-one criterion; which is criticized by many investigators as extracting too many factors in some situations [11]. In an effort to find the best factor structure for the engineers' data, factor analyses were conducted with the number of factors extracted varying from 3 to 7 factors and the results are listed in Table II.

According to Costello and Osborne [12], a factor structure is considered "cleanest" and best fit to the data when factor loading tables have: a) no or few cross-loading items which are the ones loaded on two or more factors at the same time, b) three or more items per factor, and c) loading values from 0.3 and above. The four-factor model was ultimately chosen as the representation of the engineer's data set because it can explain 47.6% of total variance of the original data set and all factors have at least three measured variables loaded on them. Also, the four factor model proved to be the most interpretable because it had a minimum number of cross-loading items. Other factor models that have too many low communality or cross-loading questions may not fit to this study's data.

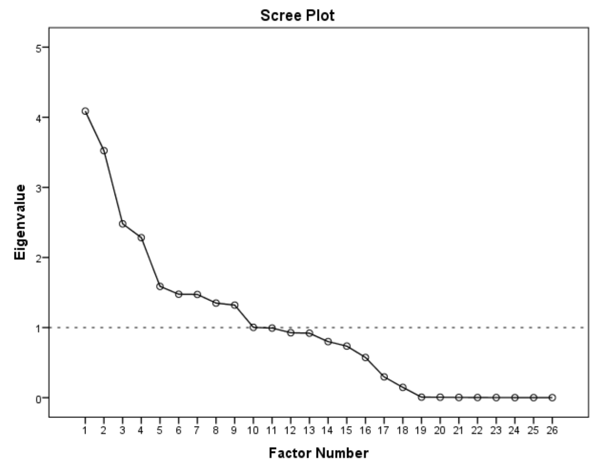

Fig. 1. The scree plot of the SCI engineers' data.

TABLE II. NUMBER OF FACTORS EXTRACTED AND TOTAL VARIANCE EXPLAINED (26 QUESTIONS)

Number of extracted factors	Total variance explained before rotation	Number of factor with two variables or less		Number of cross-loading variables		Variable has no loading on any factor (communality)
		Varimax	*Promax*	*Varimax*	*Promax*	
3	38.81	0	0	1	0	Q7 (0.11) Q14 (0.11) Q18 (0.04) Q22 (0.04) Q27 (0.00)
4	47.59	0	0	2	1	Q18 (0.05) Q22 (0.05) Q27 (0.00)
5	53.69	0	0	4	1	Q18 (0.05) Q22 (0.05) Q27 (0.00)
6	59.37	2	2	6	3	Q18 (0.05) Q22 (0.05) Q27 (0.00)
7	65.03	3	3	4	3	Q18 (0.05) Q22 (0.05) Q27 (0.00)

D. Removing low communality items from the SCI

SPSS generated two statistical measures to help determine the factorability of the data: the Bartlett's test of sphericity and the Kaiser-Meyer-Olkin (KMO) of sampling adequacy. The factor analysis is considered appropriate if the *p* level of the spherricity test is significant ($p < 0.05$) [13]. The KMO test values can be from 0 to 1 and values greater than 0.5 are considered acceptable, values below 0.5 are unacceptable and require more attention from researchers to either get additional data or eliminate low loading variables [14].

The factor analysis test revealed that the engineers' data meets the Bartlett's test ($p < 0.001$) but has a very low KMO measure (0.41). Consequently, as an effort to improve the KMO measure, the removals of low communality questions from the SCI were conducted because getting more data from the engineers is impossible at this stage. Questions Q18, Q22, and Q27 had very low communalities and did not load onto any factor regardless of how many factors had been extracted (Table II). Communality is calculated as the variance in each variable accounted for by an extracted factor and a low communality value indicates that the item has low correlations with all other items in the inventory.

There are three rationale that can be used to justify the removals of low communality items from SCI question pool in this study. First, removing variables with low communalities increases the KMO value, and consequentially, the factorability of a data set [14]. Second, it is anticipated that the future uses of the SCI might not be limited as a testing instrument in the academic environment. Vocational schools and industries might use the SCI, entirely or partially, as a testing instrument to assess underlying traits the people may have on basic Statics knowledge and determine proper training and placements. Finally, the Cronbach's alpha of the reduced SCI test (Table III) after removing the four items ($\alpha = 0.889$, $N = 23$) is better than that of the original SCI test ($\alpha = 0.886$, $N = 27$). Therefore, removing low communality questions from the SCI in this study will not undermine the integrity of the SCI.

TABLE III. CRONBACH'S ALPHA AND TOTAL VARIANCE EXPLAINED OF REDUCED SCI TEST (23 QUESTIONS)

Factor	Number of variables	Cronbach's Alpha	Total Variance Explained
1	6	0.887	21.58
2	6	0.855	16.31
3	8	0.800	10.86
4	3	0.804	10.20
Total	23	0.889	58.95

E. Extracting underlying traits from the engineers' data

Tables IV and V show factor loading tables of the four-factor model with orthogonal (Varimax) and oblique (Promax) rotations, respectively. For factor analysis with oblique rotation, SPSS also reports the inter-correlations among four extracted factors. As a rule of thumb for interpreting the correlation coefficient offered by [15], a correlation less than 0.3 was considered as negligible, from 0.3 to 0.5 as low, from 0.5 to 0.7 as moderate, and greater than 0.7 as high. The inter-correlations among four extracted factors with oblique rotation Promax vary from 0.04 to 0.28 and therefore were considered as negligible. In the oblique rotation table (Table V), Q16 loads on Factor 3 and 4, but because the total variance explained by Q16 in the factors represented by its squared up values, the loading of Q16 in Factor 4 is dropped because of small loading value ($0.37^2 < 0.45^2$). Other cross-loading variables such as Q24, Q16, Q23, and Q15 in Table IV, Q24 and Q15 in Table V were processed using the same rationale.

TABLE IV. ROTATED FACTOR

Item	Factor 1	Factor 2	Factor 3	Factor 4	Communality
Q3	0.85				0.77
Q10	0.85				0.77
Q8	0.72				0.53
Q1	0.72				0.53
Q2	0.69				0.50
Q9	0.69				0.50
Q5		0.75			0.58
Q12		0.75			0.58
Q4		0.69			0.53
Q11		0.69			0.53
Q6		0.66			0.43
Q13		0.66			0.43
Q21			0.64		0.42
Q20			0.63		0.40
Q24		0.44	0.62		0.59
Q19			0.55		0.32
Q16			0.51	0.43	0.61
Q17			0.47		0.23
Q25			0.47		0.25
Q23	0.30		0.34		0.23
Q14				0.96	0.93
Q7				0.96	0.93
Q15			0.32	0.45	0.31

TABLE V. PATTERN MATRIX

Item	Factor 1	Factor 2	Factor 3	Factor 4	Communality
Q3	0.85				0.77
Q10	0.85				0.77
Q8	0.74				0.53
Q1	0.74				0.53
Q2	0.69				0.50
Q9	0.69				0.50
Q5		0.78			0.58
Q12		0.78			0.58
Q4		0.69			0.53
Q11		0.69			0.53
Q6		0.67			0.43
Q13		0.67			0.43
Q21			0.67		0.42
Q20			0.67		0.40
Q24		0.34	0.58		0.59
Q19			0.57		0.32
Q17			0.51		0.23
Q25			0.47		0.25
Q16			0.45	0.37	0.61
Q23			0.32		0.23
Q14				0.98	0.93
Q7				0.98	0.93
Q15			0.31	0.44	0.31

IV. CONCLUSIONS AND FUTURE WORK

The underlying, unobservable trends of engineers' data differ from that of students' data (Table I). The new factors generated from the engineer's responses revealed the changes of underlying, unobservable traits that the engineers might have as the new factors combined knowledge from more than two old factors. Factor 1 combines all questions from Free Body Diagram (Q1, Q2, and Q3), two questions from Statics equivalent (Q8 and Q9), and a question (Q10) from Roller. Factor 2 now includes all Newton's Third Law questions (Q4, Q5, and Q6), two questions from Roller (Q11 and 12), and a question from Slot group (Q13). Factor 3 combines two Slot questions (Q14, and Q15) with a question from Statics equivalent group (Q7). Factor 4 combines Negligible Friction questions (Q16 and Q17) with questions from Representation (Q19, Q20, and Q21), Friction (Q23 and Q24) and Equilibrium (Q25). The new loading patterns of the SCI from engineer data may reflect their conceptual coherence.

These changes might result from the conceptual changes associated with the practices engineers performed in their engineering work. In other words, the engineers may no longer use the basic Statics knowledge as discrete and individual concepts in their designs. Instead, they might integrate the basic Statics concepts into whole and broader concepts that are meaningful and helpful to them. The engineers' ability of combining discreet concepts into broader and meaningful concepts in this study aligns with the research findings about experts' characteristics from the literature. For example, Glaser [16] noticed that experts process and organize knowledge in chunks and then store them in memory in a meaningful manner. Moreover, experts can perceive the meaningful deep structure of the situation while novices have difficulty determining the surface features of the same situation. It was the well-organized chunking system that helps experts have high speed cognitive process [16]. More research is needed to have deep insights into how and the extent to which the basic Statics knowledge and socio-technical context cohere in real engineering practices. Future research on conceptual change in civil engineering could include a longitudinal study to better understand the evolution of basic Statics knowledge for students from junior year to practicing engineers.

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