Characterizing Students' Intercultural Competence Development Paths Through a Global Engineering Program

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Characterizing Students' Global Competence Development Paths Through a Global Engineering Program

Introduction

Global competence is increasingly recognized as an important skill for engineering students to develop in preparation for their entrance into the engineering workforce [1], [2]. A variety of global engineering programs have been developed to achieve this goal [3], and several studies have assessed the outcomes of such programs [1]. To date, literature on global engineering programs has emphasized program overviews and assessment of student learning outcomes. Although outcomes-based assessment is important for the continuous improvement of such programs, recent critiques of global education research suggest that another perspective is missing from the literature [4]. Few studies explore student conceptions of their global programs and how students may experience the same program in different ways. Understanding variation in students' experiences is important to developing effective global programs, particularly as educators seek to improve the diversity of such programs. To address this need, our study piloted a fully-integrated complementary mixed-methods approach to identify and characterize unique student paths through a single global engineering program.

Literature Review

Global Programs

Much of the literature on global engineering programs explores different program formats and their influence on student learning outcomes. Many studies have focused on the assessment of individual programs [1], although more recently, national studies have begun to compare outcomes across program types [5]. The study abroad literature has similarly emphasized program outcomes, with particular focus on global competence [6]. Such studies have been essential in identifying strengths and weaknesses of existing programs and encouraging best practices across the global education community. Nevertheless, one critique of global education research to this point is that the focus on specific outcomes limits our ability to understand how students experience global programs. Streitwieser and Light [4] argue that emphasizing a single developmental path toward global competence fails to account for individual student identities and prior experiences. These authors present an alternative typology that explores *student conceptions of international experience* and identify four different conceptions that students report in interviews after their global experiences.

A limited number of studies in the global education literature have explored this idea of unique student experiences of global programs. Prior studies have considered student meaning making and transformative learning through study abroad or international service learning experiences [7]–[10]. These studies have highlighted the influence of students' individual characteristics (e.g., personality, prior knowledge, values, motivations) on their interpretation of their experiences and subsequent understanding or perspective shifts [8]. Further, student decisions to engage in global activities after returning from a global experience can increase the long-term influence of the global program on their attitudes and career plans [9]. These studies suggest that although the structure and components of global programs can influence program outcomes, there can still be different pathways for students who have the same experience. As argued by Streitwieser and Light, global education research has often focused only on aggregate program outcomes and not individual student experiences, but individual student considerations should also influence program design [4]. Prior studies on individual student experiences have employed relatively similar methodologies: interviewing small samples of students with supplemented insight from student journals and instructor observations. The current study seeks to complement this previous work by introducing a different method for exploring student pathways through global programs.

Mixed Methods: A Pragmatic Form of Inquiry

As a distinct methodology [11], mixed methods approaches enable researchers to draw inferences beyond what a single paradigm (e.g., quantitative or qualitative) can offer. Each paradigm has unique strengths; the qualitative paradigm emphasizes inductive inquiry and exploration, while quantitative work emphasizes deductive inquiry and prediction [12]. In addition to inherent strengths, each paradigm also includes weaknesses and limitations. Mixed methods research is rooted in pragmatism, so it seeks to leverage the breadth of quantitative inquiry and the depth of qualitative inquiry by "mixing" them in a non-trivial manner; therefore, Creamer defines mixed methods as:

Mixed Methods = QUAL (inductive) + QUANT (deductive) [13]

In Creamer's conception of "mixed methods," studies claiming this label should include at least one deductive component (most often through quantitative inquiry) and one inductive component (most often through qualitative inquiry) [13].

Drawing from both strands of inquiry is particularly useful for examining multifaceted phenomena [14], such as the learning and experiences of students in a global engineering program (the focus of this study). In mixed methods research, quantitative and qualitative strands need not corroborate findings in the sense of triangulation [13]. In fact, mixed methods for the purpose of *complementarity*, or examining different aspects of the same phenomena, may reveal contradictions between quantitative and qualitative strands of data. Unexpected disagreements between qualitative and quantitative strands can prompt the researcher to further examine the phenomena, often resulting in meaningful insights.

In engineering education, mixed methods approaches have been largely underutilized. As a brief example, a review of studies in the *Journal of Engineering Education* revealed that mixed methods have been used in engineering education to explore topics such as instrument development [15], faculty motivation [16], and graduate research group interactions [17]. The studies reporting to have "mixed" in engineering education have been rather homogenous in design – relying, for example, on surveys for quantitative data and interviews for qualitative data [14], [18]. Bryman urges researchers to creatively explore mixing during analysis [19], and O'Cathain, Murphy and Nicholl note that little work has explored mixing qualitative and quantitative strands of data during analysis [20]. Additionally, mixed methods studies in engineering education have been critiqued for failing to establish a clear purpose for mixing, with Kajfez and Creamer calling upon the engineering education community to clearly explain how mixing aligns with the research question(s) [18].

Heeding these calls from literature, our mixed methods study uses a fully-integrated approach to examine the complex experiences of students in a global engineering program. By using an underexplored mixed methods approach to data analysis, we respond to Bryman's request that the community more broadly incorporate mixing strategies in data analysis [19]. We also follow Kajfez and Creamer's suggestions by making explicit our purpose for mixing, emphasizing the alignment between this mixed methods approach and our research questions [18].

Background

The Rising Sophomore Abroad Program (RSAP) is a global engineering program for first year students. It combines a spring semester course on global engineering practice with international modules immediately following the semester. The goals of the program are to help students consider context in their engineering problem solving, develop intercultural teamwork skills, and become interested in and prepared for future global engagement. The course covers these topics through speakers from different departments and industry, group projects, journaling, and case studies. The international modules are 1-3 weeks in length and involve visits to engineering companies, universities, and cultural attractions. The program has grown in recent years to include 180 students on seven different international modules in the 2018 cohort.

Purpose and Research Question

This mixed methods study explores the variation in student experiences in a global engineering program to inform the design, implementation, and research of these programs. Complementarity is the primary rationale for this mixed methods study; more explicitly, our purpose is to meaningfully mix data to draw more powerful inferences than either data source could provide alone. The following mixed methods research questions (RQ) guided our study:

RQ1: How can we characterize the development of global competence among students in a global engineering program? [quantitative]

RQ2: What global engineering experiences are associated with students' varying development of global competence? [qualitative]

RQ3: How can we characterize varied student developmental experiences within a global program? [mixing]

Put simply, utilizing the Cultural Intelligence Survey (CQS), this study examines broad patterns in the development of intercultural competence (quantitative analysis), the global experiences associated with these patterns (qualitative analysis), and a method for characterizing the variation in student development through the program (mixing).

Methods

Our study represents what Creamer refers to as a "fully integrated" mixed methods study, where mixing occurs in the development of research questions, data collection, sampling, analysis, interpretation, and reporting [13]. To elaborate, the following sections will outline the mixing strategy employed.

Mixed Methods Strategy

To address our research questions, we combined cluster analysis of student responses to the CQS with coding of student journals [21]. This study utilized a fully integrated, mixed methods approach with emphasis on the quantitative strand of data. A mixed methods approach was chosen for the purpose of achieving complementarity [13]. This purpose can be achieved by weaving the quantitative and qualitative strands together to create a more comprehensive understanding of the phenomenon of interest: how different students describe their experiences in the study abroad program. We also made use of the sequential nature of our study to inform our purposeful sampling for the qualitative portion of the study. We used the quantitative results to determine different groups of students from which a subset of the participants could be sampled for the second half of the study.

Table 1, modeled after Creamer's overview of mixed methods studies, summarizes features of our mixed methods design. The following sections will describe in more detail the mixed methods strategies, including timing and priority, used in data collection and data analysis [13].

Table 1: Summary of mixed methods characteristics for the study

Feature	**Description**		
Rationale/Purpose	Complementarity		
Priority	Equal		
Timing of Data Collection	Sequential		
Timing of Data Analysis	Quantitative → Qualitative		
Stages Where Mixing Occurs	Design	✓	QUAL, QUANT, and MIXED research questions, methods chosen to intentionally integrate results and refine inferences.
	Data collection	✓	QUANT used to inform sampling in the QUAL data.
	Data analysis	✓	QUANT factors employed as a priori codes for QUAL.
	Inferences	✓	QUAL and QUANT results compared, alignments and misalignments documented.
Meta-Inference	No meta-inference has been generated thus far, as we feel that further qualitative analysis is necessary,		
Value-Added	Analyzing the journals revealed that some student experiences were not captured by coding with the cultural intelligence model, nor did the results of the coding seem related to the differences seen in the cluster analysis. This information will guide future work to understand what factors do influence differential student learning paths. Reading the journals also prompted the coordinators of the program to adjust journaling questions for future offerings of the experience after engaging in the coding process because of the nature of the reflections (e.g., describing what they ate in considerable detail).		

<u>Participants</u>

This paper describes the first stage of analysis in this project. For this stage, we used data from the 2016 cohort of RSAP, which included 91 students who participated in three different tracks: Europe (Italy, Switzerland, and Germany), China, and the Dominican Republic. Demographic information for this cohort is in Tables 2 and 3. In general, the program has larger representation of women and underrepresented students than the population of the College of Engineering (CoE), and the 2016 cohort is no different. All participants signed consent forms agreeing to participate in the research study in accordance with IRB.

Table 2. Gender Breakdown for the 2016 Cohort

Gender	2016 Students
Women	43
Men	36
Not Reported	12

Table 3. Race/Ethnicity Breakdown for the 2016 Cohort

Race/Ethnicity	2016 Students
Two or more	4
Asian	4
Black	3
Hispanic/Latino	6
White	60
Not Reported	14

Out of the 91 participants from 2016, 41 completed the surveys necessary for use in this study. These students represent the sample for the quantitative portion of the study. Nine of these students were purposefully selected for the qualitative portion of the study, using the results of the cluster analysis to guide purposeful selection of these nine students. The full process of selection is described in the data analysis section below.

<u>*Data collection*</u>

The CQS survey was developed and validated using data from undergraduate business students [21]. The survey asks students to self-assess themselves on four scales of Cultural Intelligence, which are described in Table 4 with sample items.

Table 4. CQS Scales and Sample Items

Scale	Description	Sample Item
Cognitive	Awareness of cultural norms, practices, and conventions.	I know the legal and economic systems of other cultures.
Meta-Cognitive	Monitoring and adjusting mental models surrounding cultural norms and practices.	I am conscious of the cultural knowledge I use when interacting with people with different cultural backgrounds.
Behavioral	Using appropriate actions when interacting with another culture.	I vary the rate of my speaking when a cross-cultural situation requires it.
Motivational	Interest and confidence in interacting across cultures.	I enjoy interacting with people from different cultures.

As part of the program assessment process, the CQS survey is administered three times throughout the program: the first day of class, the last day of class, and immediately following the international module. For this study, we used data from the *post-course* and *post-trip* administrations to focus on the influence of the international travel portion of the program specifically.

The qualitative portion of this study examines student journals, which were completed while the students are traveling abroad. The assignment asked students to write an entry each day answering the questions: *What did I do? What did I think? What did I learn?* Student responses vary in length and detail, but all students submitted a journal after returning from their time abroad. The journal was a graded assignment within the course, but grades received on this assignment were not considered for this study.

Data analysis

The data were analyzed in two main phases, quantitative and qualitative, featuring the mixed methods analysis strategy called cross-case comparison [13]. Not to be confused with a case study analysis in qualitative inquiry [22], cross-case comparison involves the construction of holistic and internally coherent profiles by weaving quantitative and qualitative data together such that comparisons can be drawn [13]. In this study, we created the basis of the profiles from our cluster analysis solutions by calculating descriptive statistics for each cluster and tabulating the distribution of the international modules across the clusters. We then used the means (cluster centroids) for the four CQS scales to select student journals written during the international experience to analyze in the qualitative analysis. The journals were coded using an *a priori* set of codes codes based on the four scales of cultural intelligence to explore how students' experiences related to the cultural intelligence model. To integrate the qualitative strand back into the profiles, characterizing quotes for each of the clusters were then appended to the appropriate cluster to complement the descriptive statistics.

Quantitative Strand

Although the CQS measures a form of global competence, its use in this study was not to assess the program but rather to capture variations in student experience. To capture this, we calculated the difference between student *post-course* and *post-trip* scores for each scale on the CQS and used these four variables in the cluster analysis. By looking at differences in scores rather than absolute scores, we could see different types of change (or lack thereof) experienced by students through the international experience. This may not be an ideal way to capture this information, but until Streitwieser and Light complete development of their proposed instrument [4], no existing instrument focuses explicitly on student experience as opposed to global competence outcomes. Because the CQS is a self-assessment, one could view this analysis as exploring how students' perceptions of themselves in relation to other cultures changed over time.

All analysis in the quantitative strand was conducted using R, an open-source programming environment [23]. The quantitative strand utilized *K*-means cluster analysis. *K*-means cluster analysis is an unsupervised machine learning technique that classifies *n* observations into *K* categories, called clusters, centered at their mean such that the within-cluster sum of squares is minimized (i.e., the sum of the Euclidian distances to all the points in the cluster). *K*-means was run using the Hartigan and Wong algorithm [24]. As mentioned, the four variables were simply the changes in the constructs on the CQS (i.e., the students' scores after the international experience minus their scores before the international experience).

The points in the dataset were then matched with the international module in which the corresponding student participated. This was separate from the clustering procedure since categorical data does not mix well with the interval variables in the *K*-means algorithm. Two statistics were calculated for each of the clusters: track frequency and sample mean of the differences. These statistics were used to compare multiple clustering solutions with different numbers of clusters, and the clustering solution with the most coherent profile was chosen through a majority vote during a meeting of the full research team. In making this selection, we looked for the solution where the clusters were of approximately equal size and where each cluster seemed to represent a unique student experience.

Qualitative Strand

Using the selected of the clustering solution, one author not involved in the quantitative analysis sampled journals using the descriptive statistics as the sampling criterion. This process involved identification of three students from each cluster whose CQS scores were close to the average for that cluster. As the goal of the sampling was to further characterize these clusters, we identified representative cases rather than extreme cases through this purposeful sampling process [25].

Two authors were assigned journals for coding without knowing which clusters the journals were a part of or which journals belonged to the same cluster. Both coders coded journals from each of the three clusters to improve the consistency in coding across clusters. The coders used a hypothesis coding strategy [26], which involved coding using the cultural intelligence scales (described earlier). The purpose in selecting this coding strategy was to enhance alignment between the quantitative and qualitative strands of the study, and to explore whether the CQS scales align with the responses students have to their global experiences. Once coding was completed, the codes were quantitized [27], allowing for direct comparison of coding results across clusters. Visual diagrams of coding results were used to aid in the cross-case comparison process and to identify potential connections back to the quantitative results [28].

Mixing the Strands - The Profiles

After the coding was completed, we constructed the profiles for each of the three clusters by comparing the descriptive statistics for each of the clusters with the quantized results of the coding. We looked for patterns in the diagrams of the coding results that might correlate with the differences between clusters that were identified in the quantitative strand. Through this comparison process, early drafts of profiles were developed for each of the clusters. One outcome of this mixing process was the realization that more analysis of the journals using different coding methods would help develop the profiles further. These insights highlight the potentially iterative nature of mixed methods research [29].

Research Quality

Quantitative Strand

The first important figure to consider in cluster analysis is the sample size. Formann recommends a sample size of at least 2^f where f is the number of features (or variables) [30], which was achieved in this study. A more desirable sample size is $5(2^f)$, but this was not feasible for the 2016 data.

Next, determining the optimal number of clusters to use in the *K*-means algorithm can be somewhat overwhelming as no deterministic formula for *K* exists. However, several indices have been proposed to cope with the uncertainty and to guide the researcher in choosing the optimal value of *K*. To calculate a suite of 30 indices, the NbClust package was run on each of the datasets to be clustered [31]. When run, the function outputs the majority ruling on the most popular value of the 30 indices and the totals across the other popular number of clusters.

Pragmatically speaking, the clusters should be logically coherent with respect to the data, which is not necessarily captured within the indices themselves. The internal coherence is stressed, as it is an important feature of the profiles for the cross-case comparison analysis strategy [13]. Three "optimal" solutions to the *K*-means clustering problem with the NbClust's values of *K* were chosen as candidates for the set of profiles based on the three most popular values of *K*. A visualization of the clusters and the respective descriptive statistics - including cross-tabulations of the categorical variable (international module) - were evaluated and ranked by the authors in a meeting. The clustering solution with the most descriptive groupings were chosen then revisited after coding the journals to examine inconsistencies.

Qualitative Strand

In qualitative research, it is important to use multiple methods of increasing the trustworthiness of the results [25], [32]. In this study, we have provided a detailed description of the program and participants, which can help in determining the transferability of our results to a different context [32]. In addition, our team of authors worked together to analyze the results of the qualitative coding process. As only two authors completed the coding, the others provided an external viewpoint on the results and their interpretation. Finally, we report several student quotes as a part of the results, allowing the reader to assess our conclusions themselves.

Mixed-Methods
With the complexity of designs and integrations commonly applied in mixed methods studies, the need for methodological transparency is imperative for assessing quality. The clear identification of design type, rationale, sampling techniques, timing, priority, and mixing strategies all contribute to the quality of the findings generated from a mixed methods study [13]. To maximize the methodological transparency of this study, we have outlined the design approach, timing, priority, and the steps of analysis, each of which are important steps for clearly communicating how and when strands were integrated and what meta-inferences may have resulted from these integrations.

Limitations
There are several limitations in this study. As it is an early attempt at using the cross-case comparison method with cluster analysis and hypothesis coding to explore student experiences, we used only the data for 2016 which represents a relatively small sample size. Further, only about half of the 2016 cohort completed the post-trip survey, which may result in bias within the post-trip results. We believe attrition occurred because the survey was administered in the summer, but there may be other reasons of which we are unaware. Finally, the use of hypothesis coding in the qualitative analysis improved our ability to merge the two parts of study, but also limited the insights that might be gained through the qualitative analysis. We learned valuable lessons through this initial study and discuss our planned adjustments to our methods in the discussion section of the paper.

Results

This section is arranged following the order of the analysis. We begin by discussing the clustering solutions to establish the skeleton for the profiles. Next, we present the results of coding after journals were sampled from each of the clusters. Finally, we bring the two strands together to present the profiles in full.

Quantitative Strand
The *K*-Means Clustering Algorithm produced three viable solutions with 2, 3, and 6 clusters respectively based on NbClust's recommendation. After performing the cross-tabulations of the international modules to determine their frequencies in each cluster and examining the logical cohesion of the groupings given the context, the 3-cluster solution was chosen as the profiles for the 2016 program. The 6-cluster solution contained 2 clusters with 1 and 3 participants respectively, which were determined to be inadequate sizes. Likewise, the 2-cluster solution was heavily skewed with a split of 34 and 7 participants in the clusters. Thus, the 3-cluster solution was chosen due to the more sensible distribution of the data. The centers of the clusters are given in Table 5, and he cross-tabulation of the international tracks across the three clusters is displayed in Table 6.

Table 5. Three Cluster Solution for 2016 Program

	Cluster 1	**Cluster 2**	**Cluster 3**
	Small losses across dimensions, small behavioral gain (n = 14)	Small gains across dimensions (n = 21)	Large gains across dimensions (n = 6)
Features	**Cluster Centers**		
Change in Cognition (M = 0.4674)	-0.3330	0.8827	2.3056
Change in Metacognition (M = 0.3109)	-0.5000	0.7315	2.1250
Change in Behavior (M = 0.3512)	0.2286	0.4148	2.1670
Change in Motivation (M = 0.4780)	-0.1420	0.8000	1.9000

Table 6: Cross-Tabulation of 2016 International Tracks by Cluster

	Cluster 1	**Cluster 2**	**Cluster 3**
	Small losses across dimensions, small behavioral gain (n = 14)	Small gains across dimensions (n = 21)	Large gains across dimensions (n = 6)
Tracks	**Frequency**		
China	2	7	3
Dominican Republic	6	4	2
Europe	6	2	1

Qualitative Strand

This study was a first attempt at coding the student journals for student experience and used a hypothesis coding method aligned with the cultural intelligence scales. We found evidence of each scale within the journals, although some scales (e.g., Cognitive) were far more common than others. We also saw significant variation across journals in terms of how much of the journal content was coded. Although some students wrote much longer journals (page length varied from 4-35 pages), and therefore had larger numbers of codes, the coded portions that mapped onto the CQS dimensions might still represent only a small portion of the total journal content. Figures 1 and 2 depict the coding results by participant.

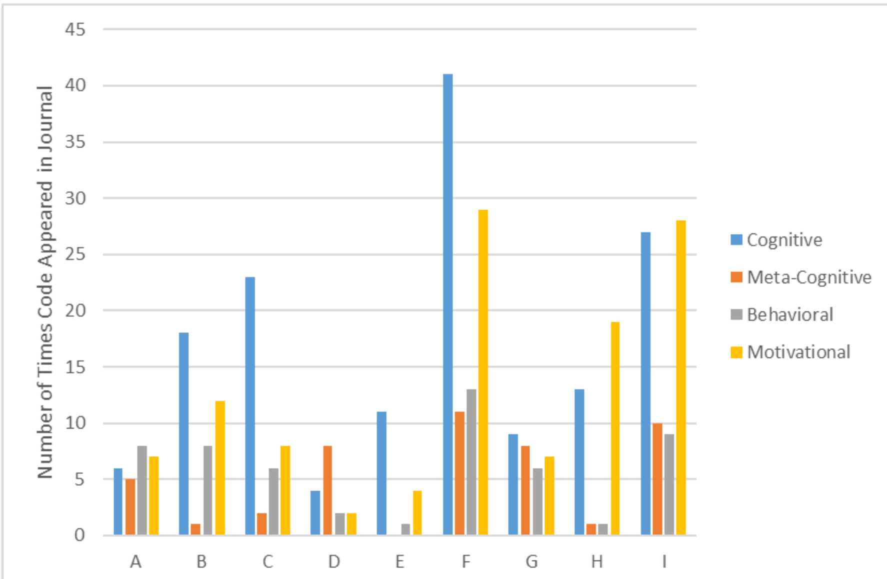

Figure 1. Number of Cultural Intelligence Codes by Participant

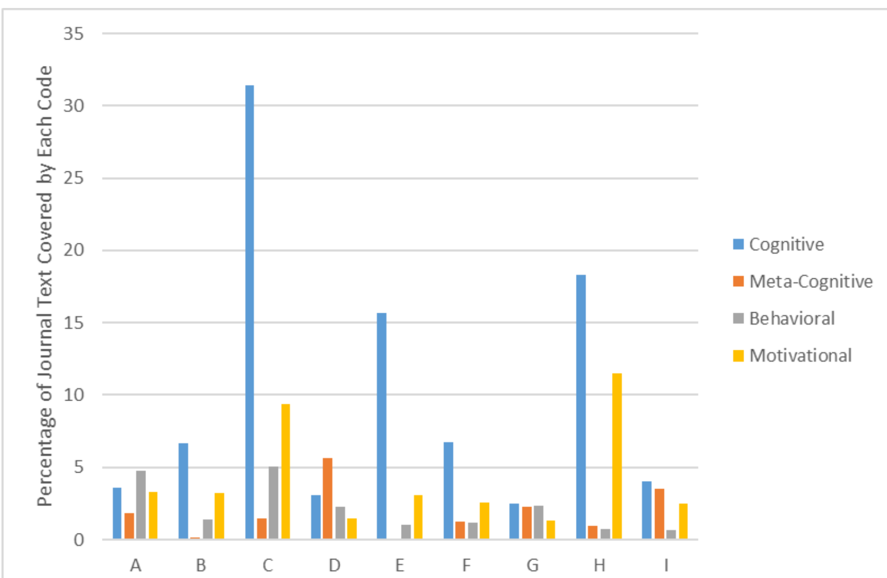

Figure 2. Cultural Intelligence Code Percentages by Participant

To give a more detailed picture of how these scales were demonstrated in student journals, summaries and representative quotes are provided below for each scale.

Cognitive

The cognitive dimension of cultural intelligence was represented most frequently in student journals. It typically took the form of students stating facts about the local culture that they had learned during their activities each day. Some statements were offhand comments during a larger story of what they had done, such as the following quotes:

"We learned that cars do not yield to pedestrians in China- that it actually is the opposite."

"At the same time, Italians seemed more relaxed and less precise in business."

Other participants provided a little more information or context to the cultural differences they had observed, saying things like:

"When Dominicans say it's a lunch break, they actually mean it. We were idle (done eating) for a solid hour before any notion to go back to work."

"Everyone had a "smelling cup" and a "drinking cup" and a lady performed intricate tea ceremonies for us and told us how to properly drink and appreciate tea, as well as the health benefits of each different type of tea."

Finally, there were some cases where participants would make connections between the culture of the local country and previous knowledge or other cultures. For example, some students made the following comparisons to American culture:

"Engineering was very product based as in the United States is a lot more business focused. They were really pushing on the amount of products made and the amount of different types of products produced."

"In the Dominican Republic, people are much more relaxed than in the US. It is ok to be late to things. People are often playing loud music and out in the streets. People in the DR seem to be very happy as they are always dressed in bright colors."

Overall, students talked about cognitive dimension-related topics most naturally in their journals to explain their activities each day. Every journal had several codes from this dimension, and some students had journals substantially focused on these sorts of topics.

Meta-Cognitive

On the other hand, the meta-cognitive dimension was the least likely to appear in student journals and was also the most challenging to code. Because this dimension describes monitoring and adjusting of mental models, the coders needed to determine whether a student statement indicated a change of perspective versus simply learning new information. After some negotiation between the coders, there were three main types of comments that were coded in this dimension. The first were general statements of gaining a new perspective, such as:

"I really got a feel of their culture that day."

"I really have learned a lot about how similar but also different cultures can be and how this can have a dramatic influence on not just engineering, but almost any profession."

Somewhat more specific were cases where students stated that they were "shocked" or "surprised" to learn something, which indicated a change of understanding, such as:

"I was a bit surprised to learn that he listens to artists like 50 Cent and Katy Perry."

"It felt exactly like the street I used to live on, which kind of surprised me."

In other cases, students intentionally reflected on an experience and talked about learning a new way to look at the situation. For example, two students said:

"I was being unintentionally extremely rude by wasting the shopkeeper's time. After that experience, I now know to only give monetary values of items if I actually want to buy them."

"Would I expect the people working in Reagan back home to understand and speak Chinese to a Chinese tourist who lost their luggage? Of course not. Privilege: checked."

Despite the rareness of this dimension of cultural intelligence in the journals, there was evidence that students were thinking this way from time to time. It is possible that the journal prompt did not lead them towards these sorts of reflections as directly as it did toward the cognitive types of comments.

Behavioral

Only slightly more common than the meta-cognitive dimension, the behavioral dimension was also hard to find in student journals. In this case, it might be the nature of the dimension that makes it less likely to occur in student journals. Students would spend most of their time talking about the scheduled activities they had participated in, but rarely got to the level of detail where they would describe specific actions they had taken. The few cases where it came up was when students were describing learning a new skill, such as:

"[Student Name] and I learned how to bargain well and we were having so much fun practicing our new skill."

"I used chopsticks so I was proud."

"I also learned how to properly eat some of the foods I have questioned how to eat for years."

Or alternatively, students talked about trying to use the local language, such as:

"I really attempted to use my Spanish but was disappointed that I couldn't understand them."

"We tried to communicate with the staff as best as possible, but there were moments that we just gave up and spoke in English, I don't think our waitress minded."

"I was overly enthusiastic that I read the correct Chinese symbol for 'bird' in the 'Bird's Nest' sign."

Once again, the fact that these codes occurred so rarely does not necessarily indicate that students were not behaving differently in the cultures they visited, but rather that they failed to talk about it much in their journals.

Motivational

Motivational codes were much easier to apply than the previous two. Students were quick to express interest in the culture around them and willingness to engage with it. In some cases, this was a general expression of excitement, such as:

"I was fully prepared to be amazed and to learn."

"I want to seize this experience to engage myself in the culture and learn from the locals."

"I am hoping to interact more with the locals to get a better understanding of the culture."

In other examples, students talked about specific cultural activities they were excited to engage in or enjoyed. Some students said:

"The food in the Dominican Republic is much better than anything I would have ever expected."

"I loved exploring Lucerne, I would definitely want to return some day."

"The tea house was super cool."

In a few cases, students described steps they took to engage further with the culture beyond the regularly scheduled activities. For example:

"After this I contacted one of the students from Shanghai Tech and asked if he wanted to come out with me and show me the city."

"We've asked him about specific Chinese phrases and words, Chinese culture and customs, what it's like to live in China, where to eat and what to do, lots of things. He's only ever been patient with us and he explains things very well. I absolutely love him as a tour guide."

This dimension was the second most common in the student journals. Although the journal prompt did not ask about motivation specifically, many students seem to have interpreted the "what did you think?" question as an invitation to talk about what they enjoyed or did not enjoy, rather than critically thinking about their experiences.

<u>*Cluster Profiles*</u>

After completing the coding of the journals, we moved to comparing the journal codes across the clusters identified in the quantitative portion of the study. Figures 3 and 4 show the distribution of codes across the clusters based on number of codes and journal percentages.

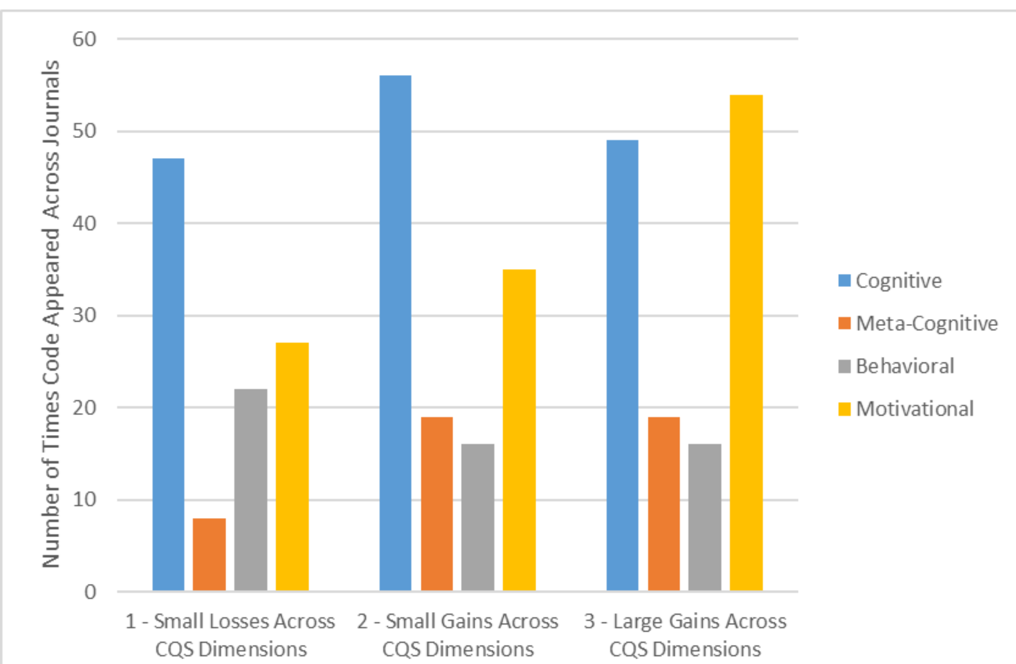

Figure 3. Number of Cultural Intelligence Codes by Cluster

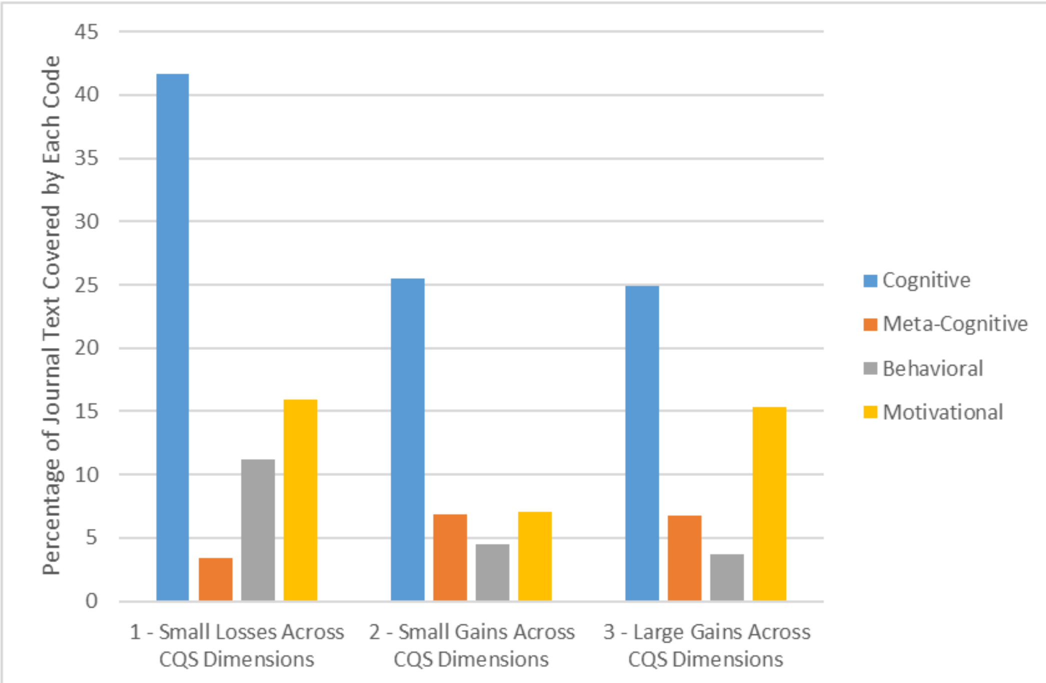

Figure 4. Cultural Intelligence Code Percentages by Cluster

The results from the qualitative coding did not map onto the results from the quantitative clustering as we had anticipated. Although the motivational dimension shows notable differences in Figure 3, these differences are not supported when considering the percentages in Figure 4. Considering both the absolute number of codes and the percentages may be particularly important in this analysis because there were noticeable differences in journal length by cluster. Cluster 1 had the fewest number of pages, while Cluster 3 had the most. This means that Cluster 3 is more heavily weighted by looking at the absolute numbers, while Cluster 1 appears much stronger when using percentages. Although considering page length may be a worthwhile comparison on its own with respect to the depth of reflection, it does not say much as there was also considerable variation within clusters. Table 7 summarizes the page lengths of the journals by cluster. *Average length* indicates the average number of pages across the three journals in each cluster, while *total pages* is the sum of pages across the three journals.

Table 7. Summary of Journal Lengths by Cluster

Cluster	Average Length	Minimum	Maximum	Total Pages
1	6.67	4	10	20
2	11.33	5	22	34
3	17.67	6	35	53

Thus, the real differences appear to be in the maximum length of the journals, which brings up the average and the total number of pages, while the minimum remains approximately the same.

In summary, our attempts to merge the quantitative clusters with the qualitative coding revealed no apparent alignment. This was disheartening, but the disappointment reveals the triangulation mindset common to mixed methods approaches. As described earlier, although researchers hope that the different strands of a study will lend strength to their overall arguments, another possible outcome is that the different strands will disagree. In our case, we did not see complete disagreement, but rather that the connection between the clusters and student journal content was not as strong as we had suspected. We see two possible reasons for this: a) the coding process we used failed to capture student experiences that are tied to changes in CQS scores or b) the journals are not the best way to understand these key student experiences. These findings caused us to go back and reconsider our earlier decisions about both the cluster analysis and the coding processes.

We decided to conduct further descriptive statistics on the original participants to see if other defining characteristics of these clusters might help tell their stories. Specifically, we looked at the *post-course* and *post-trip* CQS scores themselves (across all 41 participants). This process uncovered insights that provide a useful starting point for future research. We particularly observe different starting points for the clusters on some or all of the scales, in contrast to relatively similar ending points. Figures 5 and 6 summarize the results of this analysis.

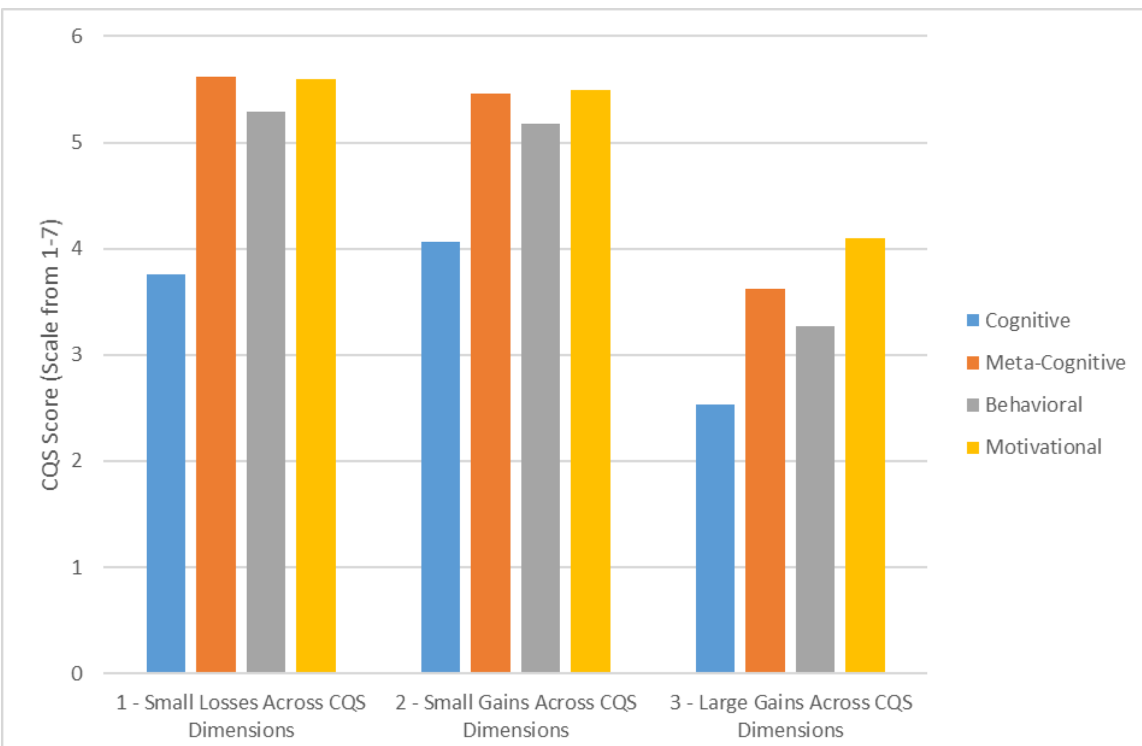

Figure 5. Post-Course Mean CQS Scores for All Participants

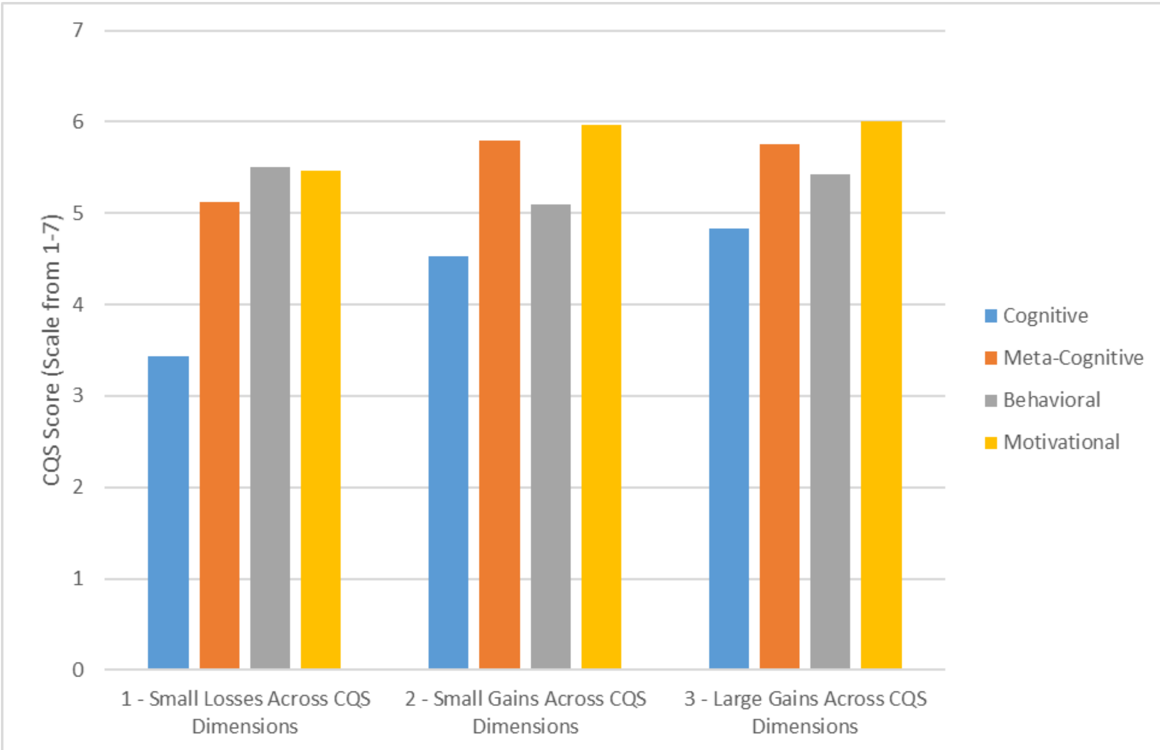

Figure 6. Post-Trip Mean CQS Scores for All Participants

At this point, we do not have a full story about the experiences of students in each cluster, and plan to continue further analysis of the journals. What we have observed so far across our various types of analysis is summarized in the sections below.

Cluster 1 – High Scores, But No Change

Students in this cluster start out with high CQS scores post-course, particularly in meta-cognitive and motivational scores. However, they see little to no change in their post-trip scores, or perhaps have realized that there is a lot more they don't know about the world, which results in a drop in Cognitive scores. The Cluster 1 students' journals have the highest percentages that are coded, which may indicate more focused writing. It is notable that they have nearly equal total numbers of codes in their journals to the other clusters despite having significantly fewer pages total and on average.

Cluster 2 – High Sores, Little Change

These students start out with nearly identical CQS scores to those in Cluster 1. However, they see small increases (i.e., 0.5 points) in all their CQS scores, except for the behavioral scale, after traveling abroad. Their journals include similar percentages as the other clusters for most dimensions except for motivational, where this cluster has a noticeably lower percentage of codes. Thus, although they start at a similar place to the students in Cluster 1, something about the students in this cluster or their experience seems to be different, although we have little evidence currently to explain causes for this differential.

Cluster 3 – Low Beginnings, But Large Growth

Students in the final cluster start out with the lowest CQS scores, giving them much more space to grow. Accordingly, they tend to see much larger growth (i.e., 1-2 points) in CQS scores for all dimensions. In the end, they catch up to the other clusters in CQS scores by the end of the trip, and in fact have the highest averages post-trip for both the cognitive and motivational dimensions. Their journals are the longest on average in pages, but only achieve the same percentage levels of coding as the Cluster 2 students, except for higher incidence of motivational codes. It is possible that the exceptional growth experienced by these students is simply due to where they start off, but their long journals could indicate a greater focus on reflection, which could be a contributing factor.

Discussion

This study explores a unique way to study student learning through global experiences. First, by incorporating both post-course and post-program assessments, we focused on the pathways a student follows through the program as opposed to simply the outcomes achieved at the end. Second, we presented a mixed-methods approach to capturing this experience, unique from the mostly interview-based studies that have been done before. The quantitative strand of our study used a *K*-means clustering analysis to identify three clusters from differences in student CQS scores before and after their travels abroad. We used these results to purposefully sample participants to focus on during the qualitative strand of the study, where we coded participant journals using hypothesis coding based on the CQS dimensions. Finally, we attempted to combine these results into cohesive stories characterizing the experiences of students in the three clusters.

The cluster analysis revealed three trends in the ways that students change in their self-assessment of their cultural intelligence before and after traveling abroad. We anticipated that students' self-assessment before traveling might be a meaningful factor in how much change they experienced, but we were surprised to find that two clusters started at the same point and experienced different levels of change. To date, our qualitative analysis has not provided enough insight into why these differences occurred. We believe the limited insight may be related to our decision to use hypothesis coding, which may have limited the insights that we were able to draw from the journals. Through conducting this coding process, however, we now have a better sense of the kinds of information students include in their journals. This pilot study has sparked several ideas for alternative coding methods that might reveal more notable insights into the reasons for the cluster results. We have plans to continue the coding analysis of these journals to see if we can understand our current findings at a deeper level. If we can identify a coding scheme that captures differences in student experiences more thoroughly, we will expand this study to include the 2017 data, for which we have a larger sample available.

A second major outcome of this project has been the re-design of the journal assignment for the study abroad program. Having multiple readers of the journals and coding for multiple dimensions revealed that students tend to focus heavily on cognitive-related topics and fail to reflect much deeper than the facts that they are learning each day. Part of the difference is connected to differing rates of development for different scales, but we suspect that part of it is also due to the specific questions used in the assignment prompt, which asked "what did you learn?" The question may be most easily interpreted by students to refer to facts, since that is often what engineering students are learning in their classes. In response to these observations, we presented an introduction to reflection at the beginning of the 2018 course, and incorporated reflective components with opportunities for feedback throughout the course. Finally, we adjusted the journal assignment to include a full page of reflection questions that students can ask themselves to step beyond simply the facts of what they have learned or experienced to consider how they responded, how it relates to their previous experiences, and how they might apply these lessons moving forward. We look forward to analyzing the journals that result from this adjusted assignment and comparing them to the 2016 and 2017 journals to see how the changes in the course influence student reflection.

Finally, this study highlights opportunities offered by mixed-methods research. Although we found thought-provoking results in our quantitative cluster analysis, the quantitative strand does not help us understand what experiences are correlated with the observed results. To address this weakness of quantitative research, it is helpful to complement it with a qualitative component to dig deeper into the phenomenon of interest. In our case, we have not yet succeeded in identifying aspects of the student experience that characterize the identified clusters with the desired level of description. Other approaches to coding will likely be needed to tease out the nuance in the different student experiences. Nevertheless, we believe that the potential is there and will continue to build on these initial results. If we cannot find differences in the journals, we may reconsider whether the quantitative instrument is a reasonable way to explore the questions we are interested in or pursue alternative methods for gathering qualitative data. The lack of clear alignment in the results from our methods is always a potential outcome of using a mixed methods approach, and indeed, might be considered one of the strengths of this methodology. In this case, the benefit of mixing methods and producing a contradictory result is that it may help us improve our data collection procedures. We hope that by sharing what we have tried so far, other researchers will able to build upon these ideas about how to study global engineering programs in a creative and exploratory fashion.

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