Empirical Foundations for Improved Engineering Education: Differences Between Engineering Students and Professional Expert Engineers while Designing

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Introduction

Engineering design education strives to equip students with the capability of becoming expert design engineers. To bridge the gap between the design competencies of undergraduate engineering students and expert engineers in the field, educators and researchers require a detailed knowledge of the cognitive behaviors of both cohorts. This research aims to identify novel pathways to approach the cognitive transformation from novice to expert in engineering education.

Dyads of freshmen engineering students, senior engineering students, and professional engineers were recruited to participate in the study. Tools and processes developed in previously funded NSF projects provide a uniform basis; independent of participant educational and experiential background, for measuring and comparing the cognitive behaviors of engineering students and professional expert engineers. It brings together the beginning of engineering education (freshmen), works with students completing engineering education (seniors), and completes the longitudinal development of engineering design by studying professional experts. Understanding differences and similarities between novices as developing learners and expert target performance is essential to identify appropriate learning experiences to reduce this performance gap.

This paper presents updated and additional results to the 2018 ASEE paper on this project (Becker, Gero, et al, 2018).

Design Cognition Research

Building on previously NSF-funded projects that looked at the longitudinal development of design cognition of undergraduate engineering students across two contiguous years (Williams, Lee, Gero & Paretti, 2013), this research seeks to further understand undergraduate student design cognition, but more importantly, to establish an inventory of expert design cognition. Results from a pilot study at a western land-grant university show there is a significant gap between the cognitive behavior of novice and professional expert engineering designers (Song, 2014). Additionally, a meta-analysis of design cognition studies indicated that there are commonalities, as well as differences, between students and professional designers (Gero, Kannengiesser & Pourmohamadi, 2012).

The 10 years and 10,000 hours of professional experience set the benchmark to be an expert engineer (Cross, 2004; Dufresne, Gerace, et al, 1992; Ericsson, Charness, Feltovich, & Hoffman, 2006; Kaufman, & Kaufman, 2007; Kavakli, & Gero, 2002). Unfortunately, the design cognition of expert design engineers is inadequately characterized. Previous studies on expert design behavior have focused on case studies that produced qualitative results (Ahmed 2001; Ahmed, Wallace and Blessing 2003; Baird, Moore, et al, 2000; Marsh, 1997).

Although cognitive studies of design thinking behavior have started to emerge, engineering education research in design is still dominated by explorations of design teaching. Cognitive studies fall into five main methodological categories: protocol studies, interviews (Cross & Cross, 1998), input-output experiments; where the designer is treated as a black box which produces the behaviors in the outputs for changes in inputs (Purcell, Williams, et al, 1993), anthropological studies (Lopez-Mesa & Thompson, 2006), and questionnaires. While each of these methods produce intriguing results, protocol studies is superior. It has become the basis of the current cognitive study of designers (Atman, et al. 2008; Badke-Schaub et al 2007; Becker & Mentzer, 2012; Christensen & Schunn 2007; Gericke, et al 2007; Gero, Kan & Jiang, 2014; Kavakli & Gero, 2002; McDonnell & Lloyd, 2007; McNeill, et al, 1998; Song, 2014; Suwa, et al, 1998; Suwa, Gero & Purcell, 2000; Williams, et al, 2013).

Methodology

Methodologies from design theory, cognitive science, and statistical modeling are used to characterize and model educational experiences of engineering students' and expert engineers' design cognition. From design theory, design ontologies are derived. Cognitive science accommodate for protocol analysis and cognitive style, and finally, statistical modeling is utilized to obtain descriptive statistics, Markov modeling, and problem-solution index.

Since designers vary in educational backgrounds, experiences, and design requirements under different conditions, the *Function-Behavior-Structure (FBS)* ontology from design science is capable of characterizing designing in a uniform way that is independent of the designer, the design task, and the design situation (Kan and Gero, 2017). Consequently, FBS ontology enables the development of more complete models to articulate and quantify the differences between the cognitive behaviors of novice and expert engineering designers.

FBS Ontology

The FBS ontology of designing has been used in multiple disciplines, and one that transcends individual designers, the design task, the design environment, and whether designing individually or in teams (Branki, 1995; Hofmeister, et al., 2007; Jiang, 2012; Kruchten, 2005; Robin, et al, 2007; Van Wie, et al., 2005;Visser, 2006). It models designing in terms of three classes of ontological variables: *function*, *behavior*, and *structure* plus a design description (Gero, 1990; Gero & Kannengiesser, 2014). The goal of designing is to transform a set of functions, driven by the client *requirements* (R), into a set of *design descriptions* (D). The *function* (F) of a designed object is defined as its intended purpose. The *behavior* (B) of that object is either a *behavior derived from the structure* (Bs) or the design itself or an *expected behavior* (Be) from the design. *Structure* (S) represents the components of an object and their relationships.

Different functions for the same design produce different expected behaviors that generate different structures. An example of two different functions invoking different behaviors and different structures for the same design using a cell phone is show in Figure 1.

The FBS coding scheme can be summarized using the design terminology embodied in Figure 1. This produces six codes for the design issues (segments) and those six codes (Table 1) and can be combined to produce eight design processes (Table 2). Figure 2 shows the relationship between the FBS codes and processes.

Figure 1. *An example of functions (F), expected behaviors (Be) and structures (S)*

Table 1. FBS Codes

Code
R
F
Bs
Be
S
D

Table 2. FBS Processes

Design Process	
Formulation	R>F, F>Be
Synthesis	Be>S
Analysis	S>Bs
Documentation	S>D
Evaluation	Be<>Bs
Reformulation I	S>S
Reformulation II	S>Be
Reformulation III	S>F

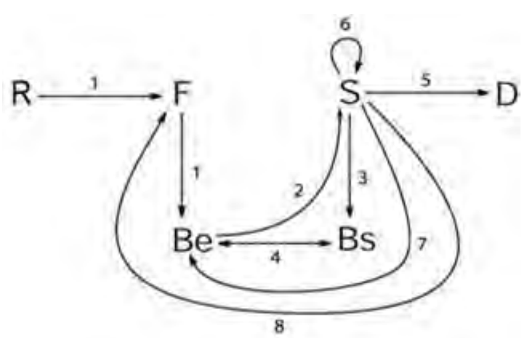

Figure 2. *FBS Codes and Processes*

Research Design

A flowchart of the research design is shown in Figure 3. Grounded in empirical research and the FBS ontology, verbal protocols of 60 dyads of undergraduate engineering students and 20 dyads of professional expert engineers while designing were collected. Twenty sessions from each cohort is sufficient for statistically reliable measures of any differences when the differences are based on a single variable. Expert engineers are selected from design companies in Seattle, Washington, Los Angeles, California and Salt Lake City, Utah. Recruiting expert engineers from multiple geographic location across the country provides a representative sample of the expert engineers in the US.

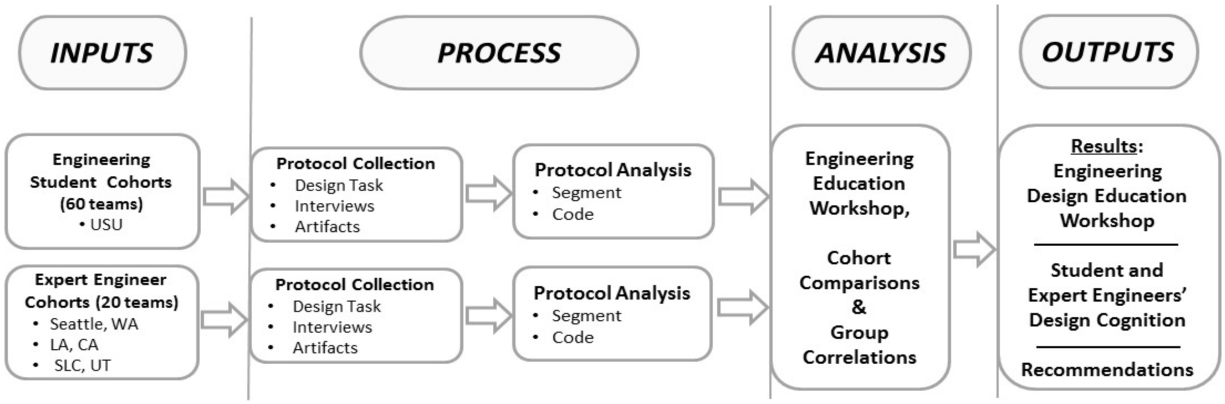

Figure 3. *Research Design: Inputs, Process, Analysis and Outputs*

All teams were presented with the same design task so that they all completed the same functional level engineering design task. The task is related to a window design that is foreign to either the students or the experts. Doing so brings both cohorts on a level plane that is independent of educational background or knowledge domains. Under a one-hour time constraint, teams were encouraged to brainstorm and discuss their ideas. Upon completion, they are asked to present a final sketch of their design. Additional resources including the Americans with Disabilities Act (ADA), ADA Accessibility Guidelines for Buildings and Facilities, a video of the window, and a detailed description of the window's parameters was provided to support their design process.

Twenty-four teams of freshmen students, 19 teams of senior students, and 18 teams of professionals form the source data for further analysis. Due to unexpected challenges in recruiting professionals, the teams of professionals had more diverse background knowledge domains than originally intended. Participants were volunteers who were compensated with Amazon gift cards for their time. Since team members were collaborating, they naturally verbalize. Individual teams' dialogues were video recorded as they progressed through the design session. The verbalizations and gestures are transcribed and the resulting transcripts were coded by two independent coders using a 6 element coding scheme based on the FBS ontology: R, F, Be, S, Bs and D. The coders then arbitrated between themselves when there are disagreements in their coding. In the case where the coders could not come to an arbitrated agreement, the project's principal investigator carried out the final arbitration in conjunction with the session's coders. Four coders were used and were rotated between the coding of the design session to ensure coder triangulation. Cohen's kappa was used to measure the inter-coder reliability, which came up to 0.72. The project also measured each coder's agreement with the final arbitrated code. The average agreement across all design sessions between the coders' codes and the final arbitrated codes was 87.8%

Protocol analysis transformed the video of each design session into a sequence of codes, where each code is associated with a semantic designing concept (Kan & Gero, 2017). These sequences of codes became the data for later analysis. LINKODER (http://www.linkoder.com/) (Gero, Kan & Pourmohamadi, 2011), a publicly available software tool, carries out the standard statistical analysis and other modeling on protocol data.

Statistical Modeling

Various statistical analysis techniques are employed to obtain models from the data sets of the final arbitrated protocols. These techniques enable quantitative comparisons between the different levels of design experience. Other modelling approaches that analyse data at a more granular level will be presented in future papers.

Standard statistical analysis generates the statistical distributions along with their variances of codes in segments in each of the final protocols. This provides the foundation for the characterization of the design cognition of participants.

Two additional specialized analysis; cumulative occurrence models and Problem-Solution (P-S) index, have been developed (Kan & Gero, 2017) and are used. The analysis takes into account the impact of time on design cognition.

The cumulative occurrence $\boldsymbol{c}$ of design issue $\boldsymbol{x}$ at design step $\boldsymbol{n}$ is defined as $c = \sum_{i=1}^{n} x_i$ where x_i equals 1 if design step $\boldsymbol{i}$ is coded as $\boldsymbol{x}$ and 0 if design step $\boldsymbol{i}$ is not coded as $\boldsymbol{x}$. Plotting the results of this equation on a graph with the segments $\boldsymbol{n}$ on the horizontal axis and the cumulative occurrence $\boldsymbol{c}$ on the vertical axis will show the occurrence of the design issues (Kannengiesser, et al., 2013; Pourmohamadi, 2010). In summary, the cumulative design issues are a measure of the time-distribution of cognitive effort across a design session as compared to just the design distributions which have no time dimension. It measures the rate at which participants' expended cognitive effort on the design session is measured by the cumulative occurrence of design issues (Kan and Gero, 2017).

The sequential P-S indexes across different sections of a designing session generate a time-based "signature" of the cognitive style of the activity. When the session is divided into quartiles, the P-S index for each quartile is calculated and used in a sequence of temporally ordered P-S indexes to represent the design style changes during the session. In summary, the *P-S index* is a meta-level model generated by dividing the designing activities into two cognitive spaces: problem space and solution space. Table 3 maps design issues and design processes into the problem and solution space. P-S index is a quantitative measure of the cognitive effort distributed between these two spaces (Jiang, et al., 2012). And is calculated using Equation 1 (below). P-S indexes with a single value facilitate comparisons across multiple sessions and across sessions involving different situations.

$$\text{P-S index (design issue)} = \frac{\sum(\text{Problem}-\text{related issues})}{\sum(\text{Solution}-\text{related issues})} = \frac{\sum(R,F,Be)}{\sum(Bs,S)} \qquad \text{(Equation 1)}$$

Correspondence analysis (Husso, Le & Pages, 2011) is a form of principal component analysis applied to categories rather than individuals. It produces a semi-qualitative representation of the relationships between the categories from which qualitative assessments can be made.

Table 3. *Mapping Design Issues and Design Processes onto Problem and Solution Spaces*

Problem/Solution Space	Design Issue	Design Processes
Reasoning about Problem	Requirement (R) Function (F) Expected Behavior (Be)	1 Formulation 8 Reformulation II 7 Reformulation III
Reasoning about Solution	Behavior from Structure (Bs) Structure (S)	2 Synthesis 3 Analysis 4 Evaluation 6 Reformulation I

Results

Currently, results are based off 18 teams of freshmen, 17 teams of seniors and 18 teams of professional engineers. The last few remaining sessions will be coded and added to the overall results. This draft paper includes tentative results of all the data that are currently available. The *complete* set of results will be ready by and be presented in June 2019.

Standard Statistical Analysis

Here, design sessions are treated as a single unit and statistical results at the aggregate level. The distributions of the cognitive design issues and design processes expressed as percentages are shown in Figure 4 and Figure 5 respectively. Figure 6 shows the slope of cumulative issues of the three cohorts. Results of testing whether there are statistically significant differences in the distributions of the design issues, design processes, cumulative design issues, and P-S indexes between the cohorts are presented. In a future paper, design sessions at a smaller level of granularity, which includes the effect of time across the sessions, will be considered.

From Figure 4, the design issue of *structure* dominating the cognitive effort of the three cohorts is consistent with results from previous design studies (Gero, Kannengiesser and Pourmohamadi, 2014). Design issues of *behavior from structure* and *expected behavior* also played a major role in the cognitive design process. From Figure 5, the dominant design process for all three cohorts is *Reformulation 1*; operating in the structure space. The second dominant process is *Analysis* and the third dominant design processes are *Synthesis*, *Evaluation*, and *Reformulation 2*, which were all approximately in the same range. From Figure 6, the rate at which the structure design issue was generated precede that of *structural behavior* and *expected behavior*.

ANOVA tests with $\alpha = 0.05$ were carried out for the cognitive design issues distributions, design process distributions, cumulative design issues and quartile P-S indexes. Their results are summarized in Tables 4, 5, 6, and 7 respectively. The Between Group degrees of freedom is 2 and Within Group degrees of freedom is 49. Design issues and processes marked with an asterisk (*) indicate that they have smaller samples to draw statistical conclusions from as compared to other issues and processes.

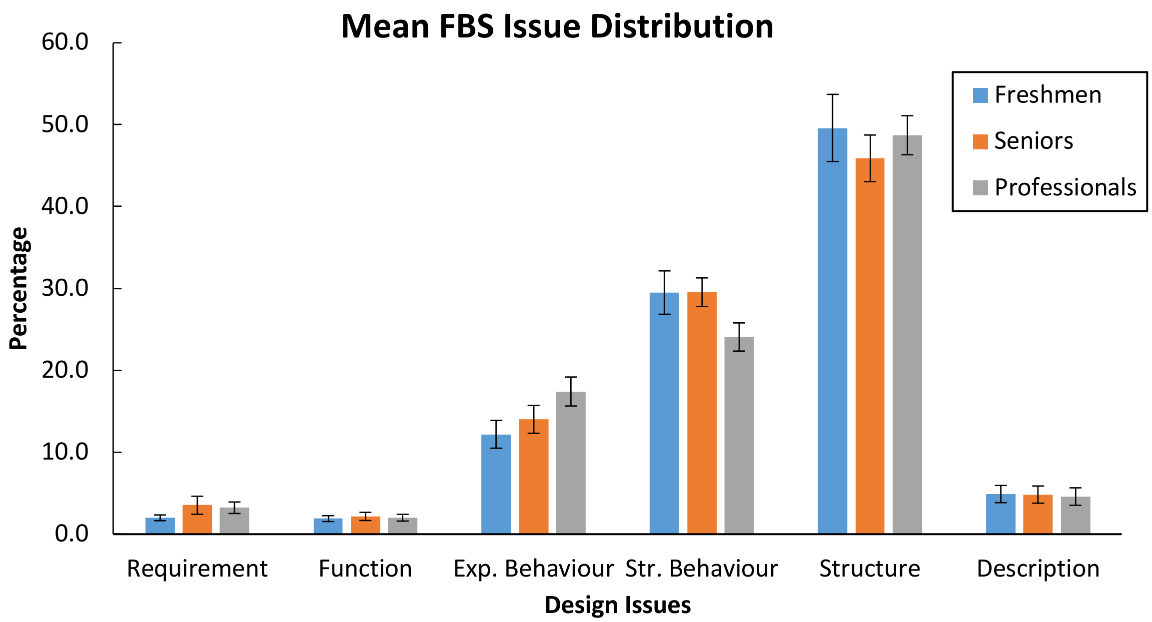

Figure 4. *Distributions of Cognitive Design Issues for Freshmen Seniors and Professionals*

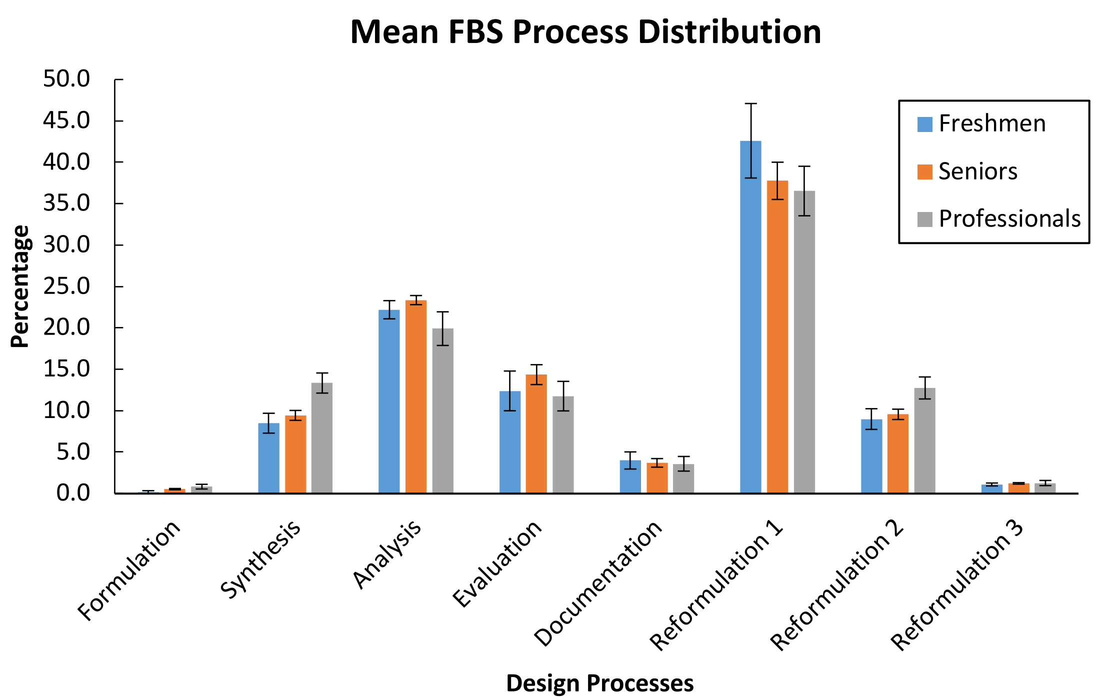

Figure 5. *Distributions of Cognitive Design Processes for Freshmen, Seniors and Professionals*

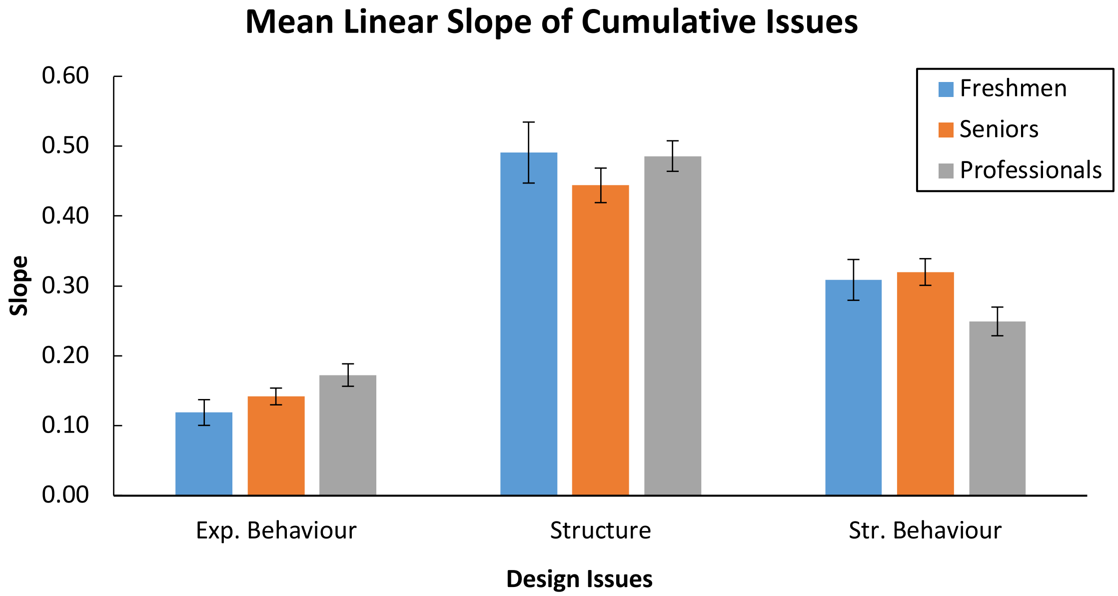

Figure 6. *Mean Slopes of Cumulative Design Issues of Freshmen, Seniors and Professionals*

Table 4. *The ANOVA p-values for Issue Distributions*

Issues Distribution	*p*-Value
R*	0.012*
F*	0.557
Be	0.001*
Bs	0.001*
S	0.220
D*	0.910

*$p < 0.05$

Table 5. *The ANOVA p-values for Design Process Distributions*

Process Distribution	*p*-Value
Formulation	0.002*
Synthesis	< 0.001*
Analysis	0.001*
Evaluation	0.184
Documentation	0.788
Reformulation 1	0.043*
Reformulation 2	< 0.001*
Reformulation 3*	0.529

*$p < 0.05$

Table 6. *The ANOVA p-values for Cumulative Design Issues*

Cumulative Design Issue	*p*-Value
Be	0.0006*
Bs	0.0013*
S	0.1723

$^{*}p < 0.05$

Table 7. *The ANOVA p-values for Quartile P-S Indexes*

Quartile P-S Index	*p*-Value
1st Quartile	0.0090*
2nd Quartile	0.0024*
3rd Quartile	0.0659
4th Quartile	0.0289*

$^{*}p < 0.05$

Table 4 shows that there are statistically significant differences between the three cohorts in the distributions of the design issues of R, Be and Bs. Table 5 shows that there are statistically significant differences between the three cohorts in the distributions of the design processes of Formulation, Synthesis, Analysis, Reformulation 1 and Reformulation 2. Table 6 indicate that there are statistically significant differences between the three cohorts in the cumulative design issues of Be and Bs. Table 7 indicate that there are statistically significant differences in the 1st, 2nd and 4th quartiles of the P-S index.

Correspondence Analysis

To determine if there are categorical differences between the design cognition of the three cohorts, correspondence analysis was carried out on all the data for each of these three cohorts. The six cognitive codes are treated as categories, and Figure 7 shows a qualitative representation of their correspondence analysis. This allows for the determination of whether the codes are indicative of distinct categories of cognitive concepts. The two dimensions generated by the correspondence analysis respectively cover 74.9% and 25.1%, i.e., a total of 100% of the variance implying that these two dimensions are sufficient to describe the categories. In correspondence analysis, which is a form of dimensional reduction, the dimensions are in mathematical space and not in the original problem space. The dimensions are those that minimize the variance of the data coverage and are used to assess qualitative differences between the categories.

Observing the locations of the codes in these two dimensions. R and F sit in the same quadrant, implying that categorically they are close to each other. This matches their roles in designing because functions are driven by client requirements. R, F and Be all sit on the positive side of Dimension 1 implying that they are categorically distinct from the other three codes; Bs, S and D. This aligns with their roles in designing in that they are all associated with the problem space while the other three are associated with the solution space. Bs sits in a different quadrant to S and D, which makes sense because structure is the thing and Bs is derived from, therefore Bs and S should be similar in one dimension but different in another dimension because they are essentially not the same thing. This categorization of the codes used to divide and structure each design session provides an empirical foundation for their use in this research.

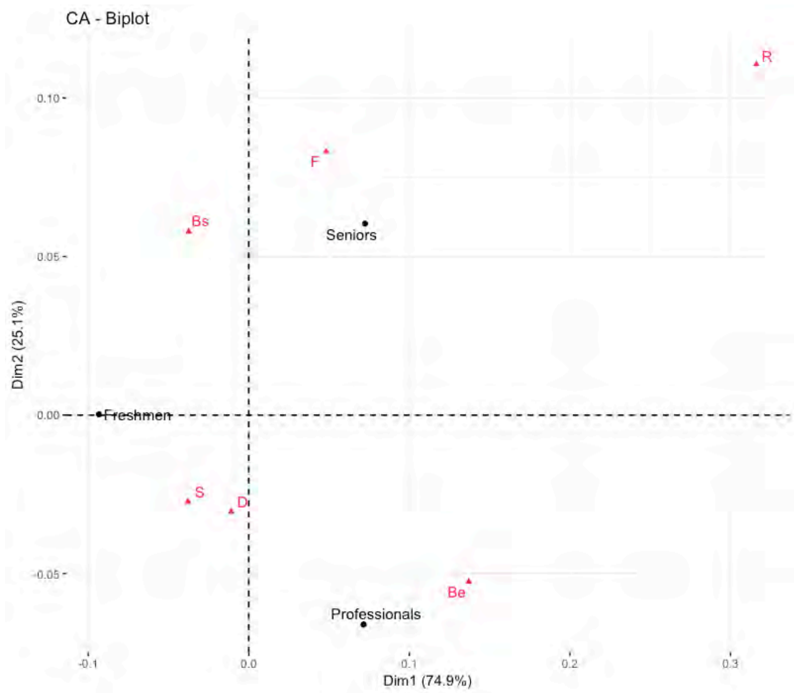

Figure 7. *Correspondence Analysis of Freshmen, Seniors and Professionals in Six Cognitive Categories*

Looking at the three cohorts; freshmen, seniors and professionals, they sit in three separate quadrants as shown in Figure 7. This implies that they are categorically different. The professionals and seniors sit in the positive side of Dimension 1, implying that in that dimension they have some similarities. The freshmen sit on the negative side of Dimension 1, implying that in that dimension they are different to both the seniors and the professionals. The professionals and seniors sit on the opposite sides of Dimension 2 implying that they are different, whilst the freshmen sit in between.

These results establish that there are categorical differences between the design cognition of freshmen, seniors and professionals.

Sentiment Analysis

Sentiment analysis is a technique in natural language processing that determines the sentiment expressed in words or text and categorizes it as either positive, neutral or negative (Baccianella, Esuli, and Sebastiani, 2010; Guerini, Gatti, andTurchi, 2013). It is used here to determine if the cohorts have different sentiments. Later we will see if the sentiments correlate with other design behaviors. As part of the study on the effect of gender diversity we divide the freshmen and senior cohorts into two groups: those with all male teams and those with mixed gender teams and analyze the text from their protocols for their sentiment. Only the sentiment analysis of freshmen and seniors is presented here. We used the Syuzhet method, which is a package in the R statistical language (Ihaki, 2013), based on a custom sentiment dictionary developed in the Nebraska Literary Lab. It iterates over the vector of segments (strings) and returns sentiment values based on a default dictionary whose entries were extracted from a collection of 165,000 human coded sentences (https://github.com/mjockers/syuzhet).

Freshmen had a lower positive sentiment than seniors irrespective of gender, $p < 0.05$ from a repeated ANOVA test. Freshmen had a lower neutral sentiment than seniors irrespective of gender, $p < 0.01$ from a repeated ANOVA test. Freshmen had a higher neutral sentiment than seniors, $p < 0.01$ from a repeated ANOVA test. That is, the sentiments of the participants varied by their seniority in the program but not by gender.

Conclusions

Protocol studies were carried out for freshmen, seniors and professionals while designing with the same design prompt. Results indicate that there are categorical differences between each of the cohorts. Preliminary statistical testing for differences indicated statistically significant differences in design issue distributions and design process distributions between the cohorts. Since statistically significant differences were found, categorical differences are expected.

Cumulative occurrences, which measured the rates of cognitive effort of students and professionals of the design issues, are significantly different – specifically, behaviors (Be and Bs).

Sentiment analysis showed differences between freshmen and seniors, with freshmen being less positive than seniors. This could be due to freshmen's lack of confidence in their design ability. Sentiment analysis of professionals have yet to be carried out.

Further statistical modeling such a Markov modeling will be used to distill this significance at a granular level. Although Markov modeling is not commonly used, it can be applied to design protocols. Design styles and designer's strategies in terms of repeated processes can be assessed by building Markov models of the transitions between design issues and design processes (Kan & Gero, 2017). Markov models (Kemeny & Shnell, 1960) generate the probability of a particular design issue following another particular design issue. Markov models to represent cognitive design style have been used across multiple domains (Kan & Gero, 2017; Jiang, 2012; Pourmohamadi, 2013) and is one foundation for measuring quantitative differences between students and experts. Richer design patterns can be found using second- and third-order Markov analysis.

These results need to be related to specific curricula to determine whether and where curriculum changes could be made to aid students to improve their design cognition in the course of forming themselves into engineers. The results from these types of empirical investigations inform leaders in engineering education and developers of instructional materials and curricula, as well as teachers and designers planning classroom strategies, of initiatives in formal engineering education. The development of educational strategies is explored with the intent to move students along a trajectory towards expert design behavior.

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